

The effect of gamification elements on novice users' cognitive load while learning software applications via e-learning systems

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The effect of gamification elements on novice users’ cognitive load while learning software applications via e-learning systems

Ali Darejeh

A thesis in fulfilment of the requirements for the degree of

Doctor of Philosophy

SCHOOL OF COMPUTER SCIENCE

FACULTY OF ENGINEERING

THE UNIVERSITY OF NEW SOUTH WALES



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Chapter 1

Introduction

1.1. Introduction and problem statement

Lack of computer literacy is a serious problem which can hinder those with lower computer literacy from many opportunities and isolate them in society (Eliana, et al., 2016; Ivanković, Špiranec, & Miljko, 2013; Koltay, 2011; Popovic, 2003; Wilson, Scaliseb, & Gochyyev, 2015). Computer illiterate people or users with limited computer literacy are users who have lack of knowledge and working experience with computer software which can be because of users' age or a variety of cognitive, emotional and sociological difficulties (Goldman et al., 2010; Martin & Madigan, 2006; Sengpiel & Dittberner, 2008; Tyner, 2014).

Learning a new productivity software application can be difficult for novice learners as it often involves menus, tabs, and toolbars laid out with many different sections and a great number of tools and functions, that can make the application incomprehensible for novice users (Fang, Luo & Xu, 2011; Reis et al., 2012). Productivity software applications are designed to generate databases, documents, spreadsheets, charts, presentations, paintings, video, audio, etc (Strickland, 2008).

In order to have an efficient use of software, an effective training method is essential that integrates psychological based guidelines with modern training technologies in order to increase learning performance by decreasing learners' cognitive load, which means decreasing the total amount of mental effort in learners' working memory (Sweller,

1988). To the best of this researcher's knowledge, few studies have been conducted on facilitating learning software especially for novice users (Dong, et al., 2012).

Software teaching is considered as one of the most important topics in human computer interaction (HCI). Based on HCI studies, in order to optimize software teaching, three strategies should be implemented: a) enabling learners to explore software features, b) centering training around the real tasks of users, and c) using appropriate computer-based tools to facilitate learning (Bannert, 2000). It is also very important that the teaching method can decrease learners' cognitive load as well as providing practical knowledge.

To this end, this series of studies tried to find a solution to provide practical knowledge to learners and decrease their cognitive load using real world examples in addition to enabling learners to explore different software features using real tasks in e-learning platforms. Narrative, which is a core element of gamification science (Dickey, 2020; Plass, Homer & Kinzer, 2015), is selected in this research as a technique to integrate examples and connect the new information with the existing knowledge in long-term memory of the learners. The narrative provides a theme to training and gives a role to the learner in a scenario (Pagulayan et al., 2002; Palomino et al., 2019). The positive effects of using integrated examples and connect the new information with the long-term memory are supported based on linking principle of cognitive load theory (Sweller, 2016).

In addition to evaluating the effect of narrative, the effects of two other elements of gamification, including interactivity and talking avatars on learners' cognitive load, were evaluated in this study. Interactivity is involved in delivering the narrative-based content through clickable animations that can simulate software environment and the talking avatar is added to play the role of a virtual teacher in a narrative-based e-learning system.

Gamification is an emerging research area in computer science, especially human computer interaction (Deterding et al., 2011; Huotari & Hamari, 2012) which is defined as having game thinking in software design in order to engage users in the context by creating a sense of fun (Hakulinen, Auvinen & Korhonen, 2013; Hamari, Koivisto, & Sarsa, 2014). Although, there are different studies that evaluated the effect of gamification elements on motivation, to the best of researcher knowledge, the effect of gamification elements including narrative, interactivity and avatar on cognitive load have not yet been examined. Furthermore, there is no study that emphasizes how to provide practical software knowledge to users by considering their cognitive load, in order to learn software applications with the use of e-learning platforms. Therefore, this series of studies tries to fill these gaps through investigating the effect of narrative on cognitive load and how its efficiency can be increased through different delivery approaches and adding a talking avatar.

1.2. Purpose of the study

This series of studies are an attempt to investigate the effect of three elements of gamification including Narrative, Interactivity and Avatar on the cognitive load of learners in order to learn elements with low and high interactivity of software applications through e-learning platforms. To this end there are three research questions:

1. How is the cognitive load of novice users affected by applying a narrative with a familiar and unfamiliar Context to the tutorials of elements with low and high interactivity?
2. What is the effect of interactivity on delivering narrative-based content (animation versus interactive animation)?

3. What is the effect of a talking avatar versus plain audio on the cognitive load of learners in narrative-based interactive e-learning systems?

Based on the research questions, three integrated experiments were conducted. In the first experiment, the effect of familiar and unfamiliar narrative was evaluated. The results showed that familiar narrative led to superior performance when compared to an unfamiliar narrative and no narrative. Therefore, in the second experiment, the effect of interactivity was evaluated in order to deliver the narrative-based contents. Teaching software using e-learning systems including animation and interactive animation, were compared. The findings revealed that the interactive animation was superior to the animation-based version. Finally, the last experiment evaluated the effect of a talking avatar versus plain audio on cognitive load of learners in narrative-based e-learning systems that used interactive animation.

Although there are three types of cognitive load including intrinsic, extraneous, and germane load that can affect the learning performance, when the teaching approach is manipulated just the extraneous cognitive load can be affected directly. Therefore, the focus of this study is on evaluating the effect of gamification elements on extraneous cognitive load. A complete explanation of different types of cognitive load is presented in the next chapter (section 2.3.1).

It should be noted that, the purpose of this study is not designing a gamified system or evaluating the effect of gamification elements on a gamified e-learning system. Since if the experimental elements of this study are evaluated in conjunction with the other elements of gamification, there will be different variables at the same time that can affect the study accuracy. Also, it will be difficult to understand whether the difference between

the groups was because of the experimental element or it was the effect of combination of the existing gamified elements.

1.2.1. Justification of selecting Narrative, Interactivity and Avatar

There are many different gamification elements such as Point, Badge, Level, Status, Interactivity, Avatar, Map, Narrative, and Leaderboard, however, most of them can only influence the learners' motivation and engagement with the system. By considering the purpose of this study, which is evaluating the effect of gamification elements on cognitive load, therefore only narrative, interactivity and avatar were selected to explore further. In contrast with the other elements of gamification, these three elements are added to the content of the teaching materials that can potentially affect cognitive load.

1.3. Scope of the research

This study uses quantitative measurement methods in order to evaluate the effect of five independent variables on cognitive load of novice learners while learning productivity software applications through e-learning platforms. A summary of the research scope can be seen below:

- Theoretical framework: Cognitive load theory.
- Target user group: users who are above 18 years old and are not very computer literate.
- Target software group: Productivity software applications.
- Learning environment: E-learning platforms that use multi-media content that is not gamified.
- Measurement method: Quantitative with a mix of subjective and objective measurements.
- Dependent variables: extraneous cognitive load is measured through difficulty Likert-scale questionnaire, learning duration, test performance mark and duration,

mouse movement and number of clicks. Measuring the other types of cognitive load and motivation are out of the scope of this research.

- Independent variables: Familiar Narrative, Unfamiliar Narrative, Interactive Animation, and Talking Avatar.

1.4. Significance of the study

Since there are few studies in the area of teaching software applications and how we can provide practical knowledge to learners, this study can be used as a reference. Designing e-learning systems based on the findings of this study can facilitate self-learning and help learners to gain practical knowledge without increasing their cognitive load. It increases the efficiency of e-learning systems which leads to decreasing cost and time of learning productivity software applications.

This research helped to understand the effects of narrative, interactivity and avatar elements of gamification on learners' cognitive load. It is important as gamification is in a preliminary level in the area of computer science and few studies exist that have applied gamification to learn productivity software. Consequently, the findings can improve gamification science as well as contribute to discover solutions for decreasing cognitive load of novice users for learning productivity applications through e-learning platforms. While there is extensive discussion and focus on the motivational aspects of gamification, very little attention has been placed on the associated cognitive load (Turan, et al., 2016).

1.5. Thesis chapters

The rest of the contents in this thesis is structured as follow:

Chapter 2 covers the literature review related to cognitive load and its application for teaching software applications. It presents a background of the cognitive load theory

including human cognitive architecture, evolutionary cognitive principles, different types of cognitive load, and cognitive load effects. Then, a detailed review of various techniques that can be used to reduce cognitive load in teaching software while using e-learning systems will be elaborated. Afterwards, various approaches that can be used to measure cognitive load especially in the context of e-learning systems will be presented. Finally, I will discuss the effect of different types of teaching methods on cognitive load and at the end a conclusion will be drawn.

Chapter 3 presents a literature survey related to gamification followed by the studies that applied gamification in the e-learning systems and used gamification techniques for teaching software applications. The chapter ends with a discussion on the gaps identified in the literature.

The next three chapters describe the empirical studies carried out as part of this thesis and present the methodology and the core findings of the research. Chapter 4 presents the first experiment in which two contextual types of narrative were compared with a no-narrative condition in order to teach software applications. Chapter 5 covers, the second experiment which evaluated the effect of interactivity in order to deliver the narrative-based contents. It is compared, the effect of animation versus interactive animation on cognitive load of learners while learning software using narrative-based e-learning systems. Chapter 6 describes the third experiment in which a talking avatar is added into the narrative-based e-learning system that used interactive video to see whether the talking avatar can affect the cognitive load of novice users while learning software applications.

Finally, chapter 7 concludes with a concise summary of a critical analysis of all the three experiments findings. Then the findings are tied into the existing literature and their implication for cognitive load theory, gamified e-learning systems, and teaching software

applications are presented. Finally, the limitations and future directions of this study are listed.

Appendices A, B, and C present the content of the no-narrative, familiar and unfamiliar context narratives. Appendix D presents the test tasks and appendix E shows marking rubric of the test tasks. Appendices F and G present the Likert scale questionnaires of the tutorials and the test tasks. Finally, appendix H presents the computer skill placement test form and appendix I shows the project consent form.

Chapter 2

Literature review on cognitive load theory

2.1. Introduction

In this chapter cognitive load theory and its application for teaching software applications is discussed. We started by describing human cognitive architecture followed by different types of cognitive load and instructional effects of cognitive load. Then, the techniques that can be used to reduce cognitive load in teaching software while using e-learning systems is elaborated. Afterwards, different methods for measuring cognitive load, especially the methods that can be used in the context of e-learning systems, are presented. Finally, different types of teaching methods based on the amount of guidance and their effects on cognitive load are discussed and at the end a conclusion is drawn.

2.2. Human Cognitive Architecture

Based on Atkinson–Shiffrin memory model, human Cognitive Architecture consists of three main parts including sensory memory, working memory, and Long-term memory (Atkinson & Shiffrin, 1968). Sensory memory is responsible for collecting stimuli from different senses, working memory holds and manipulates small amount of information in a short period of time, and Long-term memory is used to store and retrieve information (Shaffer, Doube, Tuovinen, 2003). Figure 2.1 shows the interaction between different memory units.

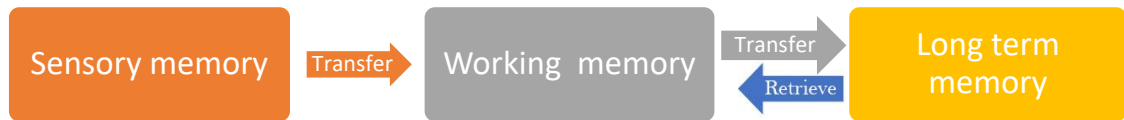


Figure 2.1: Interaction between different memory units (Atkinson & Shiffrin, 1968)

2.2.1. Sensory memory

This memory obtains stimuli from different senses including hearing, sight, smell, touch and taste, then transfers them into the working memory. However, the duration that this memory can keep the information is very short and if the mind cannot identify and make meaning from the input stimuli, the information will be lost (Paas & Sweller, 2014; Shaffer, Doube, Tuovinen, 2003). In sensory memory, the information is raw data that is only a snapshot of a person's overall sensory experience (Istvan & Cowan, 2005). An example of sensory memory is when we see or smell something and can remember what it looked like with just a second of observation.

In contrast with the other types of memory, sensory memory is out of cognitive control and cannot be developed via practice. Although, sensory memory is considered as a part of the process of perception, it is not an essential step to process information in working memory.

2.2.2. Working memory

Working memory refers to structures and processes for temporarily storing and manipulating small amount of information (Diamond, 2013). Working memory performs information manipulation and involves active processing of information. Therefore, working memory is an important element of logical analysis and decision-making processes, consequently thinking highly depends on working memory and attention together (Malenka, Nestler & Hyman, 2009). Based on Miller (1989), the number of

elements that can be held in working memory is 7 ± 2 at any given time, however, Cowan (2001) believes that this number is 4 ± 1 elements.

2.2.3. Long-term memory

Long-term memory is a large storage of information which is the central structure of human cognitive architecture (Sweller, 2008). It is a permanent storage of experiences and knowledges in a highly structured manner. The stored information in long-term memory is held outside conscious awareness until specific information is recalled into working memory. In other words, Long term memory is just a structured storage capacity and cannot execute information without transferring them into working memory (Baddeley, 1992). By increasing knowledge in long-term memory, information is refined, and automation of schemata is enhanced.

2.2.4. Schemas

A schema refers to the information that is stored in long term-memory as structured knowledge that helps problem solvers to recognize the type and category of a problem, and retrieve an appropriate action to solve the problem (Sweller, 1988). In other words, schemas describe patterns of thought or behavior that are formed in the long-term memory of experts based on their previous experiences. It is used to retrieve information for the problems that completely or partially match the existing schema (Ericsson and Kintsch, 1995; Sweller, 1994).

When people start to learn a new concept, information is divided into the small chunks, however, as learners' familiarity with the domain of concept is increased, these small chunks of information will be integrated and form a schema. Thus, schema for a complex

concept may have multiple relationships to other schemas (Bruning, Schraw, & Ronning, 1999; Sweller, 2003).

A schema represents information in different levels of complexity and forms hierarchies of different information categories and the relationships between them. In fact, learning occurs once a new schema is shaped or existing schema is changed, or individual schemas combine to shape complex schemata.

For example, imagine young children who have not seen any animal, see a dog for the first time. They may develop a schema for the dog with these characteristics: dog walks on four legs, has a tail and is hairy. However, when these children go to a zoo for the first time and see the other animals such as lion, tiger or cheetah, they may initially think these animals are dogs as well, since these animals have similar characteristics as the dog schema.

If the children's parents explain that these animals are different as they are wild animals, they do not bark, etc., the existing dog schema of the children will be modified and create a new schema for the wild animals. As the children learn more about animals, they will develop more animal schemas. Furthermore, their existing schemas for different animals will be updated to accommodate any new information they learn about animals. The schema formation process is the same for learning any knowledge such as mathematics, science, new languages, etc.

After a schema is constructed, it should be automated by sufficient practice in order to enable learners to use the schema to solve the similar problems and tasks (Baddeley, 1992; Sweller, 2003). Automation of schemas can save working memory resources as less effort is needed in order to process the new information that is in the framework of the

constructed schema. Therefore, when a schema is automated the familiar tasks are performed more accurately and easily, and unfamiliar tasks can be learned more efficiently as maximum working memory capacity is available. Without automation of schemas, familiar tasks may be completed, but performance is not as efficient as using an automated schema (Sweller, 1998). Therefore, when we learn a new mechanical, geometrical or computer programming concept, we should practice the newly learnt concepts using different examples in order to form an automated schema (Cooper & Sweller, 1987; Van Merriënboer & Paas, 1990).

2.3. Cognitive load theory

Cognitive load theory (CLT) is a pedagogical theory that provides instructional guidance based on human cognitive architecture and our knowledge of evolutionary psychology (Sweller, Ayres, & Kalyuga, 2011a; Sweller, Van Merriënboer, & Paas, 2019). Cognitive load is defined as the total amount of mental effort which is utilized in working memory to learn a concept or solve a problem (Sweller, 2011; Sweller, 1988). CLT places emphasis on the limitations of working memory to accept new information during learning (Paas Renkl, & Sweller, 2004; Sweller, 1988; Sweller, Ayres, & Kalyuga, 2011a).

As explained above, human cognitive architecture refers to the elements of human cognition including sensory-memory, working-memory, long-term memory and the way that they organized and interact with each other. Although, long-term memory capacity is not limited and humans can memorize and recall unlimited information during their lifetime, working memory is limited and can be overwhelmed if the input information is out of its capacity (Cowan, 2001).

Evolutionary psychology indicates the categories of knowledge that are important when considering instructional design (Geary, 2008, 2012; Geary & Berch, 2016; Sweller, 2016a). Geary divides knowledge into biologically primary knowledge that we have evolved to acquire automatically and biologically secondary knowledge that is acquired by conscious effort and that we have not specifically evolved to acquire (Sweller, 2011).

Primary knowledge consists largely of generic-cognitive skills such as general thinking skills, or general problem-solving skills such as means-end analysis that involves comparing the current state of a problem with the desired outcome and any skill that we learn unconsciously. In contrast with primary knowledge, secondary knowledge consists largely of domain-specific skills that require conscious effort to learn and we generally must be taught. Based on this explanation, learning software applications that are the main focus of this study require the acquisition of secondary knowledge and the teaching approach plays an important role in acquiring the necessary knowledge to work with software.

The human cognitive architecture relevant to domain-specific, secondary knowledge can be described by five principles that in more general terms also describe the processes of biological evolution (Sweller & Sweller, 2006). Information can be acquired in two ways: by obtaining information from other people, incorporated in the borrowing and reorganizing principle or by a random generate and test process during problem solving, incorporated in the randomness as genesis principle.

Based on the borrowing and reorganizing principle almost all information that is stored in our long-term memory is borrowed from the long-term memory of the other people either through listening, reading or imitating. Although, the new information is borrowed

from other humans, that information does not copy exactly, and it is constructed and combined with existing information in our long-term memory.

The borrowing principle only works when previously learned schemas are available, however, in the absence of those schemas either the problem solver cannot solve the problem or novel moves are generated via trial and error to find a solution which is supported by the randomness as genesis principle (Sweller, 2006). When information cannot be obtained from the available information through the borrowing principle, the only way to obtain the new information is the randomness as genesis principle. In fact, new information is created via the randomness as genesis principle and the borrowing principle just re-organizes information and cannot create new information.

New information is first processed in a limited capacity, limited duration working memory via the narrow limits of change principle before being stored in long-term memory via the information store principle. The narrow limits of change principle states that obtaining information through both the borrowing and the randomness as genesis principles is a slow and incremental process as human working memory is severely limited. In contrast, the information store principle emphasizes that human long-term memory is sufficiently large to store a great range of information (Sweller, Ayres, & Kalyuga, 2011).

Lastly, the environmental organizing and linking principle allows us to transfer very large amounts of stored information from long-term memory back to working memory in order to generate action that is appropriate to the environment in which we find ourselves (Sweller, 2016). Without the information store and environmental organizing and linking principles, our natural information processing system will not be functional as the stored

information in our long-term memory should produce an action that is adapted to the environment (Sweller, Ayres, & Kalyuga, 2011).

This cognitive architecture indicates that the purpose of instruction is to allow us to store large amounts of domain-specific information in long-term memory in order to allow us to function effectively in the variety of contexts. Cognitive load theory has used this cognitive architecture to generate a wide variety of instructional effects with each effect based on multiple, overlapping randomized, controlled trials. The aim of those effects is to reduce the number of elements that need to be processed simultaneously in our limited working memory and so to facilitate the transfer of information to long-term memory.

2.3.1. Types of cognitive load

There are three types of Cognitive load including Intrinsic load, Extraneous load and German load. These cognitive loads interact to impact on the total cognitive load of a learner.

2.3.1.1. Intrinsic load

Intrinsic cognitive load is defined as the natural complexity level of a specific instructional topic. It is fixed and cannot be changed, except by alerting the learning content or knowledge level of the learner. Intrinsic load is related to the amount of required activities to achieve a learning goal and determined by the level of element interactivity of learning materials (Sweller, 1994).

2.3.1.1.1. Element interactivity

In cognitive load theory, Element interactivity is an index to measure the complexity of a learning topic and depends on the learners' prior knowledge, nature of the materials and

the relationship between the concepts that learners should connect and process simultaneously (Chen, Kalyuga, & Sweller, 2015; Marcus, Cooper & Sweller, 1996; Sweller, 2010; Sweller, 1994). Elements with low interactivity can be learnt in isolation, without or with the minimal reference to other learning elements, for example, learning the features like bold, italic and underline in MS Excel. However, elements with high interactivity consist of different integrated elements that cannot be learnt in isolation, for example, typing functions in MS Excel (Sweller, 2010). By increasing the number of interacting elements, working memory load will be increased, that can make learning the target concept more difficult.

We can decrease the element interactivity and intrinsic load of high element interactivity software tools either by decreasing the amount of content learners must assimilate or by increasing learners' expertise. In fact, isolated information can help the novice learners learn each element of a complex concept separately without overwhelming their working memory (Cowan, 2001).

2.3.1.2. Extraneous load

Extraneous cognitive load is related to the difficulty level of instructional materials. In comparison with intrinsic load that depends on the nature of instructional content, extraneous load depends on the way that instructional materials are designed and presented (Van Merriënboer & Sweller, 2005). Therefore, instructional designers can enhance learning performance by designing appropriate teaching materials that increase working memory resources by reducing extraneous load (Chandler & Sweller, 1991). In fact, when the intrinsic load is high the best way to reduce cognitive load is decreasing extraneous load by minimizing mental resources that are allocated to deal with teaching

materials so that working-memory can use its maximum capacity to deal with the instructional topic (Sweller, 2010).

As an example, in order to teach geometric shapes, there can be two different ways, the first one is drawing the shape and the next one is describing it verbally. Describing a shape verbally can increase extraneous load since students need to process extra information to visualize and understand the shape. Therefore, if the instructor draws the geometric shape, it can increase the available capacity of working-memory that result in a more efficient learning.

Similar to intrinsic cognitive load, element interactivity can affect working memory load underlying extraneous load. If element interactivity can be reduced with altering the teaching approach, the load is extraneous, however, if element interactivity can only be altered by modifying the nature of the teaching content, the load is intrinsic (Beckmann, 2010). Applying instructional design techniques such as using worked examples (see 2.4.1) rather than problem solving and teaching the new concepts using familiar information that already has been stored in long-term memory can be useful approaches to decrease element interactivity underlying extraneous load. Also, extraneous load can be decreased by providing necessary fundamental knowledge before teaching a concept (Sweller & Cooper, 1985).

2.3.1.3. Germane load

Germane load is defined as the process of construction and automation of schemas associated with learning a new topic (Sweller, Van Merriënboer & Paas, 1998). Germane load, similar to extraneous load, depends on the quality of designing and presenting instructional materials. In other words, an instructional design that uses working memory

capacity efficiently will decrease extraneous load, consequently germane load can be increased, and formation of schema will be facilitated (Paas & Van Merriënboer, 1994). While we want to keep intrinsic and extraneous load to minimum, germane load should be increased by using the techniques such as connecting new information with the learners' prior knowledge or applying worked examples (Grobe & Renkl, 2007; Van Gog et al., 2009).

Some researchers consider Germane load as a complementary load to intrinsic and extraneous loads as it is not distinguishable from intrinsic load (Kalyuga, 2011). However, based on Sweller (2010), germane load can have an independent role within cognitive load framework if it is considered as the working memory resources allocated to dealing with intrinsic rather than extraneous load. When learners need to devote more working memory resources to extraneous cognitive load because of inappropriate teaching approach, fewer resources will be available to deal with intrinsic cognitive load, resulting in reducing Germane load and decreasing learning performance.

2.4. Instructional effects of cognitive load

Different Instructional factors exist that can affect cognitive load including: Worked example, Expertise reversal, Guidance fading, Split attention, Redundancy, Modality, Transient information, Animation, Element interactivity, and Embodied cognition theory. There are a number of other cognitive load effects in the literature, but in the next paragraphs just the mentioned effects that are related to the context of this study will be discussed.

2.4.1. Worked example effect

Worked examples include a problem statement, solution for the problem, and the steps taken to solve the problem and reach the solution (Chen, Kalyuga, & Sweller, 2015; Renkl, 2014b). Worked-examples can facilitate initial acquisition of cognitive skills and learning complex problem-solving skills through introducing step by step solutions for a formulated problem (Renkl, 2005). The main function of worked examples is constructing correct schemas for learners to enable them solve the relevant problems (Van Merriënboer & Sweller, 2005). Germane load can be used to justify learning effects observed with worked examples (Grobe & Renkl, 2007; Van Gog et al., 2009).

Based on Renkl (2005), in order to increase the efficiency of worked examples, the examples should be: a) self-explanatory, b) provide a clear guideline for the problem, c) show relations between different elements of the problem, d) highlight main features in order to select the correct solution for the problem. Also, the effectiveness of a worked example depends on the element interactivity and level of intrinsic cognitive load. It is more effective when element interactivity is high, since when intrinsic cognitive load is low, the total cognitive load may not exceed working memory capacity and controlling extraneous cognitive load will not be necessary (Chen, Kalyuga, & Sweller, 2015).

The positive effects of worked examples is demonstrated in comparison with minimally-guided methods (Sweller & Cooper, 1985). Van Gog, Kester and Paas (2011) found that the worked example condition versus problems solving yields a higher learning performance and learners had less mental efforts during learning. Also, Van Gerven et al. (2002) examined the efficiency of worked examples in training elderly and young adults in comparison with the problem-solving method. They found that applying worked example is a more efficient training method for learning complex skills than solving

conventional problems especially for the elderly learners. Schwonke et al. (2009) compared the effect of worked example-based instruction with a tutored- supported problem-solving instruction. The finding showed that, worked example-based instruction decreased learning time and students acquired a deeper conceptual understanding. It proves that the worked-example effect can improve the learning performance even when there is tutor support in the problem solving-based approaches.

Tuovinen and Sweller (1999) compared the effect of applying worked examples versus discovery-based methods for teaching FileMaker Pro which is a database management system. The study was started by presenting an overview of the software and introducing the main tools of the system. Then students were randomly assigned to one of the discovery-based or the worked-example groups. In the discovery-based group the written version of the instruction was given to the students but in the worked-example group, a problem and its solution was provided to the students. The results of the mental effort ratings demonstrated the efficiency of the worked examples for the students with no previous database background knowledge. However, the advantage of worked examples for the students with some experience in the database area was eliminated.

Rourke and Sweller (2008) examined if applying worked examples can improve higher education students' ability to recognize designers' styles and gain the required characteristics to identify a designer's work. The researchers found that students who studied worked examples was more successful at recognizing designers' works compared to the students provided with problem-solving tasks.

There are also a great number of studies that proved the positive effects of worked-examples in teaching different concepts such as algebra, geometry, mathematics, physics,

law and English. In one of the earliest studies by Sweller & Cooper (1985), the results showed that worked examples can facilitate the acquisition of algebra knowledge and decrease learners' errors and time duration of solving the equation.

Retnowati, Ayres and Sweller (2010) and Schwonke et al. (2009) evaluated the effects of worked example versus problem-solving methods on learning geometry. Supporting data revealed that students who learnt the geometry concepts using worked examples had a deeper understanding and could complete learning in less time compared to the students in the control group. Paas and Van Merriënboer (1994) evaluated the effects of worked example on geometrical problem solving in the area of computer programming for low and high interactivity elements. Findings showed that for high interactivity elements, students who used worked examples had a better learning performance in less time and with less mental effort.

Van Loon-Hillen, Van Gog and Brand-Gruwel (2012) investigated the effects of implementing worked examples in a primary school mathematics course in a real classroom situation. Although the results did not show any significant differences in the test performance marks, the learning duration decreased significantly. Saw (2017) proved the efficiency of sequential worked examples for teaching physics through e-learning systems to undergraduate students.

Nievelstein et al. (2013) evaluated the effect of worked examples on law students. The results revealed that students who learnt the law concepts using worked examples had a better argumentation of civil law cases in comparison with the students who learnt the same concepts using problem solving approach. Kyun et al. (2013) examined the effect of worked examples on learning English for Korean university students. The results

showed that the learners who had access to worked examples had a better performance in the test questions compared to the students who learnt English using problem solving method.

As it can be seen from the review, the effect of world examples is evaluated in teaching different concepts including geometry, mathematics, physics, law, English and database concepts. However, there is a lack of study in evaluating the effect of worked examples for teaching computer related concepts including software applications, programming and network related concepts. Since the existing studies showed that the world examples-based methods are more efficient compared to the other teaching approaches such as problem-solving, it is worth evaluating the effects of worked examples on teaching computer related concepts to see if the same results will be achieved.

2.4.2. Expertise reversal effect

Although, applying the techniques such as worked example can be beneficial for novice learners, by increasing the expertise level of the learners, their effectiveness can be decreased, eliminated or even reversed which is called the expertise reversal effect (Chen, Kalyuga, & Sweller, 2017). This effect relies on redundancy which shows that essential information that is vital for the novices can become redundant for the expert learners and consequently increase extraneous cognitive load (Kalyuga et al., 2003). Therefore, the type and amount of information that are presented to learners should be adapted to their knowledge and level of expertise.

For example, Oksa et al. (2010) found that novice literature learners, can understand and learn Shakespearean play extracts with the use of line-by-line modern English translation that is synced with Shakespeare's original text. However, for the expert learners the

modern English translation was not beneficial and also increased their cognitive load level as the learners tried to cross-check the accuracy of the modern English translation with their own interpretations. Nückles et al. (2010) evaluated the effect of prompts on Journal writing ability of the novice versus the expert journal writers. The results showed that when journal writers are novices, the prompts are beneficial for them since the hints can stimulate their writing at the initial stage of learning. However, by increasing the knowledge level of the learners, the prompts become ineffective and interfere with learners' tendency to apply the writing strategies.

2.4.3. Guidance fading effect

The guidance fading effect occurs when worked examples are replaced by completion problems when the expertise level of the learners increases (Renkl, Atkinson, & Große, 2004; Van Merriënboer et al., 2002). Completion Problems are similar to the worked examples, however, the solution is not provided to the learners completely and they should complete some parts of the solution themselves. For example, for teaching a mathematical equation to novice learners, a worked-example can be used to provide a complete solution for a sample equation. However, by increasing the familiarity level of the learners with different types of equations, an example with a partial solution can be provided and learners can be asked to complete the solution (Sweller, Ayres & Kalyuga, 2011). In fact, as the expertise level of the learners increases, worked examples should be converted to completion problems and finally with full problems to decrease extraneous cognitive load. This effect is in line with expertise reversal effect that emphasis on adapting the amount of provided information with the knowledge of learners.

2.4.4. Split attention effect

Split-attention effect occur when learners need to integrate different information sources, such as text and pictures, into one schema to learn a concept. If learners cannot connect these sources their attention shifts since they need to keep information from one source active in their working-memory in order to understand the information from the other source (Ayres & Sweller, 2014). Chandler and Sweller (1992) showed that learning through integrated instruction can decrease learning time and increase test performance marks.

Therefore, an efficient instructional design should try to integrate related graphical and textual information by placing them close to each other and in an appropriate place (Al-Shehri & Gitsaki, 2010; Schroeder & Cenkci, 2018). As an example, Cerpa, Chandler & Sweller (1996) showed that if software instruction is integrated into the body of software, it can decrease cognitive load of the users in comparison with users reading the hard-copy of the instruction or reading the instruction as a separate file. The reason for cognitive load decreasing is that users do not need to split their attention between the software interface and the instruction.

Furthermore, labeling pictures and text segmentation can decrease split attention (Florax & Ploetzner, 2010). It should be noted that split-attention does not occur when different sources of information are not linked together and can be understood separately (Sweller, 2008).

2.4.5. Redundancy effect

The Redundancy effect occurs when the same information is presented with the use of multiple sources (Jin, 2012; Mayer, 2005). In instructional design, most of the

redundancies are textual information which repeats information of a picture or presenting the same verbal information in spoken and written forms (Chandler & Sweller, 1991; Sweller, Van Merriënboer, & Paas, 1998). Since during information processing, learners try to integrate auditory and visual information, redundant spoken or written materials can have a negative effect on cognitive load.

For example, adding auditory explanation for a picture or a diagram which is clear enough, can increase cognitive load as the audio is redundant (Cheah & Leong, 2019; Jamet, 2017; Morrison, Watson, & Morrison, 2015; Sweller, 2011). Also, having on-screen text while there is an animation can be redundant (Arslan, 2012; Mayer & Moreno, 2003; Moreno & Ortegado-Layne, 2008). These forms of presenting information can waste working-memory capacity and increase cognitive load, since learners process all sources of information first, only then can they determine that some sources are redundant. Therefore, additional text for a picture or a diagram can be beneficial just when visual materials are incomprehensible without a descriptive text.

Furthermore, unnecessary or additional elements such as background sound, animation, and decorative pictures that aim to make a teaching environment aesthetically appealing are considered redundant information and can increase cognitive load (Bus, Takacs & Kegel, 2015; Jaeger & Wiley, 2014; Jonassen & Driscoll, 2003; Jonassen et al., 2008; Lehmann, Hamm, & Seufert, 2019; Rey, 2012; Rey, 2014; Sanchez & Wiley, 2006; Sung & Mayer, 2012; Vössing, Stamov-Roßnagel, & Heinitz, 2016; Wang et al, 2017).

The decorative elements can distract learners and decrease their concentration level on the main learning contents (Craik, 2014). Moreno and Mayer (2000b) found that when students learn in an environment with music or any other sound, their learning performance decreases significantly. However, Lehmann & Seufert (2017) showed that

the negative effects of background music can be decreased when learners have a higher level of working memory capacity. Regarding visual elements, Liang and Lee (2010) indicated that minimizing visual demand is very important in the design of in-vehicle systems to decrease distraction and risk of drivers' errors. Also, He & McCarley (2011) showed that by increasing distracting elements, drivers' reactions will be decreased which proves that the distracting elements could affect drivers working memory. Goodell and Schwaitzberg (2006) demonstrated that decorative visual elements in a virtual reality surgical environment can decrease test performance marks.

The detrimental effect of the decorative elements can be increased when they are attractive for the users and can change the focus of their concentration (Mayer et al., 2008; Sung & Mayer, 2012). The techniques such as allowing learners to take notes during the learning phase or repeat the learning content can decrease the detrimental effect of the decorative pictures (Muller, Lee, & Sharma, 2008; Wang et al., 2017).

However, if the decorative pictures such as instructor picture, or talking head play the role of a motivator, they can be harmless, but it depends on the type of learners and the difficulty level of the teaching contents (Lenzner, Schnotz, & Müller, 2013; Park et al., 2015; Morrison, Ross, & Kemp, 2001; Schneider et al., 2018). For example, Kizilcec, Papadopoulos and Sritanyaratana, (2014) revealed that learners prefer an instructional video that shows the face of the instructor. Although, showing the instructor's face did not have any positive effect on the test marks, learners preferred to see the instructor's face as they perceived the learning environment to be more educational. However, Díaz, Ramírez and Hernández-Leo (2015) did not find any significant difference between showing the instructor talking head and only playing the instructor's voice. The only

negative effect on cognitive load was in a condition where the talking head is presented at the beginning and then disappeared.

Based on some studies the decorative elements can facilitate learning only for the learners with higher background knowledge, but not for the novice learners, who are already experiencing a higher cognitive load while learning unfamiliar materials (Lenzner, Schnotz, & Müller, 2013; Magner et al., 2014; Shangguan et al., 2020; Wang & Adesope, 2016).

2.4.6. Modality effect

Working memory has separate channels for processing visual and auditory information (Mousavi, Low, & Sweller, 1995; Sweller, Ayres, & Kalyuga, 2011b). If a concept is taught only through the visual channel such as text and picture or only with the audio channel, it can overwhelm a part of working memory without using the other parts. Therefore, in order to increase the capacity of working memory and decrease cognitive load, both visually and auditory channels should be engaged simultaneously through presenting a part of information in an auditory format and the rest in a visually format (Berney & Bétrancourt, 2016; Clark & Mayer, 2016; Tabbers, Martens, & Merriënboer, 2004).

For example, Barton (2018) showed that students will have a better learning performance when images or diagrams are presented alongside verbal narration in comparison with on-screen text. The issue of on-screen text is that the text would be processed as an image, and our brain will need to process two visual elements at the same time. Therefore, only one part of our brain which is responsible for processing the visual contents will be engaged or potentially overloaded, but the brain part which is responsible for processing the audio content will not be engaged at all. Engaging both visual and auditory channels

of the brain, can help to use the capacity of working memory efficiently in addition to decreasing the split-attention effect where the text and image should be integrated. However, in order to increase the efficiency of the modality effect, the audio component must not be too long or complex, due to the transitory nature of auditory information.

One of the best models that shows dual-channel processing in multimedia learning is developed by Mayer and Moreno (2003) based on cognitive theory of multimedia learning. This theory is based on the three cognitive principles of learning: a) the human information processing system that includes dual channels for visual and auditory information, b) the limited processing capacity of visual and auditory channels, and c) active learning that involves performing a set of cognitive processes during learning (Mayer, 2014). See figure 2.2.

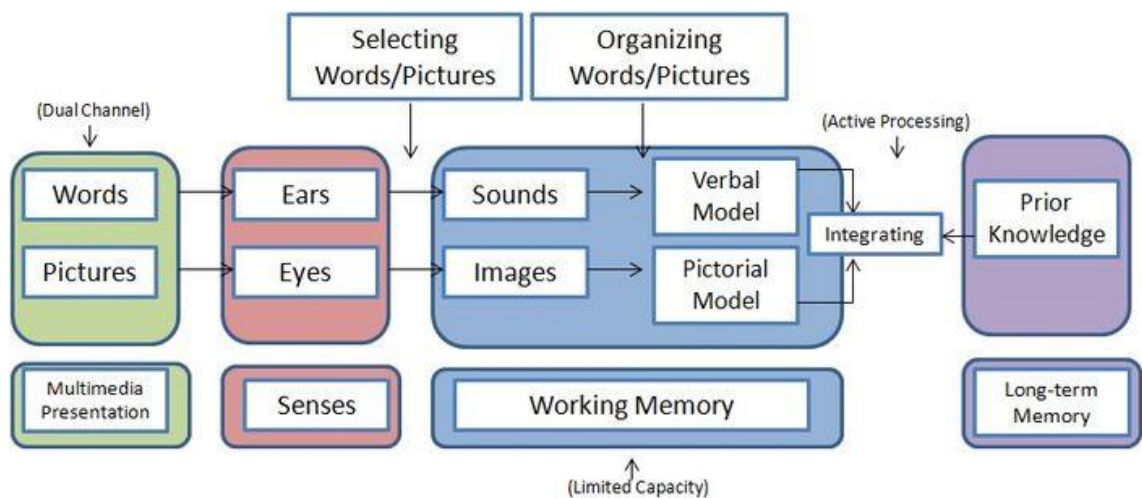


Figure 2.2: Cognitive theory of multimedia learning model (Mayer & Moreno, 2003)

2.4.7. Transient information effect

Transient Information occurs when information is presented in a form of audio or animation instead of static content which can make retrieving information difficult for learners (Leahy, & Sweller, 2016; Sweller, Ayres, & Kalyuga, 2011b). Transient

information can increase cognitive load since the previous information is replaced with the new information continuously that can overwhelm working memory when learners need to connect different parts of information to learn a concept.

This effect should be considered in e-learning design as most of these systems use multimedia learning content such as audio and video that can result in a transient information effect if they are not used appropriately. Wong et al. (2012) compared the effect of transient versus permanent information while using animation-based content and audio-visual content in two different experiments. The results showed that transient information including animation and audio that were presented in short sections with pauses between sections, were superior to static content. However, in long sections the transient information lost its superiority over static content, since large amounts of transient information can overload our working memory.

Therefore, in order to avoid the transient information effect, we should decide when static content and when animation should be used based on the nature and the length of the learning content (Leahy, & Sweller, 2016; Wong et al., 2012). Furthermore, adding play, pause and trackbar features can help to decrease the effect of transient information (Ng, Kalyuga, & Sweller, 2013).

2.4.8. Animation effect

Animation can help us to learn by observing instead of reading and the need to connect text with pictures (Ayres et al., 2009). Animation effect occurs when a series of static graphics that are used to teach a concept are replaced by animation. Although, animation can help learners to learn some concepts such as the steps of performing motors skill tasks easier (Marcus et al., 2013), there are different factors that can affect the efficiency of animation and make it beneficial or harmful for the learners:

Spatial ability: There is a direct correlation between the spatial ability of learners and learning from instructional animations (Hegarty et al., 2006). When static pictures are used in demonstrating dynamic processes, the learner must mentally animate the processes to understand the concept, therefore, the efficiency of animation can be affected by the spatial ability of learners. Since, it will be difficult for learners with low spatial ability to mentally animate the processes, using animations versus statics can be beneficial for them (Wong et al., 2018; Höffler, 2010).

Gender effects: There is evidence that instructional animations can be more beneficial for females than males (Sánchez & Wiley, 2010; Wong, Castro-Alonso, Ayres, & Paas, 2015), since, the spatial ability of females is lower in comparison with males (Maeda & Yoon, 2013).

Duration of animation: as was explained when discussing the transient information effect, if animation is used for teaching long content, it can overwhelm working memory load, since information from previous frames should be kept active in the working memory in order to understand later frames and enable learners to integrate the newly presented information with the previous information (Wong et al., 2012). Also, when animation is used for teaching concepts that learners need to spend more time or focus on a specific part of the content such as learning words or symbols, the transient nature of the animation can increase cognitive load (Castro-Alonso, Ayres, & Paas, 2014).

Prior knowledge: in order to teach long content using animation, a segmentation strategy can be used to decrease the transient information effect (Spanjers et al., 2011; Kalyuga, 2008). However, it should be noted that the segmentation strategy is more effective for learners with low domain-specific knowledge. It means that, segmentation will not be

very effective for learners with more prior-knowledge as they are able to deal with more information at a time (Sweller, Ayres & Kalyuga, 2011).

Type of content: studies showed that animation is superior to statics in learning procedural-motor knowledge where learners need to do a process using their body movements. For example, the efficiency of animation is demonstrated in learning how to tie knots, use Lego to build different shapes, make origami shapes, and learning surgical skills (Ayres et al., 2009; Marcus et al., 2013; Castro-Alonso, Ayres, & Paas, 2015a; Masters et al., 2008).

Signalling: one of the factors that can increase the efficiency of the animations is applying signaling to guide learners' attention to important parts of the content by using different approaches such as highlighting, drawing a line, changing the color or adding an arrow (Horvath, 2014; Mayer & Fiorella, 2014; Van Gog 2014). Signalling can decrease extraneous cognitive load by drawing learners' attention to the main points of the teaching materials so that learners do not need to check the irrelevant parts (Alpizar, Adesope & Wong, 2020).

2.4.9. Element interactivity effect

The element interactivity effect indicates that the extraneous cognitive load depends on the intrinsic cognitive load level (Sweller, 2010). When the intrinsic load is high, the high element interactivity level will have a strong effect on cognitive load effects such as worked example, split attention, and redundancy that are related to the extraneous cognitive load. Therefore, when the intrinsic load is low, a high extraneous load may not affect learning performance since the total cognitive load cannot exceed the capacity of working memory and optimizing instructional procedure may not be as necessary as for situations with a high intrinsic load (Sweller, Ayres, & Kalyuga, 2011).

Now that the relevant literature on different Cognitive Load effects has been surveyed, we will turn to a discussion of how some online instructional design techniques can be applied to software design, by harnessing the benefits of these different Cognitive Load effects.

2.5. Reducing cognitive load in teaching software while using e-learning systems

In order to learn a productivity software application, learners need to learn: a) the layout of the software, b) the usage of different tools, c) the settings of each tool, and d) how to combine the related tools. In order to facilitate learning the mentioned items when learning through e-learning systems, applying teaching techniques based on cognitive load effects can be an efficient strategy. Teaching techniques such as: Facilitating formation of schema in learners' long-term memory, Facilitating learning of high element interactivity tools, Applying Worked examples, Considering Expertise reversal and Guidance fading effects, Avoiding Split attention, Avoiding Redundancy, Considering Modality and transient effects, Considering embodied cognition theory. In this section, the mentioned techniques and how they can facilitate learning of software applications will be discussed.

2.5.1. Facilitating formation of schema in learners' long-term memory

Professional software users know where to find the desired software's tools, how to work with them and are completely familiar with the software layout, as well as, knowing how to perform different tasks using a combination of tools. These users have a complete schema of software layout, placement of different tools and relationships among them in their long-term memory. In order to facilitate the formation of schema for novice users, we can use the instructional strategies such as: a) using infographics, b) analogies and c)

narrative. A discussion of how these strategies support a reduction in cognitive load now follows.

a) Using infographics to improve recall and learning

After teaching all the steps of working with the target tool of the software, at the end of each lesson an infographic can be provided to summarize the instruction in a succinct and visual format, by indicating different steps of working with the target tool of the software visually (Lyra et al., 2016; Yildirim, 2016). These infographics are potentially useful as they summarize complex information which can lead to improve recall and learning (Clarke, Clarke & Yankey, 2006; Gobert & Clement, 1999; Marcus, Cooper & Sweller, 1996).

Studies showed that presenting some parts of the content using an illustration can decrease cognitive load, however, the illustration should be simple and self-explanatory and there is not any text that learners need to integrate with the illustration (Chandler & Sweller, 1991; Purnell, Solman, & Sweller, 1991; Sweller, 1999). As an instance, figure 2.3 shows an infographic for adding data to Excel from a text file.

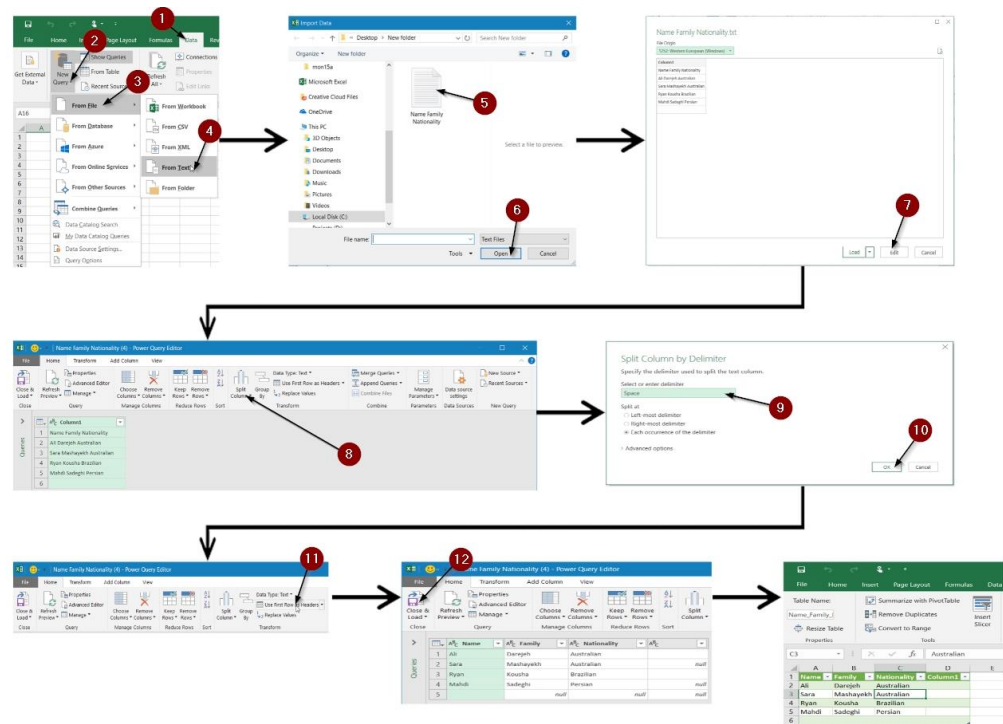


Figure 2.3: Infographic example

b) Analogies

The other solution that can facilitate formation of schemas is linking the new concepts to learners' prior knowledge, by using analogies. Linking the layout and the tools of the new software to software that learners are already familiar with can facilitate learning through supporting the formation of schemas and consequently facilitating the acquisition of new knowledge (Dahl, Flygare, & Zheng, 2008; Gick & Holyoak, 1987; Quiroga, Crosby, & Iding, 2004; Sweller, 1994). For instance, as it can be seen in figure 2.4, in order to teach a graphical software tool such as Photoshop, if learners are familiar with a simple software product like Microsoft paint, we can teach some tool component in Photoshop by comparing it to its similar but less complex tool components in Microsoft paint and discuss the similarities and differences. In this case learners can connect the usage of the new tools to the tools that they know, and they can develop a deeper understanding of what they can do when using the new tools.

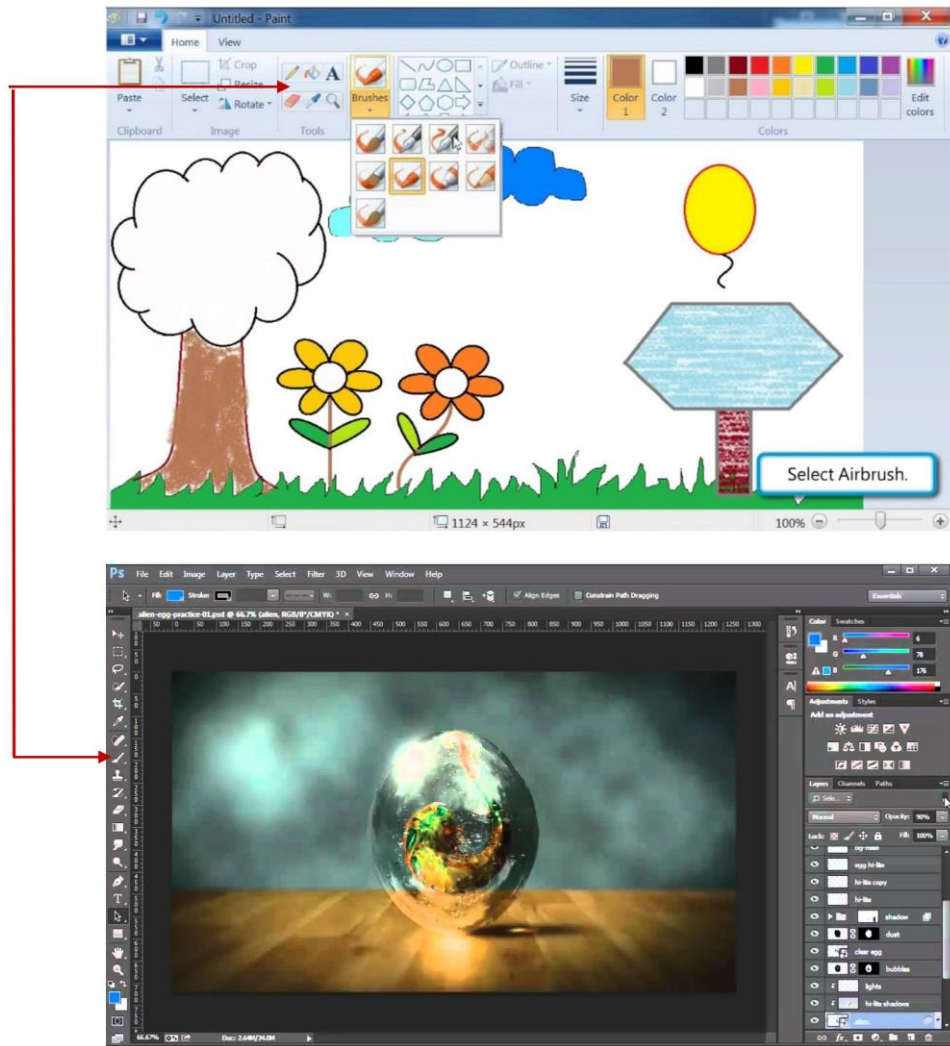


Figure 2.4: Analogies sample

c) Narrative

Each productivity software is a package of tools that users need to know the usage of each tool, in addition to how they relate to each other and how they can combine for performing a specific task. Therefore, if we teach each software tool separately without mentioning its relationship with the other tools, users cannot use the software efficiently. One of the techniques that can be used to integrate the lessons related to different software tools is using a narrative or a scenario which is an efficient instructional strategy to increase germane load (Reedy, 2015).

Narrative or scenario is an imaginary project that an instructor performs in order to teach different software tools. In each lesson the tools that are necessary to complete a part of the project and their relationship with the previous tools are taught. This integration of the lessons can help to decrease extraneous cognitive load and increase germane load by helping learners to get an overview of the software tools and understand the relationship between them (Pollock, Chandler, & Sweller, 2002; Van Mierlo et al., 2012).

2.5.2. Facilitating learning of high element interactivity tools

In order to use high element interactivity tools, users need to follow different connected steps in addition to having pre-required fundamental knowledge (Chen, Kalyuga, & Sweller, 2017; Chen, Kalyuga, & Sweller, 2015; Kalyuga, 2015). There are two techniques that can be used in order to facilitate learning of tools with high element interactivity including: a) Breaking down teaching into smaller components, and b) applying Training wheels.

a) Breaking down teaching into smaller components

Although, there is no solution to decrease the element interactivity and intrinsic load of high element interactivity tools, we can decrease extraneous load by providing necessary fundamental knowledge before teaching the tools, and breaking down instruction into the smallest teaching chunks such as step by step instructions instead of a long description (Sweller, Ayres, & Kalyuga, 2011a; Van Merriënboer, 1997). In fact, isolated information can help the novice learners learn each element of a complex concept separately without overwhelming their working memory which is limited to process 4 ± 1 elements at any given time (Cowan, 2001).

For example, typing a function-based formula in Microsoft Excel can be considered as a high element interactivity task, since users cannot use any function without having the necessary prerequired knowledge and without processing all the integrated steps of writing a function. Before choosing any function, users need to know the usage of each function. Then they should arrange different parameters in the function sections. In order to teach how to write a specific function, first the usage of that function and its differences to similar functions should be taught, followed by a step by step instruction of the parameters that should be added in each section of the function.

b) Training wheels

The other method that can facilitate learning of high element interactivity tools, is applying a training wheel. In this method, learners only see the settings of the target tool that they have learnt in the previous steps and the current settings that they are learning (Bannert, 2000). The other tools and settings are hidden or greyed out to decrease cognitive load by eliminating the number of unfamiliar elements on the screen (Fang, Luo & Xu, 2011; Pociask, & Morrison, 2004; Reis et al., 2012).

The idea of training wheels is to introduce full functionality once the basics have been taught. Training wheels should be used with care so users understand what full functionality will be made available to them down the line. For example, in order to teach formulas in Microsoft Excel, at the beginning of learning, the advanced formulas should be greyed out to keep learners' concentration on the basic ones. By having less elements available to process, learner is more likely to learn the initial knowledge.

2.5.3. Applying worked examples

Since each productivity software tool is designed to facilitate the work that we perform in the real world manually, we can teach the software tools by using real world examples and problems instead of just introducing the tools' usages. In this case the learners can get a practical knowledge and extraneous cognitive load will be decreased especially when the target tool is difficult to learn (Clark & Mayer, 2016; Sweller & Cooper, 1985). Furthermore, worked examples can facilitate learning of the tools that have multiple usages. In order to teach each usage of these tools, different examples can be used (Atkinson et al., 2000; Van Merriënboer & Kirschner, 2017).

For instance, the “Patch” tool, in Photoshop software, that is used to remove some types of skin imperfections can be considered a high element interactivity tool for novices users as they need to follow a series of integrated steps to work with this tool. Therefore, applying a worked example could facilitate the learning of how to use the patch tool by showing learners the types of skin imperfections that this tool can remove and how this tool should be used. In order to design work-examples for the Patch tool a picture of a face with the type of skin imperfections that is compatible with this tool can be provided while showing step by step instructions of how the Patch tool can be used to remove imperfections from the face (figure 2.5).

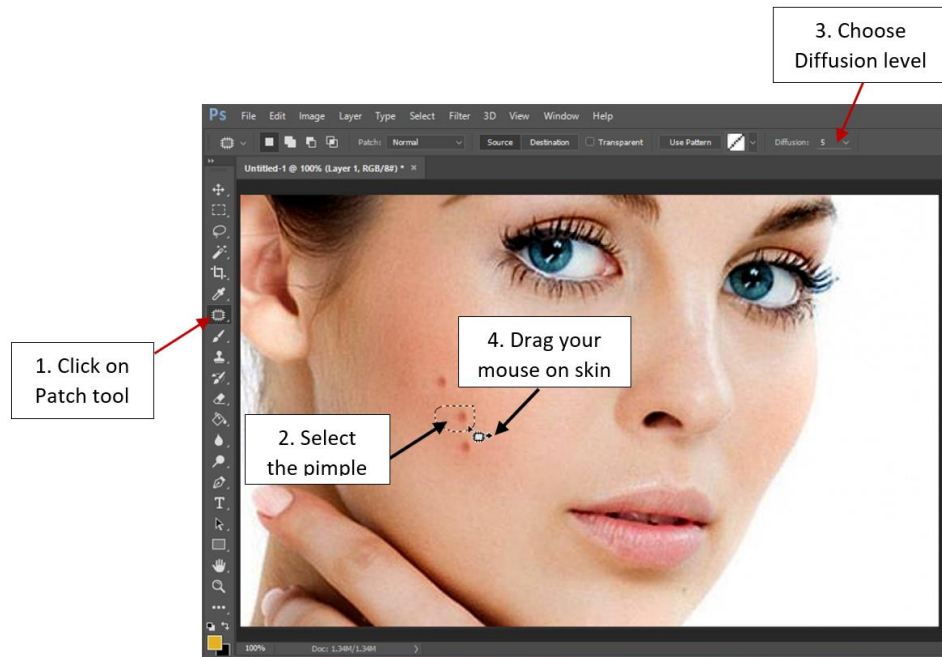


Figure 2.5: Worked-examples effect

2.5.4. Considering expertise reversal and guidance fading effects

Since based on expertise reversal effect by increasing the expertise level of the learners, the effectiveness of fully guided learning approaches can be eliminated or even reversed, after learners become familiar with the software layout and tools using worked examples, problem-solving exercises with minimal guidance can be used instead of providing a long description or extra worked examples. It can encourage learners to use the knowledges that they have learnt to learn the relationship between tools and how combinations of different tools can be used.

This method can decrease extraneous cognitive load as we adapt the amount of guidance with learners' knowledge which is supported based on Guidance fading effect where instructors replace worked examples with completion problems by increasing learners' knowledge (Kalyuga, & Renkl, 2010; Nievelstein et al., 2013; Renkl, Atkinson, & Große, 2004; Stark, 1998; Van Merriënboer et al., 2002).

An appropriate completion problems exercise should lead users to work with the group of related tools and show them some hints while solving the exercise. For example, in order to teach how to have a professional face polish in photoshop, after users have learnt all the related tools to polishing face, a picture of a face with different imperfections can be provided to learners and ask them to use different face tools to polish the skin. In order to guide learners on how they should polish each imperfection, by clicking on each part of the face a hint box opens and shows learners what tool they should use. See figure 2.6.

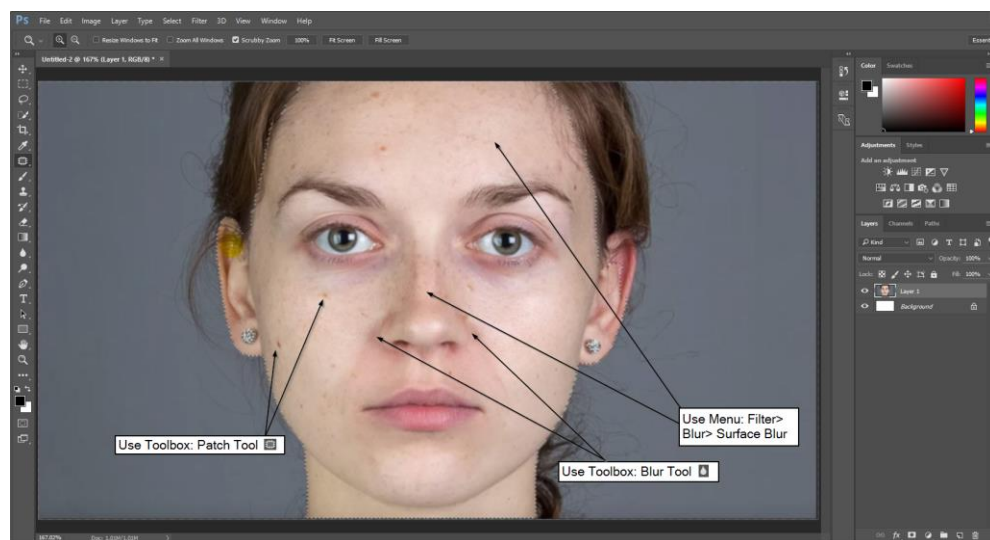


Figure 2.6: Completion problems exercise sample

2.5.5. Avoiding split attention

The crowded interface of complex software can cause split-attention when learning through e-learning systems. In particular, while learning a specific tool, there is a chance that learners lose the target tool and cannot integrate the tool with the instructional text that describes the tool usage.

In order to keep learners' focus on the target tool and its description text in e-learning systems, a rectangle with a bright background color can be drawn around the tool and its settings and an arrow could be used to connect the instructional text to the tool (see figure

2.7). This can prevent learners from losing the target teaching concept and their attention will not be split to connect the description text to its related tool (Ward & Sweller, 1990). However, to increase learners' attention using blinking shapes is not suggested, since it can increase learners' frustration.

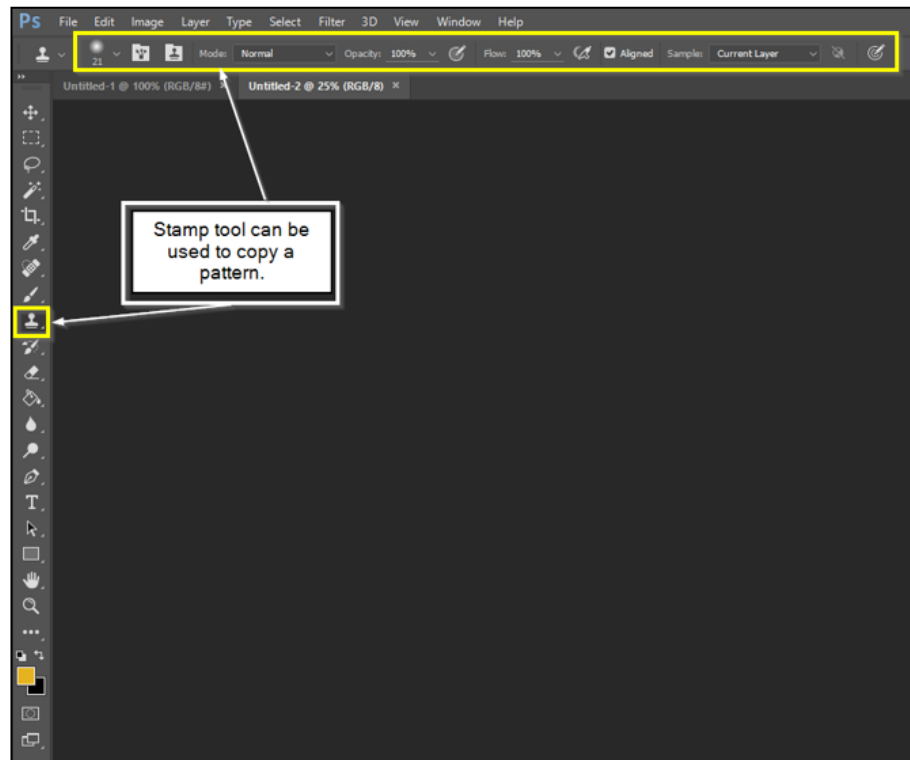


Figure 2.7: Avoiding split attention

2.5.6. Avoiding Redundancy

When a software tool is taught by using redundant texts, pictures and auditory presentations, it can lead to lower learning results. The reason of this negative effect is redundant information that requires cognitive resources to integrate that information simultaneously (Jin, 2012; Mayer, 2005). Since software has a graphical interface, we should avoid using extra pictures and text for explaining how to work with different tools. However, there can be exceptions for teaching critical concepts such as formulas that learners need to memorize in software applications such as Microsoft Excel or MathLab.

We can present the formulas in the form of text in addition to speech to have a stronger explanation, since the auditory component is both transient and complex (Singh, Marcus, & Ayres, 2017). The other option is to avoid the auditory component altogether, however this could potentially introduce text based split attention type of effects. Within a specific context the pros and cons of the different information presentation options thus need to be considered.

2.5.7. Considering modality and transient effects

Since e-learning systems provide a multimedia environment, it is important to have a balance between visual and audio in order to teach software applications. To this end, we should try to use the software interface as the only visual element and minimize the amount of text as much as possible, instead using audio to describe the tools in order to engage both auditory and visual channels and decrease cognitive load (Clark & Mayer, 2016; Tabbers, Martens, & Merriënboer, 2004). However, using long audio should be avoided as based on the Transient information effect replacing long text with transient information such as audio can decrease learning performance, since verbal information may not be retained in working memory long enough to be fully comprehended (Leahy & Sweller, 2011; Singh, Marcus & Ayres, 2017; Wong et al., 2012).

Moreover, the audio content should be kept simple to avoid cognitive overload. Therefore, we should use auditory information with care and ensure a balance. As it can be seen from figure 2.8 there is a block of a text that explains how to use the software. This part can be replaced by audio to use auditory channel in addition to the visual information in order to decrease learners' cognitive load. Some further strategies to reduce the effects of transient audio information are segmentation and including pauses (Singh, Marcus & Ayres, 2012).

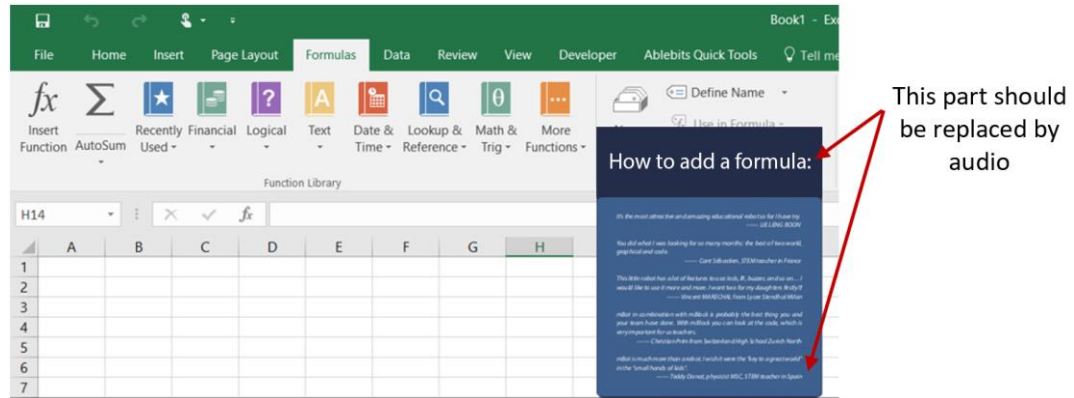


Figure 2.8: Modality effect

A summary of the solutions to decrease cognitive load of novice users in order to learn software applications through e-learning systems can be seen in Table 2.1.

Table 2.1: A summary of solutions to decrease cognitive load of novice users

Cognitive load effects	Problems	Solution
Element interactivity effect	Facilitating formation of schema	a) Using analogies. b) Providing infographic. c) Applying narrative.
Element interactivity effect	Learning high element interactivity tools	a) Providing the pre-required fundamental knowledge. b) Breaking down teaching steps into the smallest chunks. c) Applying training wheel.
Worked Example effect	Difficulty in understanding the practical usage of software tools by only describing tools.	Using real-world examples for teaching different tools.
Expertise reversal and Guidance fading effects	The effectiveness of some teaching techniques will be decreased by increasing the expertise level of the learners.	Replace worked examples with completion-problems exercises.
Split Attention effect	Losing the target tool and difficulty in integrating the tool with its settings and the instructional text.	Highlight the target tool and its settings and using an arrow to connect the instruction text to the tool.
Redundancy effect	Since software has a graphical interface, redundant pictures can lead to lower learning performance.	Avoid using extra pictures and text in the instruction.

Modality effect and transient effects	Teaching software using only visual or audio channel, can overwhelm working memory.	Engage both visual and audio channels through using the software interface as the only visual element and using short audio to describe the tools.
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2.6. Embodied cognition theory in teaching software while using e-learning systems

In addition to cognitive load effects, embodied cognition theory can be used in order to facilitate learning software via e-learning systems. Embodied cognition theory emphasizes the role of the entire body including the motor system to achieve cognitive skills. This theory explains new ways of conceptualization in which human cognition can be affected by body movements or interacting with the environment's objects physically such as using educational tools, musical instruments, or mouse and keyboard during learning software (Shapiro, 2019; Weisberg & Newcombe, 2017; Wilson & Foglia, 2017).

Many studies have proved that involving learners physically with the objects that are related to the learning content can enhance learning performance as there is a tight connection between cognitive processing and physical motion areas of our brain (Ceciliani, 2018; Glenberg, 2015; Shapiro & Stolz, 2019). Therefore, integration of physical manipulation and imagined manipulation can enhance learning (Glenberg, 2010) by decreasing the complexity level of the difficult cognitive tasks (Calvo & Gomila, 2008; Schulz, 2017).

There are a great number of studies that proved the efficiency of designing the curriculum and the teaching methods based on embodied cognition theory in different contexts such as language and translation and education (Glenberg, Witt & Metcalfe, 2013; Zhu, 2018), mathematics and geometry education (Gerofsky, 2011; Nathan & Walkington, 2017;

Radford, 2009; Zudini & Zuccheri, 2016), science and physics education (Enyedy et al., 2012; Kontra et al., 2015), music and sport education (Schiavio, et al., 2019), geosciences education (Herrera & Riggs, 2013) and children's education (Chandler & Tricot, 2015). However, to the best researcher knowledge there is no study to evaluate the effect of embodied cognition on learning computer software. In all the mentioned studies cognitive tasks were integrated with some physical activities including interacting with the learning objects, gesturing, moving, sketching, or mapping to enhance learning. The findings of all the mentioned studies showed that embodied cognition can play an important role in the construction of schema and cognitive development.

Regarding, teaching software applications, one of the techniques that can be used to facilitate learning is using interactive video tutorials, the potential efficiency of which is supported based on interacting with environment's objects which are embodied cognitively. Since this type of video enables learners to interact with the video content by moving their hand and clicking on the screen using a mouse, it could have a positive effect on learning through simulating the software environment and engaging the motor system in learning (Price et al., 2008). In other words, while learning using an interactive video, the mouse is considered as a learning tool that learners should interact with physically to learn the location and the usage of each software tool in practise. Although, to the best researcher knowledge there is no study to prove the efficiency of interactive video tutorials on cognitive load, mouse movement and clicking on the video content may be useful, due to embodied cognition effects (Barsalou, 2008) where links between mind and body allow movements to support cognitive tasks.

Embodied cognition can also be used as a measurement factor to monitor the efficiency of learning process. For example, in dual task paradigm method when mouse movement

is used as the secondary task and learners should move the mouse continuously, mouse movement decreases with increasing cognitive load, since users have less resources to perform the main tasks as load increases and so less resources left to move mouse using hand (Grimes & Valacich, 2015; Khawaji, et al., 2014; Rheem, Verma, & Becker, 2018). A complete explanation of dual task paradigm is explained in topic 2.3.5.2.1.

2.7. Measuring cognitive load

The existing methods of measuring cognitive load can be categorized into the two major dimensions: a) objectivity including: subjective and objective and b) causal relation including: direct and indirect (Brunken, Plass, & Leutner, 2003). The objectivity dimension means whether the measurement method uses subjective approaches such as self-reported data or objective approaches such as behavior observation, physiological or performance measurement.

The causal relation dimension categorizes methods based on whether the measured factor has a direct or indirect relationship with changing cognitive load. For example, there is a direct link between difficulty of the teaching materials and cognitive load, since this difficulty is a direct effect of the intrinsic and extraneous cognitive load of the materials. However, an indirect link exists between errors in solving exercises and cognitive load, since an incomplete schema can cause such errors that can affect cognitive load (Brunken, Plass, & Leutner, 2003).

2.7.1. Subjective

Subjective methods are based on self-reported approaches to collect data directly from learners who rate different factors of their learning experience on a 7 or 9 point Likert-scale questionnaire from 1 (extremely easy) to 9 (extremely difficult) (De Jong, 2010). In

subjective techniques, it is assumed that learners can reliably monitor and report their cognitive processes (Van Mierlo et al., 2012). These methods are widely used to measure cognitive load as they are easy to conduct and they are proved as reliable methods to indicate the amount of cognitive load (Ayres, 2006). In order to increase the reliability of self-reported methods, using multi question assessment is suggested (Gerjets et al., 2009).

2.7.1.1. Direct methods

One of the popular methods in this category is rating the difficulty of the teaching materials, after learners solve a problem or learn a concept (DeLeeuw & Mayer, 2008; Gerjets et al., 2009; Kalyuga, Chandler, & Sweller, 1999). This scale is very sensitive in identifying differences in cognitive load of learners while learning through different training approaches, however, learners' knowledge, attention or task difficulty can affect the results as well (Brunken, Plass, & Leutner, 2003).

2.7.1.2. Indirect methods

In the direct subjective method, the difficulty of the teaching materials is reported through a questionnaire, however, in the indirect methods, learners report their amount of mental effort devoted in understanding the learning materials (DeLeeuw & Mayer, 2008; Paas, Renkl, & Sweller, 2003). Although this method seems reliable, it is not clear how the mental effort relates to the amount of cognitive load (Brunken, Plass, & Leutner, 2003). Researchers believe that low amount of effort could be a result of low-cognitive load and when cognitive load is high, learners should expand their effort to understand the materials (Reed, Burton, & Kelly, 1985). Also, there is a significant correlation between learners' difficulty rating and effort rating results (DeLeeuw & Mayer, 2008). In fact, when learners rate the learning material difficult, they rate the effort high as well.

2.7.2. Objective

Although, subjective measurements of cognitive load are more popular between researchers, objective methods have their own benefits. The objective methods can be categorized in neuroimaging techniques, behavioral patterns, physiological measures, performance outcome analysis and dual-task-paradigm. The benefit of objective methods such as behavioral patterns and physiological measures is that they provide a continuous measure of cognitive load that enables researchers to collect and analyze fluctuations in a stream of data over time, in contrast with self-reported techniques that only provide few data points.

2.7.2.1. Direct methods

In this category use of neuroimaging techniques such as functional magnetic resonance imaging and positron-emission tomography, are popular approaches to measure brain activities during performing cognitive task by visualizing brain region activation in working memory (Anderson, et al., 2011; Just et al., 2001). One of the popular neuroimaging techniques is Electroencephalography (EEG) that is designed to capture continuous brain activity including alpha, beta, and theta waves. EEG data changes based on cognitive stimuli and working memory load (Anderson, et al., 2011). For example, when task difficulty is increased alpha and theta bands show more activity (Gevins & Smith, 2003). Although, this method is an accurate method, the problems such as difficulty of working with the EEG devices and discommodity of the device for the participants can make limitations for using this technique (Van Mierlo et al., 2012).

The other direct objective method of measuring cognitive load is dual-task-paradigm which is based on the limited capacity of cognitive resources that can be allocated to

different aspects of solving a task. Dual-task method can be used with two different approaches. The first approach is adding a secondary task to a primary task to induce memory load. In this approach the focus is on the primary task and it is expected that performance in the primary task is decreased in a dual-task condition in comparison with the single-task condition.

The second approach is versus the first approach which means that for measuring the memory load, the secondary task is induced by a primary task. Thus, the focus is on the secondary task and based on the amount of load that the primary task put on the memory, performance of the secondary task will be changed. For example, the primary task can be reading the teaching materials and the secondary task clicking on a red spot on the screen while reading. Decreasing the number of clicks can be an indicator of increasing cognitive load (Haji et al., 2015; Martin, 2014; Park & Brünken, 2015; Schoor, Bannert, & Brünken, 2012).

The main drawback of dual-task method is that the secondary task may influence participants' performance on the primary task (Van Mierlo et al., 2012). It can affect participants' concentration and change their attention from focusing on the primary task to the secondary task.

2.7.2.2. Indirect methods

One of the most common method of measuring cognitive load is analyzing performance outcome. This method is indirect because it depends on mental storage processing speed and retrieval which can be affected by cognitive load. In order to use this method, the same teaching materials should be taught by using two or more different approaches. Since the teaching materials are the same, we can expect that the intrinsic load does not

change and differences in learning outcomes are the reflection of extraneous load that is induced by the instructional method (Antonenko & Niederhauser, 2010; Brunken, Plass, & Leutner, 2003).

However, a group of researchers believe that the differences in learning outcomes are not only caused by the different types of instructional design, the type of questions and tests that evaluate learning outcomes can have a strong effect on the results (Mayer, 2001). Furthermore, learners' characteristic is the other factor that can have a direct effect on learning outcomes (Mayer, 2001; Plass et al., 1998).

The other indirect objective methods are analysis of behavioral patterns and physiological measures including learners' time-on-task, eye-tracking, heart rate and muscle response (Brunken, Plass, & Leutner, 2003; Cranford et al., 2014; Holmqvist et al., 2011; Klingner, 2010; Leyman et al., 2004). Time-on-task is the amounts of time that learner spends with different elements of learning. When learners spend more time on a specific part of learning, it shows high cognitive load (Antonenko & Niederhauser, 2010; Brunken, Plass, & Leutner, 2003; Khawaja, Ruis, & Chen, 2007). For example, in the context of multimedia systems, navigation speed and errors that increase the time duration of the target task completion can be considered as the result of cognitive load (Astleitner & Leutner, 1996; Yin et al., 2008).

Data from heart rate and eye-tracking devices can help to measure attention and cognitive processing, since learners may respond to learning materials emotionally. Thus, high-cognitive load can increase stress which may affect heart rate, eye movements and pupil dilation. Greater pupil dilation, more eye movements and increased heart rate, are related

to high cognitive load (Cranford et al., 2014; Granholm et al., 1996) because of difficult tasks (Klingner, 2010; Minassian et al., 2004; Porter, Troscianko, & Gilchrist, 2007).

Despite of all the benefits of eye-tracking methods studies showed that different factors such as depression, brightness of the stimulus, or tiredness can affect the degree of pupil dilation or eye movement (Siegle, Steinhauer, & Thase, 2004). Overall, we should bear in mind that the outcome of all the indirect methods might be the result of other factors such as motivational or attentional (Brünken et al., 2002). Table 2.2 shows a summary of different cognitive load measurement's methods.

Table 2.2: Classification of cognitive load measurement's methods

	Direct measurement	Indirect measurement
Subjective methods	<ul style="list-style-type: none"> • Rating the difficulty of the teaching materials. 	<ul style="list-style-type: none"> • Rating the amount of mental effort devoted in understanding the learning materials.
Objective methods	<ul style="list-style-type: none"> • Neuroimaging techniques such as functional magnetic resonance imaging and positron-emission tomography that measures brain activities. • Applying Dual task paradigm 	<ul style="list-style-type: none"> • Analyzing learning outcomes of the learners. • Analyzing behavioral patterns such as time-on-task. • Measuring physiological factors such as eye-gaze patterns, pupil dilation and heart rate.

2.7.3. Appropriate measurement methods for e-learning systems

Since in the related studies to e-learning systems the time duration that learners should work with the system is long, the measurement method should have two characteristics: a) it should not create any discomfort for the participants, and b) it should measure the cognitive load continuously, not just at the end of the experiment. Although, the methods

such as Electroencephalography, heart rate and muscle response can measure cognitive load continuously, they can cause stress or distraction especially when the experiment duration is long (Van Mierlo et al., 2012). Furthermore, the information from eye-tracking methods can be affected by depression, brightness of the stimulus, or tiredness (Siegle, Steinhauer, & Thase, 2004).

Therefore, it can be concluded that the best methods to measure cognitive load are performance on task, time on task and dual task paradigm, since they measure the load continuously without making any distraction for the participants. Furthermore, since self-reported difficulty or mental effort questionnaires can provide valuable information and do not create any discomfort for the participants, they can be used as a complementary method at the end of experiment.

2.8. Different types of teaching methods based on the amount of guidance during instruction

Teaching methods can be categorized in two main categories including full guided learning (FGL) and minimally guided learning (MGL) methods based on the amount of information and guidance that the instructor provides during teaching (Ertmer & Newby, 2013; Kirschner, Sweller, & Clark, 2006). There are two different views about these two methods and the amount of guidance that should be provided to learners during learning. A group of researchers such as Hmelo-Silver, Duncan, & Chinn (2007) believe that an unguided or minimally guided learning method will be efficient for all learners with any background knowledge, however, the other group believes that a full guidance should be provided to learners especially to the novice learners who do not have enough background knowledge. (Kirschner, Sweller, & Clark, 2006). In this section, both views are compared

and at the end, the teaching method which is more appropriate for novice computer users is discussed.

2.8.1. Full guided learning

FGL is a traditional type of instruction to provide a direct and structured teaching by the instructor. In an FGL environment, teaching is focused on a specific learning target and a full instruction is provided to the learners (Klahr, & Nigam, 2004). FGL is supported by a cognitivism viewpoint and cognitive load theory, that indicate the importance of providing full guided learning especially to novice learners (Ertmer & Newby, 2013; Mayer, 2004).

Based on human cognitive architecture, since learners do not have enough background knowledge about the teaching concept, if full instruction is not provided to them, their cognitive load can be increased and consequently learning performance will be decreased (Chen, Kalyuga, & Sweller, 2015). Therefore, the purpose of FGL is to teach the target teaching material as a body of knowledge and to control learners' cognitive load in addition to building a correct schema for them (Handelsman et. al., 2004).

2.8.2. Minimally guided learning

All the MGL methods are based on a Constructivism viewpoint. According to this viewpoint humans' knowledge is generated by interaction between their own experiences and their own ideas (Ertmer & Newby, 2013). Therefore, in these methods direct and structured teaching is not provided to learners.

The main training method in this category is called Inquiry-Based learning (IBL) and the other methods are derived from this method (Dostál, 2015). The methods including:

Problem-Based, Project-Based, Discovery-Based, and Experiential learning are all considered as self-directed learning methods. Self-directed learning is defined as a process that students are responsible for their own learning, therefore, learners should diagnose their own learning needs, set a learning goal, identify the necessary materials, implement a suitable learning strategy, and evaluate learning outcomes (Brookfield, 2009; Loyens, Magda & Rikers, 2008).

Inquiry-based learning starts by presenting a group of questions, problems, projects or scenarios instead of direct teaching that shows a smooth path to knowledge. In this method, students are responsible to find the answer of the questions and find solution for the problems/projects by trial and error and using all the available resources. This method is fundamentally student-centered, and the lecturer is only a facilitator who guide the students during the process of finding the solution (Dostál, 2015).

Inquiry-based learning is generally used in small scale projects or research. One of the most important aspects of inquiry-based learning is use of an open learning environment that encourages students to think about the procedures and the results deeply (Zion & Sadeh, 2007). Since, in open learning, there is no wrong result, students should evaluate the strengths and weaknesses of the collected results and assess their value. Based on Banchi and Bell (2008), inquiry-based learning can be conducted in four different levels including: Confirmation, Structured, Guided and Open.

- Level 1 (Confirmation Inquiry): The first level is similar to full guided learning. In this level, the instructor teaches a concept to learners, and develops a set of questions accordingly and presents a procedure to students that guides them to

reach the answer. Then, students should follow the procedure to collect and record data and discover relationships between variables.

- Level 2 (Structured Inquiry): The instructor provides a couple of questions and the overall procedure without its details. Then, students should justify their findings through analyzing the collected data.
- Level 3 (Guided Inquiry): In this level, there is no procedure guidance for the students and the instructor just presents the questions to the students. Therefore, students are responsible to design their own procedure for finding the answer of the questions and justify their results.
- Level 4 (Open Inquiry): In this level, instructor has only an observer role and students design research questions, and the procedures to answer the questions.

2.8.3. Comparison between full guided learning and minimally guided learning based on Human Cognitive Architecture

Advocates of FGL argue that instructional procedure should follow the structures which support our human cognitive architecture, otherwise it will not lead to an efficient learning. They claim that in unguided or minimally guided learning this structure is ignored, and it does not take into account the characteristics of working-memory, long-term memory, or the relations between them. Regarding the effect of MGL on long-term memory, since MGL cannot make accurate schemata, it cannot alter existing information in long-term memory significantly and consequently efficient learning cannot happen (Kirschner, Sweller, & Clark, 2006). Regarding working-memory, although, it is proved that the capacity of working memory is limited to a few number of elements (Cowan, 2001), MGL ignores this limitation by engaging students to search for a great number of

elements to find a solution. This has the potential to interfere with schema acquisition and learning as all cognitive resources are devoted to the searching for a solution process.

Advocates of MGL, do not provide enough evidence to reject the above claims, except they argue that all MGL methods are not minimally guided and those MGL methods that include scaffolding are not far from our human cognitive architecture (Hmelo-Silver, 2006; Hmelo-Silver, Duncan, & Chinn, 2007).

2.8.4. Comparison between full guided learning and minimally guided learning from Cognitive load theory perspective

Advocates of FGL argue that MGL is not in line with Cognitive load theory. Since free investigation of elements with high interactivity can generate a heavy working memory load and decrease learning performance especially for novice learners who do not have proper schemata to integrate the new information with their existing knowledge in their long-term memory (Chen, Kalyuga, & Sweller, 2015; Sweller, 2004). On the other hand, when learners search to answer a problem without any prior teaching, working memory resources are used for activities that are unrelated to learning. Consequently, students will engage in a time-consuming problem-solving activity that cannot lead to effective learning (Clark, Kirschner, & Sweller, 2012; Ericsson, & Kintsch, 1995).

Advocates of MGL, however, argue that inquiry-based learning methods employ scaffolding which can reduce the cognitive load and allow learners to learn the complex concepts. Scaffolding can decrease cognitive load by leading learners to concentrate on aspects of the task that have direct effect on learning (Hmelo-Silver, 2006; Hmelo-Silver, Duncan, & Chinn, 2007). In fact, since scaffolding can structure the task and restrict the available options for the learners, it can have direct effects on decreasing load on working

memory (Quintana et al., 2004). However, scaffolding is only likely to be useful once the learner has acquired some basic schemas in the domain.

2.8.5. Why FGL approach is more appropriate for the context of this research?

Since the target learners of this study are novice computer users and they do not have enough computer background knowledge, applying an FGL method is more appropriate for them. If we leave novice users to learn a complex software without any guidance, it can have a heavy cognitive load on them and make the learning very difficult. Pure MGL can make learners frustrated, confused and lead to misconceptions (Brown & Campione, 1994; Mayer, 2004). The high associated cognitive load can also interfere with learning,

In contrast with MGL methods that can impede the formation of a schema in a learners' long-term memory, FGL can facilitate the formation of schema. Since, when novice users learn software in a full guided environment, they can learn the optimized solutions for performing different tasks using software tools, consequently they can get appropriate schemata for the target software.

Finally, in the context of e-learning systems, FGL is more efficient than MGL from different aspects (Clark, et al., 2010; Mayer, 2001). It can also make longer term transfer of information and support better problem-solving skills (Clark, Kirschner, & Sweller, 2012).

2.9. Summary and conclusion

Cognitive load theory is based on extensive empirical evidence and significant number of studies have provided support for its effectiveness (Sweller, Kalyuga, & Ayres, 2011). Therefore, considering this theory can help us to design more efficient e-learning systems

which do not only provide all the necessary teaching content but also facilitate learning using appropriate instructional design strategies. Designing e-learning systems for teaching software applications based on the principles of cognitive load theory, can support learning by adapting the learning content to our cognitive architecture, preventing working memory from being overwhelmed, facilitating the formation of schemas in long-term memory, and consequently increasing learning performance. In fact, learners can have more efficient and reliable learning with less effort.

This literature review showed that most of the cognitive load effects such as worked examples, redundancy, and element interactivity have not been tested in the context of teaching software applications. Although, some solutions were proposed by the researcher on how worked examples should be presented in order to decrease cognitive load while learning software applications and how formation of schema can be facilitated for learning high element interactivity software tools, they have not been evaluated empirically. Therefore, the main gap in the literature is lack of studies in the area of teaching software applications based on cognitive load effects that will be addressed in this thesis.

In the next chapter, literature related to the application of gamification in e-learning systems especially for teaching software applications will be elaborated.

Chapter 3

Literature review on gamification

3.1. Introduction

In this chapter gamification concept and the related studies to teaching software applications using gamified e-learning systems is discussed. The chapter is started by providing an introduction about game-based learning, and describing gamification followed by a comparison between gamification and similar concepts. Then, the elements of gamification including game mechanics and game interface elements are elaborated. Some parts of these sections are borrowed from a paper that the thesis author has previously published (Darejeh & Salim, 2016). Afterwards, the related literature to e-learning systems, the gamified systems that employed narrative, interactivity and avatar that are the target experimental elements of this study are discussed and at the end a conclusion is drawn, and the literature gap is presented.

3.2. Game-based learning

Game-based or playful learning is defined as using different techniques based on games to engage learners with the learning content. There are four types of engagement including cognitive, affect, motivation and socio-cultural (Domagk, Schwartz, & Plass, 2010). One of the most important factors to achieve an effective game-based learning is considering cognitive engagement. Therefore, when designing the other types of

engagement, the main concern should be how they lead to achieve cognitive engagement (Plass, Homer, & Kinzer, 2015).

Cognitive engagement is the process of formation of schema. In this process learners process the contents that are presented in the game as visual and verbal information in their working memory and integrate the new information with the prior knowledge in their long-term memory (Mayer, 2014). From the cognitive aspect of game-based learning, designers need to consider which game elements can facilitate the cognitive processing of the learning content, and how the elements should be designed to engage learner in order to facilitate the formation of schema. In particular, designers should try to reduce extraneous cognitive load, and manage essential processing to have a better learning outcome (Mayer, 2014).

Affect and motivation engagements focus on emotional and motivational aspects of game and their impact on learners' and stickiness of the game. In fact, an effective game-based learning environment should be able to re-engage some learners who have disengaged from learning and cannot be engaged with other methods (Deterding et al., 2011; Squire, 2008).

Social/cultural engagement means games make opportunities for social engagement and provide features where social interactions occur to maximize learning (Squire, 2011; Ito et al., 2008). It means that the platform should encourage learners to participate in groups and use collective knowledge to meet the learning goals.

Plass, Homer, and Kinzer (2015) present a framework that summarises all aspects of game-based learning, see figure 3.1. As explained in chapter 1, in this thesis only the cognitive aspect of game-based learning will be evaluated.

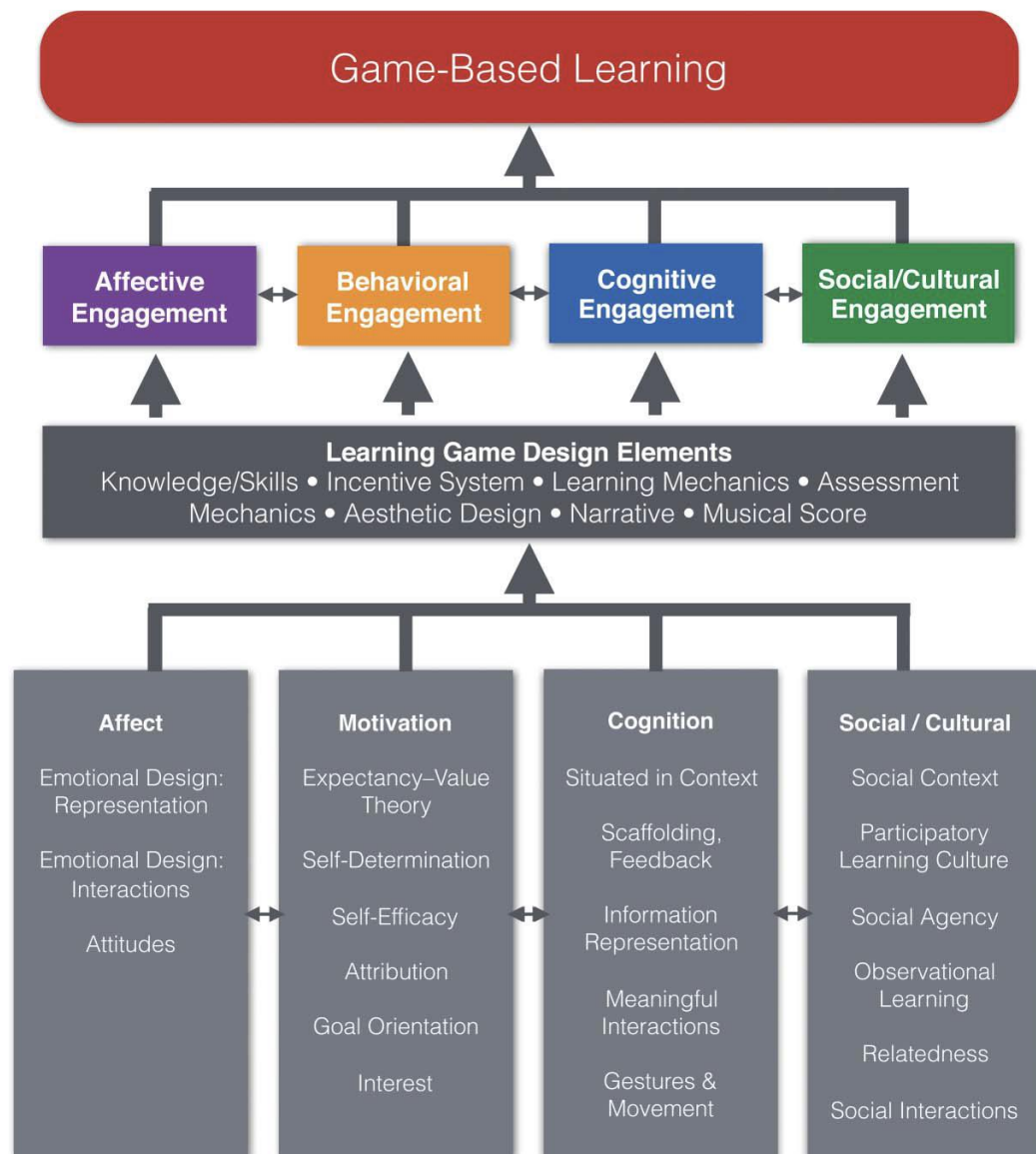


Figure 3.1. Integrated design framework of game-based and playful learning (Plass, Homer, & Kinzer, 2015)

There are different methods that can be used to make a game-based learning environment. These methods include gamification, serious games and game inspired design that will be discussed in the next sections.

3.3. Gamification concept

Gamification means having a game thinking in design which involves the use of video-game mechanics and elements in non-game contexts to encourage and engage users in the context by making sense of playfulness and fun (Deterding et al., 2011; Domínguez et al., 2013; Flatla et al., 2011; Hakulinen, Auvinen, & Korhonen, 2013; Hamari, Koivisto, & Sarsa, 2014; Huotari, & Hamari, 2012; Thom, Millen, & Dimicco, 2012; Witt, Scheiner, & Robra-Bissantz, 2011; Zichermann, & Cunningham, 2011). It is an emerging research area in computer science, especially human computer interaction (HCI) (Deterding et al., 2011; Huotari, & Hamari, 2012). The main function of gamification is engaging users in a particular task. In the recent years, gamification has attracted special attention and is popular among leading information technology companies such as SAP, IBM, AutoDesk, Adobe and Microsoft as a solution to increase software user engagement and learning performance of users to learn their product (De Jesus et al., 2019; Li, Grossman, & Fitzmaurice, 2012; Smith, & Kilty, 2014; Xu, 2011). The usage of gamification is not limited to a particular discipline; it is applicable in the related fields to education, software, website, workplace, business, sport, healthcare, etc.

3.4. Comparison between gamification and similar concepts

There have been some debates over the concept of gamification. This has led to several researchers coining different terms for similar studies (Deterding et al., 2011). In order to have a well-defined scope of gamification in this study, concepts similar to the term gamification are described in this topic.

3.4.1. Game inspired design

Game-inspired design is a user interface which adopts games' artwork such as game pictures, characters, and literature in non-game contexts; the aim is to draw users' attention or increase their engagement (Comello, 2016). These elements can be effective especially in designing software and website for children. For instance, Wook and Salim (2013) designed a game-inspired interface to assist children in carrying out searching and browsing activities in an online library.

3.4.2. Serious games

Serious games are similar to normal games, however, they are developed with the purpose of training or conveying a message to a specific group of users in a full game environment. Full-game environment means that users play in a virtual game environment by controlling a character or an object based on defined rules (Oostendorp, & Wouters, 2017). This is where a line can be drawn between gamification and serious games as there is no full-game environment or game play in the systems that are designed based on gamification (Uskov & Sekar, 2014). The term "serious" is employed, since in contrast to normal games, these games are designed with many purposes except entertainment (Cooper et al., 2010; Deterding et al., 2011; Enders, 2013; Groh, 2012; Kapp, 2012; Tsekleves, Cosmas, & Aggoun, 2016).

There are four different types of serious games: a) teaching games that are employed to teach a concept using full-game environment; b) simulator games which provides safe practice and testing of an entity in a virtual world; c) meaningful games which conveys a meaningful message to the player; and d) purposeful games which creates direct real world outcomes such as increasing users' activities. For instance, Audenaeren et al.

(2013) developed a game to predict whether a preschooler child shows high risks of developing dyslexia. Gustafsson and Katzeff (2009) proposed a game to teach and motivate people in reducing electricity consumption. Cooper et al. (2010) designed an online biochemistry game puzzle to improve players' ability to solve protein folding problems. Overall, studies showed that serious games can have positive effects in educational contexts and learning performance of different groups of learners such as school students (Jong, 2015), high school students (Tsai et al., 2013) and health professions (Abdulmajed et al., 2015).

3.4.3. Gamification

The main purpose of gamification is to encourage and engage users in a non-game context by sense of fun without having gameplay or a game-environment. Thus, the game mechanics and elements are not the center of the system, and they have a role of motivator (Deterding et al., 2011; Domínguez et al., 2013; Flatla et al., 2011; Hakulinen, Auvinen, & Korhonen, 2013; Hamari, Koivisto, & Sarsa, 2014; Huotari, & Hamari, 2012; Thom, Millen, & Dimicco, 2012; Witt, Scheiner, & Robra-Bissantz, 2011; Zichermann, & Cunningham, 2011). The most common usages of gamification are listed below:

- E-Learning: increase the efficiency of teaching materials, motivate students to spend more time in e-learning systems, motivate students to read learning content, and increase their virtual class activity such as asking and answering questions in the systems (Berkling, & Thomas, 2013; Cheong, Cheong, & Filippou, 2013; Denny, 2013; Domínguez et al., 2013; Hakulinen, Auvinen, & Korhonen, 2013; Ibáñez et al., 2014; O'Donovan, Gain, & Marais, 2013; Su, & Cheng, 2015).
- Human resource: increase personnel motivation, engagement and working performance (Ašeriškis, & Damaševičius, 2014; Makanawala et al., 2013).

- Healthcare and sport: increase physical activities, promote healthy living and motivate patients to continue their treatment process. (Cafazzo et al., 2012; Hori et al., 2013; Lin et al., 2013; Rose et al., 2013; Stinson et al., 2013)
- Data collection: motivate people to participate in data collection process such as crowdsourcing for a research, survey, etc (AlRouqi & Al-Khalifa, 2014; Bowser et al., 2013; Cechanowicz et al., 2013; Eickhoff et al., 2012; Eveleigh et al., 2013; Freeman, 2013; Gnauk et al., 2012).
- Online community: increase users' motivation to participate in a specific online community like a blog, social web site and question/answer web site (Depura & Garg, 2012; Farzan et al., 2008; Fitz-walter, Tjondronegoro, & Wyeth, 2012; Lee et al., 2013).
- Software popularity: increase users' loyalty to use specific software for a long time, increase frequency of using software and increase discovery-based learning (Dong et al., 2012; Li, Grossman, & Fitzmaurice, 2012; Montola et al., 2009; Tursi, Deplano, & Ruffo, 2014; Chua & Banerjee, 2013).

A Comparison between gamification and similar terms are presented in Table 3.1 and in the framework that is developed by Marczewski (2015), see figure 3.2.

Table 3.1. Comparison between similar terms to gamification

Terms	Game design style	Game elements	Full-game environment	Fun purpose	Serious purpose
Game inspired design	✓	✗	✗	✓	✗
Gamification	✓	✓	✗	✗	✓
Serious game	✓	✓	✓	✗	✓
Game	✓	✓	✓	✓	✗

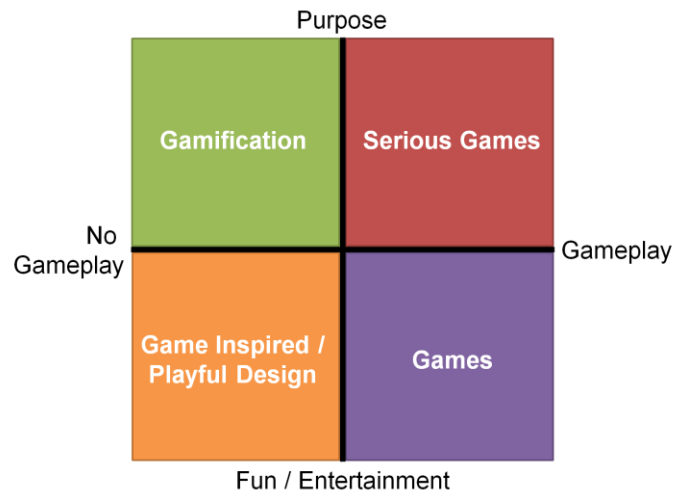


Figure 3.2: Comparison between similar terms to gamification (Marczewski, 2015)

3.5. The elements of gamification

In this topic all engaged elements in gamification including the elements that are evaluated in this research (narrative, interactivity and avatar) are explained and a framework is presented accordingly. In order to gamify a system, first a gamification type should be selected and then appropriate game mechanics and interface elements are added. Narrative and interactivity are subcategories of the game mechanics and avatars are a subcategory of the interface elements. In the sections below, gamification type, different game mechanics and game interface elements are explained.

3.5.1. Gamification type

There are two types of gamification: Structural Gamification and Content Gamification. In Structural Gamification, the software content is not game-like, and gamification is only implemented on the structure around the content. The focus of Structural Gamification is to motivate and engage users through rewards such as Points, Badges, or Achievements for special actions. On the other hand, Content Gamification which is the target of this

thesis, is about applying gamification elements on software or learning content (Kapp, 2012). For example, in an e-learning system that is designed based on Structural Gamification, the learning contents are normal, and users are rewarded by reading or practicing with the system. In contrast with structural Gamification, in an e-learning system with Content Gamification the teaching materials have one or more game-like element.

3.5.2. Game mechanics

Game mechanic refers to the contents, rules and methods designed for users to interact with the gamified system (Sicart, 2008). The most useful game mechanics in gamified learning systems are listed below.

- a. Narrative: it is a fundamental element of the gamified systems (Dickey, 2020) which is storyline and defined as a sequence of events or a scenario behind a gamified system that is used to make the system engaging for the users or teach a concept to them (Palomino et al., 2019; Plass, Homer & Kinzer, 2015; Pujolà & Argüello, 2019; Werbach, & Hunter, 2015). In e-learning systems narrative provides a theme to training and gives a role to the learner in the scenario (Pagulayan et al., 2002; Palomino et al., 2019). In fact, narrative in gamification is similar to inquiry-based learning (IBL) where learners get the desired skills by completing specific goals. In IBL one or more problems in a scenario is presented to learners and they should find a solution to the problem (Dostál, 2015). The difference between IBL and narrative is that IBL generally is used in minimally guided learning methods such as problem-based or project-based methods, however, narrative can be applied in both full or minimally guided methods. Designing a well written narrative can increase learning

performance by putting learners into a scenario which simulates a real-world condition.

- b. **Interactivity:** in the context of e-learning systems, interactivity is defined as a reciprocal activity between a learner and the system, in which the action of the learner and the system depends on each other (Domagk, Schwartz, & Plass, 2010). This definition emphasizes on providing a learning environment that enables users to interact with the teaching content through clicking or moving objects (Hung, Kinshukc, & Chen, 2018; Price et al., 2008). It can be used to simulate learning environments such as lab environments or software interface in order to enable learners to work with the different tools during learning. Based on different studies interactive content can improve learning performance as it can promote active learning (Bergman et al., 2005; Fernquist, Grabler et al., 2009; Grossman, & Fitzmaurice, 2011; Kelleher & Pausch, 2005). One of the applications of interactivity is for making interactive videos to enable users to interact with the video contents by clicking. In interactive videos, the video pauses in specific milestones and it needs users' action to continue (Price et al., 2008).
- c. **Clear goal:** it is a set of tasks or activities to reach a specific milestone or complete a mission. Usually the number of activities to complete a clear goal is specified and the next milestone is clearly stated (Federoff, 2002).
- d. **Challenge:** the definition of challenge is similar to Clear Goal; however, in order to perform an activity and get the reward, users face with some pressures like time limit to complete the tasks (Passos et al., 2011). Furthermore, challenges are normally versus other users and they compete to become the pioneer and get the rewards.
- e. **Time limit:** a time pressure to perform a special task or activity (Li, Grossman & Fitzmaurice, 2012).

- f. Progression: it is a feature to inform users about their progress toward the final goal of the system. It can be a bar or numeral percent that displays the completion degree of total goals (Xu, 2011).
- g. Immediate feedback: it is a real-time function to inform users about their success or failures (Passos et al., 2011). This feature is more often used to inform users about the correctness of their answers to a question or solutions to a problem.
- h. Reward: the motivator element of each gamified system is its reward mechanism (Xu, 2011). Each reward has specific characteristics including:
 - Reward trigger which refers to any predefined action which users should perform to get a reward (Hamari & Eranti, 2011).
 - Reward type which is the style of presenting rewards such as point, virtual money, level, badge, status, achievement (Burke, & Hiltbrand, 2011; Gnauk et al., 2012; Hamari, 2013; Liu, Alexandrova, & Nakajima, 2011; Vassileva, 2012; Xu, 2011).
 - Contextual type of reward that is about the context in which a reward can be achieved including fixed, sudden, random, rolling, prize pacing, and social (Chou, 2019).
 - Reward usage that refers to the way that the collected rewards can be used including achievement game, in-game, and out-game (Hamari & Eranti, 2011).

3.5.3. Game interface elements

Game interface elements have a different functionality from that of game mechanics, since they are used to make the interface fun or manifest information to users. The most popular game interface elements are listed below.

- a. Fantasy: using images of objects or environments which do not exist in the real world to make software interfaces interesting (Li, Grossman & Fitzmaurice, 2012).

- b. User avatar or talking avatar: User avatar is a graphical representation that represents the player's identity in the game. It is usually customisable by users to become similar to their real style (Passos et al., 2011). However, a talking avatar is an animated character that can read text and it has different gestures such as lip syncing and body movement based on what it says (Chen et al., 2012; Cook et al., 2017; Fabio et al., 2019; Rueda, Estupiñán, & García, 2016).
- c. Map: a visual presentation of all the tasks that users should perform (Morrison & DiSalvo, 2014).
- d. Leader board: it shows users' rank, progress and achievement in comparison with others in a competition (Xu, 2011).

The gamification framework below shows the relationship between all the above-mentioned gamification mechanics and elements in order to gamify an application (Darejeh & Salim, 2016). This framework indicates that the first step for gamifying a system is selecting gamification type and then choosing game mechanics and interface elements based on the selected gamification type. Furthermore, the framework illustrates the process of giving rewards to users. The gamification framework is illustrated in Figure 3.3.

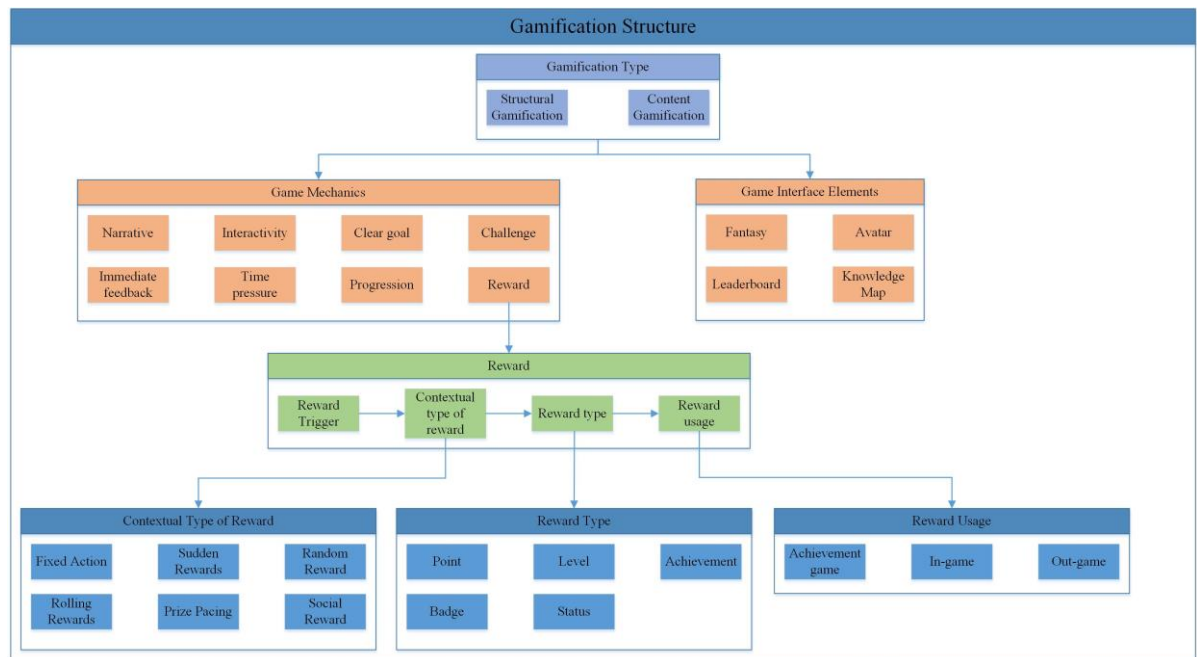


Figure 3.3: Gamification Framework

3.6. Gamification and e-learning systems

In the previous section, all the elements of gamification were explained. In this section, the e-learning systems that are gamified with the use of different gamification elements are presented. Specifically the gamified e-learning systems that utilized the target gamification elements of this study (narrative, interactivity and avatar) are discussed in detail.

Before talking about the gamified e-learning systems, a short description of different resources that are used for learning software and why e-learning systems are the best way for teaching computer software to novice learners is presented. In order to learn a new software application, there are different ways including: training classes, training books, online resources such as software forums and YouTube videos, software help that is commonly text-based and developed by the software company owner and integrated into the software interface, and e-learning platforms such as Linda, Coursera, or universities'

teaching platforms that present the teaching content in a systematic manner using multimedia content. Today the most popular way of learning new software is using online resources, software help, and e-learning platforms. Since they are cheaper and less time consuming than participating in training classes or reading training books. However, online resources, and software help are not good solutions for novice users, since they introduce software features separately and novice learners cannot get an overview of the software structure (Carroll, & Rosson, 1987; Shackel, & Richardson, 1991).

Therefore, it can be concluded that one of the best solutions for novice users to learn new software is using e-learning platforms. e-learning is defined as an online system based on Web 2.0 technology which provides teaching and learning services through multimedia and interactive learning contents to promote self-learning (Anderson, 2008). Multimedia learning means learning from a combination of text, pictures and sound in a software-based environment (Mayer, & Moreno, 2003; Wankel, & Blessinger, 2013). Interactive learning is about the role learners have with the e-learning system through interactions with the learning content, solving the exercises, participating in discussions or commenting on the teaching materials, instead of having a passive role where they just read the content (Banday, 2012).

E-learning systems can provide an efficient learning experience as they engage both auditory and visual senses through presenting information in audio and visual format (Moreno, & Mayer, 2000a). The main component of e-learning systems is their content and instructional methods (Clark, & Mayer, 2016). In fact, instructional design is the most important phase of developing e-learning systems, and the effectiveness of e-learning systems highly depends on the instructional approach (Margaryan, Bianco & Littlejohn, 2015).

Therefore, an efficient e-learning system to teach software applications requires the integration of appropriate technologies with innovative instructional approaches (Aliguro-Bravo, & Agila-Palacios, 2016). To this end gamification elements can be used to increase the effectiveness of learning methods and enhance learners' engagement with the e-learning system. Existing studies showed that applying gamification techniques can compensate for monotony of the learning content and increase students' motivation and engagement with the content (Berkling, & Thomas, 2013; Betts, Bal, & Betts, 2013; Campos, et al., 2015; Fotaris et al., 2016; Hasegawa, Koshino & Ban, 2015; Morrison, & DiSalvo, 2014; Osipov et al., 2015). Increasing motivation can affect learning performance as it can help learners to prioritise and allocate the working memory limited capacity to learn the target teaching concepts. In fact, there is a connection between emotion and cognition (Izard, 2009) and motivational factors can influence cognition by facilitating self-regulation (Pekrun & Stephens, 2010; Rutherford & Lindell, 2011). Positive emotions and self-regulation can support information processing and improve the skills such as negotiation, decision-making, and problem-solving (Erez & Isen, 2002; Konradt, Filip & Hoffmann, 2003). Figure 3.4 shows how learning occurs using separate visual and auditory channels in multimedia learning environments and how motivation can affect the information processing in working memory (Plass & Kaplan, 2016).

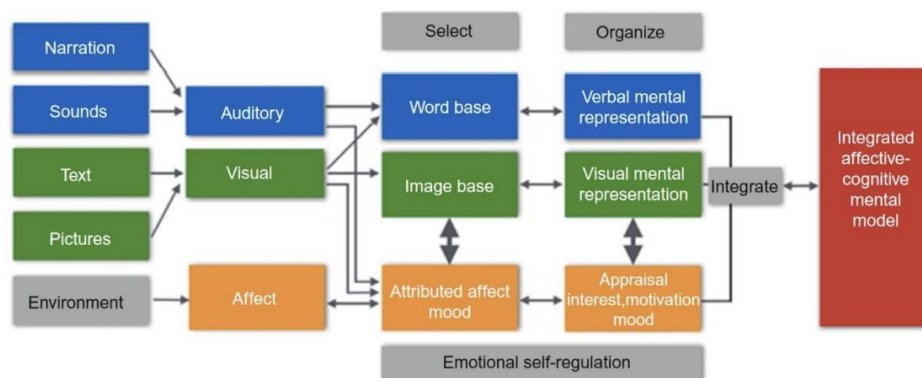


Figure 3.4. Integrated Cognitive Affective Model of Learning with Multimedia (Plass & Kaplan, 2016)

However, it should be note that in contrast with the existing studies that evaluated the effects of gamification elements on motivation, the focus of the current study is on evaluating the effects on learners' cognitive load as explained in chapter 1.

3.6.1. Gamified e-learning systems that used interactivity

In e-learning systems, interactivity is used for two different purposes: a) making a software simulated interface to teach specific software tools, b) making interactive video tutorials to increase learners' engagement with the learning content. In the following sections, studies related to each category will be outlined.

a) Teaching software applications

In the context of teaching software applications, interactivity can be used to simulate the software environment in order to enable learners to work with the different software tools during learning. One of the best examples of applying interactivity in learning productivity software is Microsoft Ribbon Hero. Ribbon Hero is a gamified learning system that was developed to help users to learn useful features in MS Office 2010. The system followed the narrative of a character who is a time traveller and tries to get back home. In each lesson, learner had to read the instructions and solve some challenges in an interactive environment that simulated Microsoft Office to get some points (scores), a badge and unlock the next levels. The teaching method of Ribbon hero was designed based on discovery-based learning and the instruction was minimal (Shane, 2013). The efficiency of Ribbon hero is not clear, since no study has been conducted to evaluate the effect of system on learning performance.

Li, Grossman, and Fitzmaurice (2012), proposed a gamified tutorial called GamiCAD to help new users, learn AutoCAD. The system was designed based on a group of learning tasks and a story behind the tasks. In each level, learners should complete a group of tasks in an interactive simulated AutoCAD environment to get some points (scores) and badges for going to the next level. Although, learners could see the instructions for performing each task, there was not a full teaching component in the system to teach each part of the software systemically. In order to compare the learning performance of the gamified system with the none-gamified version, the completion rate of the test tasks and time duration to complete each task were measured. Also, participants were asked to convey their perceptions of load and difficulty of the gamified system, using a subjective questionnaire. The test results of the gamified system showed that learners had better learning performance in comparison with the non-gamified version.

The other similar system to GamiCAD is Adobe Level up. The system is designed to help novice users, learn a group of tools in photoshop (Dontcheva, et al., 2014). The learning was based on assigning a task related to editing a picture and providing the steps to perform the task to learners. At any given time, only one step of performing the target task was presented to learners and by completing the task using the interactive simulated Photoshop environment, learners could see the rest of the tutorial and get a specific number of points (scores). In order to collect participants' opinion about the system, a combination of interview and questionnaires were used. The results showed that most of the participants enjoyed using the system and they mentioned that their Photoshop knowledge was improved. Also, checking the design quality of images that were designed by the participants showed that the gamified system could improve the design ability of the participants.

In order to learn Adobe Photoshop, there is another system that was developed by Dong et al., (2012) and used minimally guided learning methods similar to the already explained systems. The system had a jigsaw puzzle theme which means that learners had to solve the tasks that were related to matching puzzle pieces using the interactive simulated Photoshop environment. In this system, learners were free to use any Photoshop tool to match colour, brightness, contrast or the other properties of the puzzle pieces to match them with each other. Although, the learning outcome of the system was not evaluated using quantitative methods, the interview results of the study showed a positive attitude to using the gamified system.

As it can be seen, few studies exist that provide an interactive environment in order to teach software applications. Also, they use minimally guided approaches that we suggest are not appropriate teaching methods for novice users.

b) Interactivity in the video tutorials

In addition to the above gamified systems that used interactivity in the context of teaching software, there are a group of studies that used interactivity in video tutorials to make them more engaging.

Price et al. (2008) developed an interactive video-based system to teach undergraduate/postgraduate engineering students risks and hazards associated with recording traffic in busy streets and roads. While students watched the video, they were supposed to identify the hazards by clicking on the video content. Since no experiment has been conducted in order to evaluate the effect of this system on students, its efficiency is not clear.

Singh (2004) designed an interactive video tutorial for teaching physics concepts through problem solving methods. Students were supposed to solve some problem-solving tasks and enter the results into the interactive video tutorial system. If the students' answers were not correct, the system showed them a related video tutorial to improve their background knowledge, however if their answer were correct the system showed them a video tutorial to prepare them for more advanced tasks. In order to evaluate the efficiency of the interactive video tutorial, a combination of interview and think-aloud protocols was used to collect students' opinion. The study results revealed that the interactive tutorial could improve problem solving skill of the students and enabled them to solve the tasks that they could not solve before working with the interactive tutorial system.

Hung, Kinshuk and Chen (2018) designed an interactive video-based system with the use of Microsoft Kinect in order to enable users to interact with the video content through using speech and hand movement. During learning, some questions were asked from the learners and they had to show the correct answer in the video using speech or hand movements. The experimental results showed that learners who learnt with the interactive video had a better performance in comprehension and retention of learning contents, than the control group. The positive results provide an example of the embodied cognition effect which states that involving learners physically with the objects that are related to the learning content can enhance learning performance (Shapiro, 2019; Weisberg & Newcombe, 2017; Wilson & Foglia, 2017).

Devinea, Gormley and Doylec (2015) developed an interactive video tutorial for teaching laboratory techniques and equipment handling to students. In different stages of learning a multiple-choice question appeared on the screen which asked about the target teaching content, and if the learners answered the question correctly the video continued. Based

on the survey results students had better attention during learning while using the interactive video and the embedded questions could motivate them to continue learning. However, no data were collected to evaluate the learning outcomes.

Kleftodimos and Evangelidis (2016) designed an interactive video-based system in order to teach an image editing software. The video is divided into different sections and after watching each section, an exercise was assigned to the learner. By completing each exercise, the next section of the video played. No experiment has been conducted in order to evaluate the efficiency of this system on learning performance.

Kalet et al. (2012) compared the cognitive load effects of two versions of interactive video with a normal video for teaching surgery to medical students. In the first interactive video version, students could use a mouse to click on different parts of the video and in the second version they could use drag and drop in addition to clicking in order to interact with the video content. Although, the results did not show a significant difference in knowledge across the groups, the physical exams scores of the students in the click group was higher than the other two groups. Also, in another study, Schwartz & Plass (2014) showed that an interactive learning environment can increase learning performance in comparison with the static and audio conditions.

As it can be seen, in all these systems, the video pauses at specific milestones and users should then perform an action such as clicking on the video content or answering questions to watch the rest of the video. The outcomes all suggest that interacting with the video content either through clicking the video content or answering the questions that are embedded in the video can increase learners' engagement with the learning content and consequently can increase learning performance.

3.6.2. Gamified e-learning systems that used narrative

In the context of e-learning systems, narrative can be an imaginary project that learners should interact with, using different software tools. Then, in each lesson the tools that are necessary to complete a part of the project and their relationship with the previous tools are taught to the learner. This integration of the lessons can help to decrease extraneous cognitive load by helping learners to get an overview of the software tools and understand the relationship between them (Pollock, Chandler, & Sweller, 2002; Van Mierlo et al., 2012). The purpose of the gamified e-learning systems that used narrative for teaching computer science related concepts can be placed into three categories: a) teaching software applications, b) teaching software development project management, and c) teaching computer network related concepts.

a) Teaching software applications

There are few examples of narrative systems used to teach software applications. The best examples are Ribbon Hero that was developed to help users to learn useful features in MS Office (Shane, 2013) and GamiCAD to help new users, learn AutoCAD (Li, Grossman, & Fitzmaurice, 2012). Both systems are designed based on a narrative that integrates all the learning topics and learning tasks. Moreover, in order to teach programming, Eagle and Barnes, (2009) designed a simple learning platform to teach the main programming concepts by using a narrative and a game-based interface that asks learners to complete some coding tasks based on the narrative requests. As was explained in the previous section, no study has been conducted to evaluate the effect of Ribbon hero on learning performance. However, the experimental results of the GamiCAD and the gamified

programming environment showed improvement in the learning performance and an increase in the learners' satisfaction in comparison with the control system.

b) Teaching software development project management

One of the most common usages of narrative is for teaching software development project management. For example, Calderón, Ruiz and O'Connor (2017) developed a learning platform called ProDec that is designed to teach the components that should be considered during the whole software project lifecycle. In this platform, users select one of the existing software project scenarios/narratives to learn different aspects of project management. No study has been conducted to evaluate the effect of ProDec on learning performance.

There are several similar systems to ProDec that have been developed by other researchers (Bell, Sheth, & Kaiser, 2011; Caulfield, Veal, & Maj, 2011; Hainey et al., 2011; Jain, & Boehm, 2006; Srinivasan, & Lundqvist, 2007). In these systems learners could select a role in an imaginary software project team and based on the selected role a narrative was provided to the learners and they were asked to complete a part of the project including requirement engineering, design, implementation or testing. The survey and the interview results of Caulfield, Veal and Maj (2011) and Hainey et al. (2011) showed the game-based learning method could improve software engineering and project management knowledge of the learners. However, no data was collected by Bell, Sheth, and Kaiser (2011), Jain and Boehm (2006) or Srinivasan, & Lundqvist, (2007) to evaluate the efficiency of the systems.

c) Teaching computer network related concepts

The other area that narrative has been used is for teaching computer network related concepts including connecting computers, configuring servers and network security. Denning, Kohno and Shostack (2012) and Jordan et al. (2011) designed learning systems to teach network security concepts using different narratives in regards to hardware hacking. Based on the narrative content, learners were asked to perform a variety of audit jobs and pro bono work. The systems were designed in a way that the knowledge that was learnt in each narrative then provided the base of the next narrative. The experimental results of Jordan et al. (2011) showed that participants who used the gamified system could complete the tasks faster and their interest level with respect to computer security was increased in comparison with the control group. No data were collected to evaluate the efficiency of the system designed by Denning, Kohno and Shostack (2012) on learning performance.

As can be seen from this review, the effect of most of the systems has not been evaluated or just a survey was used to collect users' opinions without measuring the actual learning performance. Also, in the studies where the efficiency of the system was evaluated, and obtained positive results, narrative was applied in conjunction with the other game elements and its effect was thus not measured in isolation. Another issue is that narrative tends to only be used as a motivational element to make the learning interesting and increase learners' engagement with the learning content. Furthermore, all the mentioned studies are based on minimally guided teaching methods such as discovery-based or problem-based learning approaches without providing systematic teaching content to the learners. To fill gaps in the existing findings, it seems necessary to conduct a study and evaluate the effect of narrative on the cognitive load of learners using a fully guided learning approach.

3.6.3. Gamified e-learning systems that used avatar

The related studies in the area of avatar-based learning systems can be categorized into the four categories including: a) increasing learning performance, b) increasing users' motivation to continue learning or performing a task, c) helping patients with special needs, and d) evaluating the effect of avatar on cognitive load. In the following topics the related studies to each category will be outlined.

a) Increasing learning performance

In the context of teaching mathematics, Rueda, Estupiñán, and García (2016) designed an e-learning system that used a talking avatar for teaching mathematics for business. The test task results showed that the system could increase learning performance significantly in addition to increasing the learners' satisfaction when using the e-learning system. Also, Cook et al. (2017) evaluated the effect of avatar's body and face gestures that are synced with what avatar says on its efficiency for learning mathematics. The results revealed that children who used the avatar version with gestures had a better learning performance in comparison with the children who learnt the lessons without gestures. The test tasks completion rate was increased and the time duration to complete each task was decreased. Also, the results showed that participants who used the avatar with gestures were more likely to transfer and generalize their knowledge to similar topics.

In the context of teaching medical concepts, Flood and Commendador (2016) used different talking head avatars including avatars of physicians, patients, nursing students, and nursing instructors in order to teach nursing concepts and for practicing how nurses should react to different medical conditions. Each avatar explained a specific case scenario related to a health issue, and nursing students were supposed to answer the

questions related to the explained issue. No data were collected in order to evaluate the efficiency of the system. Also, Commendador and Chi (2013) evaluated the effect of avatar-based learning system on gaining pre-clinical experience. Findings indicated that students had a high level of motivation and engagement to learn the nursing concepts using the avatar-based system in comparison with the no-avatar system.

In the context of teaching human science concepts, McManus et al. (2011) investigated the impact of showing character animations and self-avatars during learning, on behavioural task performance. The results showed benefits of including an avatar for the interaction tasks, which participants could perform faster and more accurately. Also, a self-avatar was found more useful in comparison with the character animation for complex tasks that involved interacting with elements in the virtual world. Crisp (2012) designed an avatar-based learning system for teaching criminology and criminal justice to postgraduate students. However, no experiment was conducted to evaluate the efficiency of the system. Ward (2010) developed an avatar-based e-learning system for teaching marketing curriculum. The results showed that students could develop new skills and gain a wider perspective of the e-marketing.

Falloon (2010) conducted a study on the efficiency of MARVIN which is an avatar-based e-learning platform that is developed for the state government in Australia's Northern Territory to convey critical health, business and cultural information to aboriginal people. The system used different customizable animated avatars to share the messages. The interview results showed that the avatar could increase users' motivation and learning quality.

Aikina and Zubkova (2015) evaluated the effect of VOKI which was an avatar-based online platform on teaching English language. This platform was designed to improve students speaking, listening and writing skills, by designing their own avatar and use it during learning. A questionnaire was used to collect students' opinion about VOKI. The questionnaire results showed that VOKI could make the studying process interesting and individual-oriented. Also, Voki increased students' willingness to speak in the target language and enabled them to remember words and grammar more easily.

In the context of teaching through simulation, Hughes et al. (2015) developed an avatar-based e-learning platform to simulate classroom and students with different characteristics to teach novice teachers how they should behave with students and react to their actions. Observation results indicated that the classroom simulator improved teaching behaviours such as the way that the teachers described questions and provided feedback to the students. Also, Yasin et al. (2010) designed an avatar-based system to teach religious practices using an animated avatar in a 3D virtual reality environment. The survey results showed the virtual world environment was more effective in comparison with showing step by step images.

Based on the existing studies in the area of using an avatar in order to increase learning performance, an avatar was found to be an effective method of teaching mathematics, marketing, criminology, English language, religious practices, gaining pre-clinical experience, conveying critical health and cultural information. Also, the efficiency of an avatar was demonstrated in a simulated classroom environment. However, it should be noted that in most of these studies, learning was not measured directly and increasing learning performance was demonstrated only through using a self-reported questionnaire.

b) Increasing users' motivation to continue learning or performing a task

Chen et al. (2012) designed an animated pedagogical agent with facial expressions and body movements to motivate students to read more content in an e-learning system. When learners were reading the content, they could express their emotions by mouse-clicks and the avatar motivated them using different facial expressions and body movements. The results showed the avatar could increase learners' motivation in comparison with the no-avatar system. Showing positive facial emotions had the most positive effect on the motivation of the students.

Theng and Aung (2012) conducted a study based on cognitive theory of emotions, to investigate primary school children emotional responses and motivations while using avatar-based e-learning systems. The observation and questionnaire results showed that students had a positive attitude towards avatars, influencing their learning motivation.

Ang et al. (2013) compared the effects of avatar-mediated communication with video-mediated communication on children in order to encourage them to brainstorm and express their ideas in special contexts. The study results revealed that the avatar version could increase the quality of the students' ideas.

Allmendinger (2010) evaluated the effect of an avatar in social interaction while using a learning platform. The study used a simulated classroom and an avatar was allocated to each student to see if use of the avatar instead of using the real name and picture of the students could increase learner's motivation in expressing their opinion. The results showed that the avatar and virtual environment could support the conversational flow of the users.

Based on the existing studies, an avatar is an effective method of increasing users' motivation to read more content in an e-learning system, encourage users to brainstorm,

and promote social interaction. Also, participants claimed that an avatar could increase their motivation and engagement with the learning system.

c) Using avatar to help patients with special needs

In the context of helping children and adults with psychological disorders, Fabio et al. (2019) examined the effect of an interactive avatar that provides feedback while performing tasks, for children with attention deficit hyperactivity disorder (ADHD). Results indicated that the avatar could improve the attention of children and consequently boosts their learning performance versus the no-avatar condition. Also, Wang, Xing and Laffey (2018) designed a virtual society platform for autistic children to examine the relationship between avatar-based social interactions and embodied social presence. In the platform, each user had an avatar and they could have different interactions with the other users through their avatar. The observation and quantitative measurements revealed how this kind of systems should be designed and how collaborative learning can be facilitated using avatar-based learning systems for autistic youth.

Pinto et al. (2013) conducted a study with the purpose of evaluating the effect of an avatar-based depression self-management intervention on young adults. The initial results showed that avatar is an efficient method to be used as health provider or coach in virtual environments to decrease depression symptoms over time.

In the context of helping deaf children, Gilani et al. (2019) evaluated the effect of an avatar-based AI system on deaf infants to see if the avatar can facilitate learning American Sign Language. The observed results demonstrated that babies will interact with the avatar and using an avatar can facilitate learning sign language in young babies. Also, Bouzid, Khenissi and Jemni (2016) created a signing avatar-based system in an

educational game to see if it can increase learning performance of sign language for deaf children. The test task results indicated that the signing avatar is an efficient method in teaching new words to deaf children in comparison with the no-avatar condition. Brun, Turki and Laville (2016) developed an avatar-based 3D application to teach words to deaf children using sign language. However, no experiment was conducted to evaluate the efficiency of the system.

Andrade et al. (2014) evaluated the value of adding avatar in an online self-management instruction program to help women with an overactive bladder and increase their life quality. The study evidence showed that the avatar-based system in comparison with the voice only version could motivate patients to adopt healthy behaviours and significantly improved patients' health-related quality of life.

Bedra et al. (2013) assessed feasibility and patient acceptance of an avatar-based interactive educational system for ileostomy management on patients with new stomas. The interview results showed a high acceptance level of the avatar-based system by the patients in addition to increasing their knowledge and their self-efficacy.

Based on these studies, using an avatar is an efficient method to help patients with special needs including patients with attention deficit hyperactivity disorder to increase their concentration, help deaf children to learn sign languages, and assist patients with chronic conditions through promoting self-management.

d) Evaluating the effect of avatar on cognitive load

Pignatiello et al. (2019) evaluated the effect of an avatar-based system that served as surrogate decision makers (SDMs) on the cognitive load of family members for critical

patients who cannot decide for themselves. The purpose of the study was to see whether an avatar-based system can facilitate decision making processes through decreasing the cognitive load of the decision makers in comparison with a video-based version. Both avatar-based and video-based systems were designed to encourage family members to provide information about the patient's history, review the clinician's recommendations about the patient condition and consider whether the plan is appropriate for the patient. The results of the self-reported questionnaire and interview showed that the avatar-based decision aid system increased cognitive load of the decision makers significantly in comparison with the video-based version.

Gentile et al. (2017) evaluated whether the existence of an avatar that replays user's movements can affect cognitive load in comparison with showing hand icons as a mouse pointer when users interact with the interface using motion sensing cameras. The interface was a university dashboard page including different elements such as weather, news, videos, campus map, etc. The questionnaire results showed that when users see the avatar that replicates their body movements, it can decrease the perceived cognitive load while interacting with the interface in comparison with having small hand icons as a pointer to click on the interface elements. The reason for the superiority of the avatar in comparison with showing hand icons may be that when a user tries to click on the upper-left side of the interface with their right hand, the avatar will show the right arm, however, when users see two handed icons, they need to decide which hand icon is easier to move to go to the target element of the interface. In line with this study, Steed, Zisch and Steptoe (2016) and Pan and Steed (2019) demonstrated that showing a self-avatar in a virtual reality system can decrease learners' cognitive processes while interacting with the objects in the virtual reality environment. The reason is that when users see an avatar that

replicates what they do, it plays the role of a mirror and users can have a more natural interaction with the virtual environment without thinking which direction they should move their hand to click on the target element.

It can be concluded that an avatar can increase cognitive load if it is used to present a concept, however, in the virtual environment, a self-avatar can be a good replacement for the mouse pointer, since the mouse pointer is an external object that must be controlled by users, however, a self-avatar is synced with the user's body movement and users do not control it in a way that they control the mouse cursor.

The main issue of the existing studies is that, most of the studies compared avatar-based system with non-computerised situations such as a classroom, not with another e-learning system that did not have the avatar. In fact, many different variables have been changed in the studies and it is not clear if avatar itself was efficient or a group of elements that were simultaneously modified, made the system efficient.

Also, a great number of the studies have just evaluated the effect of avatar-based e-learning systems on users' motivation and engagement with the use of surveys and questionnaires to gauge users' opinions, and it is not clear if the avatar has had a positive effect on cognitive load or not. Although, there are few studies on the effects of avatars on cognitive load, they are not related to the effect of avatar on learning performance when an avatar is added to an e-learning system and there are other visual elements that learners should focus on. Therefore, conducting a study to evaluate the effect of avatar on cognitive load of learners when avatar is used in the e-learning systems seems important.

3.7. Conclusion and literature gap

The existing gaps in the literature related to applying gamification to teach software application through e-learning platform can be categorized in three groups: a) purpose of the studies, b) the teaching methods and c) experimental design. A great number of studies have been conducted in order to gamify e-learning systems, however, there are few studies that utilized gamification in order to teach software applications. Furthermore, gamification is often just applied for enhancing users' motivation and engagement with the system, and none of the studies examined the effect of any element of gamification on learners' cognitive load (Darejeh & Salim, 2016). In fact, the elements such as narrative, interactivity and avatar were just used to make the system interesting and fun for the users.

Regarding teaching methods, the existing gamified systems do not provide a systematic teaching method, as they use minimally guided teaching approaches such as discovery-based or problem-based methods. Although, these methods help users to learn software in a practical context, minimally guided approaches can increase cognitive load of novice users.

Finally, there are two major issues in the experimental design of most of the gamified systems. The first one is, just a few gamified systems measured the learning performance using direct quantitative measurement methods such as a test performance mark. Instead the learning performance was measured using observation, satisfaction questionnaires and interviews. The second issue is, in almost none of the evaluated systems, the game elements were evaluated in isolation and a group of game elements was applied at the same time and the effect of the overall system was reported rather than each element

separately. Therefore, it is not clear if the positive effect was related to only one element, two elements or all of them together.

Consequently, by considering the mentioned gaps in the literature, the main issue that has not been fully researched is evaluating the effect of gamification elements that can affect cognitive load on teaching productivity software applications in a full guided learning environment, with a focus on decreasing learners cognitive load as well as providing them with practical knowledge skills.

Chapter 4

Experiment 1

4.1. Introduction

Since productivity software applications are designed to facilitate work that we otherwise perform manually in the real world, it may be better to teach the use of software tools by presenting worked examples and real-world problems instead of just introducing the tools' usage. Narrative can be used to integrate worked examples by defining a project with an associated context that learners should interact with, using different software tools. This integration of the lessons within a familiar context might help decrease extraneous cognitive load by helping learners to get an overview of the software tools and understand the relationship between them (Pollock, Chandler, & Sweller, 2002; Van Mierlo et al., 2012).

As it is defined in chapter 3, in e-learning systems, narrative is defined as a sequence of events that can be used to provide real-world scenarios to teach software applications. The narrative provides a theme to training and gives a role to the learner in the scenario (Pagulayan et al., 2002; Palomino et al., 2019). Worked examples associated with an appropriate narrative that include: a) a clear guideline for the problem, b) show relations between different elements of the problem, and c) highlight main features in order to select the correct solution for the problem, may facilitate learning (Renkl, 2014a). A familiar narrative can thus serve to integrate elements of related worked examples while

also reducing cognitive load that may be associated with an unfamiliar context of the worked examples.

Narrative has been used in many gamified e-learning systems that use serious games or gamification techniques to teach things such as project management applications (Calderón, Ruiz, & O'Connor, 2017; Caulfield, Veal, & Maj, 2011), MS Office (Shane, 2013), AutoCAD (Li, Grossman, & Fitzmaurice, 2012), computer network concepts (Denning, Kohno, & Shostack, 2012) and programming concepts (Eagle, & Barnes, 2009). The focus in these studies has been on improving motivation rather than their cognitive consequences. In other words, it is not clear if adding narrative can increase learning performance through affecting cognitive efficiency or whether it can only affect motivation and increase learners' engagement with the e-learning system.

This chapter describes an experiment in which two contextual types of narrative were compared with a no-narrative condition in order to teach software applications. Cognitive load theory provided the theoretical base. We compared the effect of no-narrative, familiar and unfamiliar context narratives on novice users' cognitive load while learning a complex productivity software application through an e-learning system, with tools involving elements that were both high and low in intellectual complexity (as measured in terms of low and high element interactivity levels).

For the familiar context narrative, we used a story of a hotel owner who is looking for a computer-based system to manage his hotel rooms and guests and for the unfamiliar context narrative, a story of a banker who wants to manage mortgage information of the customers is used.

We hypothesized that: 1) in order to learn high interactivity elements of productivity software applications, a familiar narrative will decrease the cognitive load of novice users by providing a familiar theme for the worked examples, when compared to no-narrative and an unfamiliar narrative, 2) for the elements with low element interactivity, a familiar narrative may not have any significant effect on cognitive load, when compared to no-narrative and unfamiliar narrative, as the users' processing load is still manageable. Based on these overarching hypotheses, it is predicted that:

1A) For the high interactivity teaching materials, a familiar context narrative will lead to a reduced cognitive load and consequently learners' reading time will be reduced. We predict this result based on Brünken, Plass, and Leutner (2003) who showed that by decreasing cognitive load, time duration of performing the target task can be decreased.

2A) For the low interactivity teaching materials, the familiar context narrative will not lead to a significant reduction in cognitive load and reading time will not be affected. We predicted this result because when the teaching materials are low in cognitive load due to low element interactivity, the users' processing load will still be manageable and reading duration will not be significantly affected (Brünken, Plass, & Leutner, 2003).

1B) For the high interactivity teaching materials, the familiar context narrative will lead to less cognitive load therefore, learners will report less difficulty, more confidence and less stress during the learning phase. We predicted this result because Likert scale questionnaire is a direct measurement method of cognitive load and by decreasing cognitive load, learners will feel less stress and they will express less difficulty (Ayres, 2006; Cranford, et al., 2014; De Jong, 2010; DeLeeuw & Mayer, 2008; Gerjets et al.,

2009; Granholm, et al., 1996; Kalyuga, Chandler, & Sweller, 1999; Paas, Renkl, & Sweller, 2003).

2B) For the low interactivity teaching materials, the familiar context narrative will not lead to a significant reduction in cognitive load, therefore, learners will not report more/less difficulty, confidence and stress during the learning phase.

1C) For the high interactivity test materials, the familiar context narrative will lead to less cognitive load resulting in an increase in test performance marks (e.g. Brünken, Plass, & Leutner, 2003; DeLeeuw, & Mayer, 2008; Mayer, 2001; Paas, Ayres, & Pachman, 2008; Van Mierlo et al., 2012).

2C) For the low interactivity test materials, the familiar context narrative will not have a significant effect on the test performance marks. This prediction was made because the users' processing load will still be manageable, and so test difficulty level will not be changed and consequently test performance marks will not be affected (e.g. Brünken, Plass, & Leutner, 2003; DeLeeuw, & Mayer, 2008; Mayer, 2001; Paas, Ayres, & Pachman, 2008; Van Mierlo et al., 2012).

1D) For the high interactivity test materials, the familiar context narrative will lead to a decrease in mouse movement distance and number of left and right clicks. This prediction is based on embodied cognition effects (see Barsalou, 2008), where less movements may be needed to support and improve learning outcomes when the cognitive load is lower. Furthermore, Kortum and Acemyan (2016) showed that by increasing the knowledge level of the users, mouse movement distance and number of clicks can be decreased.

2D) For the low interactivity test materials, familiar context narrative will not lead to a decrease mouse movement distance and number of left and right clicks. We predicted this result because the users' processing load will still be manageable, and so mouse movement distance and number of clicks will not be affected (Barsalou, 2008; Kortum & Acemyan, 2016).

1E) For the high interactivity test materials, a familiar context narrative will lead to a reduced cognitive load and consequently test task performance speed will be increased. We predict this result based on Brünken, Plass, and Leutner (2003) who showed that by decreasing cognitive load, time duration of performing the target task can be decreased.

2E) For the low interactivity test materials, the familiar context narrative will not lead to a significant reduction in cognitive load and test task performance speed will not be affected. We predicted this result because when the test materials are low in element interactivity, it is still manageable for the learners to process the information and test task performance speed will not be affected (Brünken, Plass, & Leutner, 2003).

1F) For the high interactivity test materials, the familiar context narrative will lead to less cognitive load, therefore, learners will report less difficulty, more confidence and less stress during performing the test tasks. We predicted this result because by decreasing cognitive load, learners will feel less stress and they will express less difficulty (Ayres, 2006; Cranford, et al., 2014; De Jong, 2010; DeLeeuw & Mayer, 2008; Gerjets et al., 2009; Granholm, et al., 1996; Kalyuga, Chandler, & Sweller, 1999; Paas, et al., 2003).

2F) For the low interactivity test materials, the familiar context narrative will not lead to a significant reduction in cognitive load, therefore, learners will not report more/less difficulty, confidence and stress during performing the test tasks.

The rationale behind these predictions is that since, a familiar narrative functions as a worked example whose context is familiar, it can reduce the learner's cognitive load which could potentially increase the test task performance including marks, speed, mouse movement distance and number of clicks, especially when the intrinsic cognitive load is already high due to high levels of element interactivity.

4.2. Participants Recruitment Method

In order to find the participants, the research was advertised on UNSW Internship Facebook page and a poster was shown in some lectures and tutorials within a couple of schools, except the school of computer science to avoid recruiting researcher's students or friends. The students who were interested to participate contacted the researcher, then they were invited to come to HCI lab or a consultation room for the experiment, if their eligibility was accepted. Eligibility was assessed by asking potential participants some basic questions about their computer background, university major, courses that they had passed and their familiarity with MS Access. In order to invite the participants an invitation email was sent to their email calendar. In addition to the UNSW students, 10 participants were selected from Shiraz, Iran and they distributed randomly between the 3 experimental groups.

4.3. Participants and Design

In total 63 users participated in this experiment and they were randomly distributed in one of the three experimental groups:

- 3 participants in the pilot group.
- 20 participants in the control group (e-learning system without any narrative).
- 20 participants in the experimental group 1 (narrative with a familiar context).

- 20 participants in the experimental group 2 (narrative with an unfamiliar context).

Homogenized participants with the characteristics below were targeted:

- Above 18 years old.
- With the good English proficiency.
- Not expert in a great range of professional software or any programming languages.
- Without any prior experience or knowledge in MS Access.

In addition to the basic questions that were asked from the potential participants about their university major and courses that they had passed, a computer skill placement test form (Singh & Dyer, 2002) was used for the selected participants to make sure that they are a relatively homogenous group. The form asked questions about: a) general computer skills of the volunteers, b) familiarity with the database management systems, c) level of working experience with MS Access and, d) level of English proficiency. Based on our exclusion criteria, volunteers who had a low level of English proficiency, or were familiar with the database management systems especially MS Access were excluded from the study. It should be noted that there was no question about volunteers' familiarity with the terminologies used in the narratives of the e-learning systems.

4.4. Teaching Material of the Experiment

In this experiment, Microsoft Access was selected as the experimental productivity software application to teach to the novice learners. The reasons for selecting MS Access were:

- a) It has enough complexity that is worth teaching. Also, its tools and features include a combination of elements with low and high interactivity levels.

- b) MS Access is not a routine software that users use it for their daily works, therefore, it is a new software for most of the users and they do not have previous experience with it.
- c) For learning MS Access, learners do not need to know any specific science such as chemistry, mathematics, or physics. Therefore, the previous knowledge of the learners is unlikely to affect their learning performance.

4.5. Developing the e-learning systems

The e-learning systems of this study was developed using HTML 5 and JavaScript. In all the systems, the teaching syllabus and the tasks were the same and the only independent variable was narrative. The learning contents in all three e-learning systems were presented using a combination of text and pictures.

In order to teach MS Access, the syllabus of the e-learning systems was adopted from two MS Access reference guides by Darejeh (2011) and Alexander and Kusleika (2015). Four topics were selected (2 with low and 2 with high element interactivity). In order to evaluate students learning performance a test task was designed for each teaching topic (Appendix D). The selected topics are listed below:

1. Create table columns and choose correct data types: the purpose of this topic is to teach users how to create a table to store information. This topic is considered as low element interactivity as creating each table column is a separate task and it is not integrated with the other columns and there is not any sequence for creating columns. It is similar to memorizing individual words where users can memorize each word separately. For creating each column, users just need to identify correct data type and type the column name.

2. Create an update query based on IF function: the purpose of this topic is to update specific data in a table based on a function-based criterion. This topic is considered as high element interactivity since in order to update the table's data users need to follow different integrated steps that should be conducted in a specific sequence. Furthermore, users need to know the format of the IF function and how the parameters should be entered in this function. The sequence of doing this task is presented below:
 1. Select the query type.
 2. Go to the update section.
 3. Open builder.
 4. Find the correct function (IF).
 5. Fill in the function parameters in the correct order.
3. Create a delete query and write 2 separate simple conditions: the purpose of this topic is to delete some table's data based on 2 separate simple criteria. This topic is considered as low element interactivity as creating this query engages 3 separate steps that each of them is just 1 click and there is not any sequence in order that is needed to perform the steps:
 - Select the query type.
 - Define a condition.
 - Define another condition.
4. Create a select query based on Datediff function: the purpose of this topic is to show specific data of a table based on a function-based criterion. This topic is considered as high element interactivity since in order to filter the table's data users need to follow different integrated steps that should to be conducted in a specific sequence. Furthermore, users need to know the format of Datediff

function and how the parameters should be entered in this function. The sequence of doing this task is listed below:

1. Select the query type.
2. Go to the criteria section.
3. Open builder.
4. Find the correct function (Datediff).
5. Type the formula and fill the function parameters in the correct order.
6. Add the NOW function to Datediff to return the current date.

In order to identify high and low element interactivity features of MS Access, the last part of the task complexity section of the Triadic Componential Framework (Robinson, 2007, 2005, 2001) was used. This framework is designed to specify component dimensions of task complexity in terms of superordinate cognitive, interactive and learner factors. As it can be seen from the highlighted section, this framework provides some criteria to classify the tasks based on their complexity. These criteria include: a) if the task involves a single task or multiple tasks, b) the structure of the task, c) number of steps of performing the task, d) integration of the steps, and e) amount of prior knowledge that is required to perform the task. Based on these criteria, tasks that involve a single task with a simple structure, have a limited number of steps that are not integrated, and do not involve a high level of prior knowledge to be performed, are considered as low element interactivity tasks. Therefore, tasks that involve some sub-tasks with complex structure and have integrated steps, that rely on a high level of prior knowledge to be performed, are considered as high element interactivity tasks. Table 4.1 shows Triadic Componential Framework for task classification.

Table 4.1: Triadic Componential Framework for task classification

<i>Task Complexity</i> (Cognitive factors)	<i>Task Condition</i> (Interactive factors)	<i>Task Difficulty</i> (Learner factors)
(Classification criteria: cognitive demands) (Classification procedure: information-theoretic analyses)	(Classification criteria: interactional demands) (Classification procedure: behavior-descriptive analyses)	(Classification criteria: ability requirements) (Classification procedure: ability assessment analyses)
<i>(a) Resource-directing variables</i> making cognitive/conceptual demands	<i>(a) Participation variables</i> making interactional demands	<i>(a) Ability variables</i> and task-relevant resource differentials
+/- here and now	+/- open solution	h/l working memory
+/- few elements	+/- one-way flow	h/l reasoning
-/+ spatial reasoning	+/- convergent solution	h/l task-switching
-/+ causal reasoning	+/- few participants	h/l aptitude
-/+ intentional reasoning	+/- few contributions needed	h/l field independence
-/+ perspective-taking	+/- negotiation not needed	h/l mind/intention-reading
<i>(b) Resource-dispersing variables</i> making performative/procedural demands	<i>(b) Participant variables</i> making interactant demands	<i>(b) Affective variables</i> and task-relevant state-trait differentials
+/- planning time	+/- same proficiency	h/l openness to experience
+/- single task	+/- same gender	h/l control of emotion
+/- task structure	+/- familiar	h/l task motivation
+/- few steps	+/- shared content knowledge	h/l processing anxiety
+/- independency of steps	+/- equal status and role	h/l willingness to communicate
+/- prior knowledge	+/- shared cultural knowledge	h/l self-efficacy

4.5.1. The detail of the e-learning systems content

In this experiment, three e-learning systems were designed. In all the systems teaching syllabus and the tasks were the same and the only independent variable was narrative.

4.5.1.1. E-learning system of the control group

The content of this e-learning system was similar to conventional e-learning system where there was not any narrative behind the learning content. Each tutorial started with a text page that described the purpose of the tutorial and what users will learn. Then step by step instructions taught the learning content with the use of text and 1 or 2 pictures. In each page just 1 step is taught in order to avoid crowding the screen. In addition to the content of each page there was a next button on the page to go to the next step. The complete scenario of this e-learning system is presented in Appendix A.

4.5.1.2. E-learning system of the first experimental group

The tutorial structure of this e-learning system was the same as the first system; however, narrative was added to integrate the content and give a theme to learning. The content of the narrative was a story of a hotel owner who is looking for a computer-based system to manage his hotel rooms and guests. He employed a software developer to implement a computer-based system for his hotel. Therefore, the focus of the learning was on developing a project for hotel management and 2 characters were engaged in the project: a) Hotel owner who has some requests and wants to use the target software to address them, and b) a software developer who develops the system (The learning steps were written from this character perspective). In order to increase the efficiency of the narrative, a simple story was included, without using any expression or professional terminology that is not familiar to the users.

Each tutorial started with explaining a request or a problem by the hotel owner and the software developer implemented the request using MS Access. In fact, this request showed the purpose of the tutorial. Then a step by step instruction showed how the request should be implemented. The steps and amount of content in each page was exactly same as the control system. The complete scenario of this e-learning system is presented in Appendix B.

4.5.1.3. E-learning system of the second experimental group

This e-learning system was same as the second system; just with a different narrative context. The narrative was a story of a banker who wants to manage mortgage information of the customers. Therefore, 2 characters were engaged: a) a banker who has some requests and wants to use the target software to address them, and b) a software developer

who develops the system (The learning steps were written from this character perspective). The main difference of this system from the second system was that we assumed the narrative content and the terminologies were not as familiar to the users as the first system. In other words, both e-learning systems had the same difficulty level, however, banking terminologies were assumed to be less familiar to the participants than the hotel terminologies which could potentially make understanding the narrative more difficult. The banking narrative included complex terminologies such as: Mortgage Principal, Term, Interest rate, Standing Order, Standing Order date, Collateral, Appraisal were used. The complete scenario of this e-learning system is presented in appendix C. It should be noted that, the participants might know the meaning of some of these words in the English language, however, we assumed that they did not know the full working meaning of the words in a banking context as people who do not work in the area of finance, normally do not have the necessary finance related knowledge.

4.6. Time duration for reading the tutorials and performing the tasks

Each experiment took approximately one hour, however, there was not any time limitation for reading the tutorials and performing the tasks and participants could spend any amount of time for learning and performing the test tasks. The reason was, we wanted to know if there is any difference between the reading time of the narrative-based and the normal tutorials, in addition to comparing the duration of performing the test tasks based on different teaching approaches. Therefore, time to read the tutorials and to complete the tasks were recorded.

4.7. Measurement methods

In order to measure cognitive load of the participants a mixture of objective and subjective measurement methods were used to increase the reliability of the measurement process. As the subjective part of the measurement, participants were asked to fill a self-reported difficulty 9-point Likert scale questionnaire about their experience after each tutorial and task (Ayres, 2006; Cranford et al., 2014; De Jong, 2010; DeLeeuw, & Mayer, 2008; Gerjets et al., 2009; Granholm et al., 1996; Kalyuga, Chandler, & Sweller, 1999; Paas et al., 2003). The questions of the Likert scale were a combination of different questions in order to evaluate cognitive load from different aspects. The questions were related to the difficulty level of the teaching materials and the test tasks for the participants, the confidence level of the participants to learn the other software with the use of the same teaching approach or completing the same test tasks, and the stress level of the participants during reading the tutorials and performing the test tasks. This questionnaire was adopted from Joseph (2013) and modified to fit the context of this study.

Although in the Likert-scale questionnaires just measuring the difficulty level is a common approach of measuring cognitive load, confidence and stress are measured in this study as complementary measurement factors (Joseph, 2013). Measuring confidence is useful based on the studies that proved the positive effects of self-efficacy on learning (Pajares & Miller, 1994; Phan, 2011; Shen et al., 2013) and measuring stress based on the studies that showed by increasing cognitive load the stress level of the learners can be increased (Bong, Fraser & Oriot, 2016; Lyu et al., 2015). In fact, if a teaching approach can increase or decrease confidence and stress level of the learners, it can potentially affect cognitive load and learning performance.

Based on the literature, utilizing self-reported difficulty Likert scale questionnaire, analyzing performance outcome and time-on-task are effective and frequently used methods in multimedia learning to measure cognitive load (Brunken, Plass, & Leutner, 2003; DeLeeuw, & Mayer, 2008; Paas, Ayres, & Pachman, 2008; Van Mierlo et al., 2012). The reason for popularity of these methods is that they do not make participants uncomfortable which can affect the study results. This is in contrast with neuroimaging techniques such as Electroencephalography devices where the wires can be uncomfortable and distracting for the participants (Van Mierlo et al., 2012). Since the experiment duration while performing multimedia learning studies is reasonably long, the comfort of the participants' measurement methods is important.

As the objective part of the measurement, participants performance including 4 factors were measured:

- a. **Time duration of reading each tutorial:** since there is a direct relationship between changing cognitive load and time duration of learning, measuring the duration of reading of each tutorial can be an indication of changing cognitive load (Brünken, Plass, & Leutner, 2003).
- b. **Test task mark:** providing a test task after learning and measuring the completion rate of the test tasks is a factor of measuring cognitive load, higher mark indicates a lower cognitive load (Brünken, Plass, & Leutner, 2003; DeLeeuw, & Mayer, 2008; Mayer, 2001; Paas, Ayres, & Pachman, 2008; Van Mierlo et al., 2012).
- c. **The time duration of performing the test task:** same as time duration of learning, there is a direct relationship between time duration of performing the test tasks and cognitive load, with lower cognitive load yielding a higher speed for performing

the test tasks (Barsalou, 2008; Brünken, Plass, & Leutner, 2003; Kortum, & Acemyan, 2016; Mayer, 2001).

- d. **Mouse move distance, and number of left and right clicks:** since in order to complete the test tasks, participants need to use a mouse, measuring mouse move distance and number of clicks can be an indication of cognitive load. Increasing mouse move distance and number of clicks means more effort to find the solution of the test task which yields an increase in cognitive load (Grimes, & Valacich, 2015; Khawaji, et al., 2014; Kortum & Acemyan, 2016; Rheem, Verma, & Becker, 2018). Table 4.2 shows a summary of the factors that were measured during this experiment.

Table 4.2: Measured factors in each stage of the experiment

<p>During reading each tutorial</p> <ul style="list-style-type: none"> ➤ Time duration 	<p>During solving each task</p> <ul style="list-style-type: none"> ➤ Time duration ➤ Mouse move distance ➤ Number of left & right clicks
<p>After reading each tutorial</p> <ul style="list-style-type: none"> ➤ Likert scale questionnaire ➤ Q1: Difficulty level ➤ Q2: Confident level ➤ Q3. Stress level 	<p>After solving each task</p> <ul style="list-style-type: none"> ➤ Performance mark ➤ Likert scale questionnaire ➤ Q1: Difficulty level ➤ Q2: Confident level ➤ Q3. Stress level

4.8. Ethics approval procedure

In order to get permission to collect data from the university students to conduct this experiment, a negligible risk research application was filled with the information of the research including problem statement, methodology, type of participants, and type of data that will be collected and submitted to UNSW Human Ethics Team. Negligible risk research is a type of research where there is no risk of harm or discomfort including physical, psychological, social, economic, or legal to human participants. After the review

of the ethics application by the human research ethics committee, and asking for some minor modifications, ethics approval code (HC17074) was issued to be used in the consent form of the experiment.

4.9. Pilot study

In order to evaluate the research methodology and the analysis method before the first experiment, a pilot study was conducted with 3 participants. Based on the results of the pilot test the data collection procedure was refined minorly. These modifications include: a) changing the location of putting Moustron software on the screen in order to measure mouse move distance and clicks, and b) adding another Likert scale questionnaire for the tutorials in addition to the tasks. In the original methodology plan, we had planned to use only Likert scale questionnaire for the tasks.

4.10. Data collection procedure

The data is collected from the participants one by one. Each participant came to the experiment location, and a summary of the project was given to them. Afterward, in order to confirm the eligibility of the participant a computer skill placement form (Appendix H) was given to them, then the participant was asked to sign the project consent form (Appendix I).

The experiment was started by reading the first tutorial. During each tutorial, time duration of reading was recorded (hypotheses 1A and 2A) and after finishing each tutorial a Likert scale questionnaire (Appendix F) with 3 questions was given to the participant (hypotheses 1B and 2B). The first question asked about the difficulty level of the teaching material, the second question asked about the degree that the participant is confident that

he/she can learn the other software with the use of the same teaching approach and the third question asked about the stress level of the participant during reading the tutorial. After answering the Likert scale questionnaire, participants could start reading the second tutorial and the same measurement procedure method was repeated. At the end of reading the second tutorial, two tasks related to the first and the second tutorials were assigned to the participant.

In order to measure participants performance while performing the tasks, mouse distance moved, number of left and right clicks (hypotheses 1D and 2D) and performance speed (hypotheses 1E and 2E), were measured using Moustron Software. Also, after finishing each test task a Likert scale questionnaire (Appendix G) with 3 questions similar to the tutorial questionnaire was given to the participant (hypotheses 1F and 2F). The first question asked about the difficulty level of the task, the second question asked about the degree that the participant is confident that he/she can solve the other tasks like the current task and the third question asked about the stress level of the participant during performing the task.

After answering the Likert scale questionnaire of the second task, participant could read the third and the fourth tutorials and did the third and the fourth tasks and the same measurement procedure was repeated. In order to calculate the test performance marks (hypotheses 1C and 2C), the MS Access files of the test tasks were saved on the computer during the experiment and the mark of each test task was calculated manually after the experiment. Based on the marking rubric of the test tasks, participants could get one mark for completing each step that asked them to find a specific feature in Ms Access and two marks for writing the codes of the queries. The detailed marking rubric of the test tasks can be seen in appendix E.

At the end of the experiment a \$20 voucher was given to the participant to express our appreciation for their participation. A summary of the data collection procedure for each participant is presented in figure 4.1.

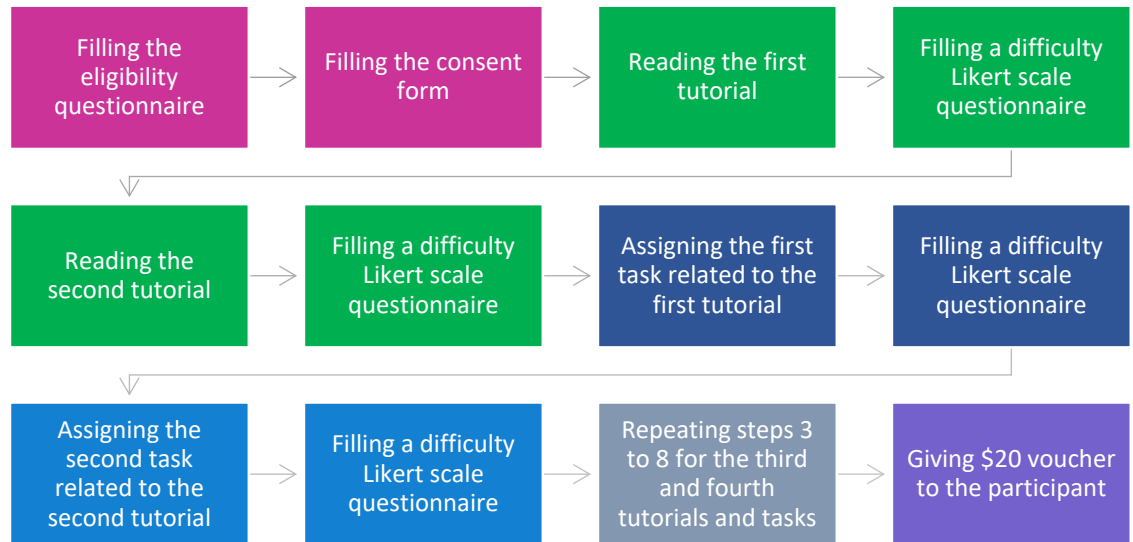


Figure 4.1: Summary of the research procedure

4.11. Results

In order to establish if there are any significant differences between cognitive load levels of the participants, SPSS and Stata software were utilized and a 3 (narrative) x 2 (element interactivity) experimental design was used with repeated measures on the second factor of element interactivity.

A Linear Mixed Model test was conducted in order to calculate the main effect of the experimental groups (i.e. no narrative [control], familiar narrative and unfamiliar narrative groups) and to check if there was an interaction between the experimental groups and task element interactivity levels of the teaching materials / test tasks for all the dependent variables including: test marks, mouse moves, left clicks, right clicks, duration, and Likert scale difficulty, confidence, and stress questions. For all the

dependent variables where the linear mixed model test showed a significant main effect or interaction, post-hoc tests were conducted to compare groups.

The means (with standard deviations in brackets) of the dependent variables can be seen in Tables 4.3 and 4.4.

Table 4.3: Test task means

Groups	Task type	Marks (out of 100)	Duration	Mouse movement	Left clicks	Right clicks	Difficulty question (out of 9)	Confidence question (out of 9)	Stress question (out of 9)
No narrative (Control)	Low element	75.4 (27)	5.1 (2.8)	11.9 (6.7)	85.7 (53.6)	3.5 (3.9)	3.5 (2)	6.8 (1.9)	3.1 (1.6)
	High element	45.2 (27.1)	8.1 (2.8)	17.5 (8.8)	130.4 (68.1)	3 (3.5)	6.1 (1.9)	4.8 (2.1)	4.9 (2.1)
Familiar narrative	Low element	89.9 (14)	4.1 (1.7)	10.6 (5.7)	77.5 (45.1)	2.3 (2.8)	2.8 (1.8)	7.7 (1.5)	2.5 (1.7)
	High element	67.1 (29.4)	6.4 (2.5)	11.9 (5.1)	90.9 (46.4)	1.2 (1.5)	4.4 (2.1)	6.5 (1.6)	3.8 (2.2)
Unfamiliar narrative	Low element	72.6 (27)	5 (2.6)	12.6 (6.3)	108.3(65.6)	3.5 (7.1)	3 (1.6)	7.4 (1.5)	2.8 (1.7)
	High element	46.7 (25.9)	6.6 (2.9)	13.3 (5.9)	114.4 (54.2)	2.4 (2.6)	5.6 (1.9)	4.2 (2.2)	4.2 (2.1)

Table 4.4: Teaching materials means

Groups	Task type	Duration	Difficulty question	Confidence question	Stress question
No Narrative (Control)	Low element	3 (1.5)	2.3 (1.3)	6.9 (1.8)	2.2 (1.3)
	High element	4.6 (1.8)	4.7 (2)	5.6 (1.6)	3.4 (1.5)
Familiar narrative	Low element	3.3 (2.2)	2.1 (1.1)	7.8 (1)	1.9 (1.3)
	High element	4.6 (1.8)	4.5 (1.9)	6.5 (1.9)	3 (1.5)
Unfamiliar narrative	Low element	3.6 (1.9)	2.1 (1.2)	7.7 (1.1)	2.3 (1.7)
	High element	5.1 (2.2)	4.6 (2)	6.1 (1.8)	3.5 (1.8)

4.11.1. Duration of reading the teaching materials

Regarding the duration of reading the teaching materials (hypotheses 1A and 2A), the main effect was not significant for the different learning methods: $F(2, 57) = .784$, $p >$

.05, however, the main effect was significant for the element interactivity level: $F(1, 177) = 65.533, p < .05$. The interaction effect analysis did not show a significant interaction between the different learning methods and the element interactivity levels of the teaching materials: $F(2, 177) = .207, p > .05$.

4.11.2. Difficulty, stress and confidence questionnaires for the teaching materials

Regarding the Difficulty Scale of the teaching materials (hypotheses 1B and 2B), the main effect was not significant for the different learning methods: $F(2, 57) = .187, p > .05$, however, the main effect was significant for the element interactivity level: $F(1, 177) = 234.590, p < .05$. The interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 177) = .019, p > .05$. Also, for the Stress Scale (hypotheses 1B and 2B), results did not show a significant main effect for the different learning methods: $F(2, 57) = .799, p > .05$, however, the main effect was significant for the element interactivity level: $F(1, 177) = 62.665, p < .05$. The interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 177) = .139, p > .05$ as well.

However, for the Confidence Scale (hypotheses 1B and 2B), the main effect was significant for the different learning methods: $F(2, 57) = 3.253, p < .05, f^2 = .011$ and for the element interactivity level: $F(1, 177) = 71.976, p < .05, f^2 = .388$. The post-hoc test results showed that the confidence question score for the control version was significantly lower than the familiar narrative version: $t(57) = -2.483, p < .05, d = 0.320$, however, there was no significant difference between the control and the unfamiliar narrative versions: $t(57) = -1.745, p > .05, d = 0.225$, nor between the unfamiliar narrative and the familiar narrative versions: $t(57) = -0.738, p > .05, d = 0.095$. Also, the interaction effect

analysis did not show a significant element interactivity by group interaction: $F(2, 177) = .261, p > .05$.

4.11.3. Test performance marks

Regarding the test performance marks (hypotheses 1C and 2C), the main effect was significant for the different learning methods: $F(2, 57) = 8.036, p < .05, f^2 = .041$ and for the element interactivity level: $F(1, 177) = 83.338, p < .05, f^2 = .426$. The post-hoc test results showed that the test performance marks of the control version were significantly lower than the familiar narrative version: $t(57) = -3.407, p < .05, d = 0.439$. There was no significant difference between the control and the unfamiliar narrative version: $t(57) = 0.126, p > .05, d = 0.016$, however, the test performance marks of the unfamiliar narrative version were significantly lower than the familiar narrative version: $t(57) = -3.533, p < .05, d = 0.456$. The interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 177) = .556, p > .05$.

4.11.4. Mouse movement distance and number of clicks while performing the test tasks

Regarding the Mouse Movement distance (hypotheses 1D and 2D), referred to as Mouse Move, the main effect was significant for the different learning methods: $F(2, 57) = 3.628, p < .05, f^2 = .021$ and for the element interactivity level: $F(1, 177) = 10.843, p < .05, f^2 = .053$. The post-hoc test results showed that mouse move distance for the control version was significantly higher than the familiar narrative version: $t(57) = 2.694, p < .05, d = 0.347$, however, there was no significant difference between the control and the unfamiliar narrative versions: $t(57) = 1.370, p > .05, d = 0.176$, nor between the unfamiliar narrative and the familiar narrative versions: $t(57) = 1.323, p > .05, d = 0.17$.

The interaction effect analysis showed a significant element interactivity by group interaction: $F(2, 177) = 4.132, p < .05, f^2 = .042$, and the simple effects of the learning methods for high element test showed a significant difference between the control version and the familiar narrative version: $t(38) = 3.538, p < .05, d = 0.456$, also, there was a significant difference between the control and the unfamiliar narrative versions: $t(38) = 2.657, p < .05, d = 0.342$, however, there was no significant difference between the unfamiliar narrative and the familiar narrative versions: $t(38) = 0.881, p > .05, d = 0.113$. For the low element tests there was no significant differences between the control version and the familiar narrative version, $t(38) = 0.824, p > .05, d = 0.106$, nor between the control and the unfamiliar narrative versions, $t(38) = -0.437, p > .05, d = 0.056$, or between the unfamiliar narrative and the familiar narrative versions: $t(38) = 1.262, p > .05, d = 0.163$. The significant differences using high but not low element interactivity materials explains the significant element interactivity by group interaction.

Regarding the Left Clicks (hypotheses 1D and 2D), the main effect was significant for the different learning methods: $F(2, 57) = 3.301, p < .05, f^2 = .017$ and for the element interactivity level: $F(1, 177) = 11.181, p < .05, f^2 = .056$. The post-hoc test results showed that the number of left clicks for the control version was significantly higher than the familiar narrative version: $t(57) = 2.07, p < .05, d = 0.267$. Furthermore, the number of left clicks of unfamiliar narrative was significantly higher than the familiar narrative: $t(57) = 2.354, p < .05, d = 0.304$. However, there was no significant difference between the control and the unfamiliar narrative versions: $t(57) = -0.284, p > .05, d = 0.036$.

The interaction effect analysis showed a significant element interactivity by group interaction: $F(2, 177) = 3.436, p < .05, f^2 = .036$, and the simple effects of the learning methods for high element test showed a significant difference between the control version

and the familiar narrative version: $t(38) = 2.834, p < .05, d = 0.365$, however, there was no significant difference between the control and the unfamiliar narrative versions: $t(38) = 1.149, p > .05, d = 0.148$, nor between the unfamiliar narrative and the familiar narrative versions: $t(38) = 1.685, p > .05, d = 0.217$. For the low element tests there was no significant difference between the control version and the familiar narrative version: $t(38) = 0.591, p > .05, d = 0.076$, nor between the control and the unfamiliar narrative versions: $t(38) = -1.62, p > .05, d = 0.209$, nor between the unfamiliar narrative and the familiar narrative versions: $t(38) = 2.211, p > .05, d = 0.285$. The significant differences using high but not low element interactivity materials explains the significant element interactivity by group interaction.

Regarding the Right Clicks (hypotheses 1D and 2D), the main effect for the different learning methods was not significant: $F(2, 57) = 2.663, p > .05$ nor for the element interactivity level: $F(1, 177) = 3.123, p < .05$. The interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 177) = .144, p > .05$.

4.11.5. Test performance speed

Regarding the duration of performing the tasks (hypotheses 1E and 2E), the main effect was significant for the different learning methods: $F(2, 57) = 2.983, p < .05, f^2 = .014$ and for the element interactivity level: $F(1, 177) = 62.138, p < .05, f^2 = .318$. The post-hoc test results showed that the test performance speed for the control version was significantly lower than the familiar narrative versions: $t(57) = 2.426, p < .05, d = 0.313$, however, there was no significant difference between the control and the unfamiliar narrative versions: $t(57) = 1.464, p > .05, d = 0.189$, nor between the unfamiliar narrative and the familiar narrative versions: $t(57) = 0.963, p > .05, d = 0.124$. Furthermore, the interaction

effect analysis did not show a significant element interactivity by group interaction: $F(2, 177) = 1.839, p > .05$.

4.11.6. Difficulty, confidence and stress questionnaire results for the test tasks

Regarding the Difficulty Scale of the test tasks (hypotheses 1F and 2F), the main effect was significant for the different learning methods: $F(2, 57) = 4.590, p < .05, f^2 = .022$ and for the element interactivity level: $F(1, 177) = 117.879, p < .05, f^2 = .588$. The post-hoc test results showed that the difficulty question score of the tests were significantly higher for the control system in comparison with the familiar narrative version: $t(57) = 3, p < .05, d = 0.387$. However, there was no significant difference between the control and the unfamiliar narrative versions: $t(57) = 1.158, p > .05, d = 0.149$, nor between the unfamiliar narrative and the familiar narrative versions: $t(57) = 1.847, p > .05, d = 0.238$. Furthermore, the interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 177) = 2.745, p > .05$.

Regarding the Confidence Scale (hypotheses 1F and 2F), the main effect was significant for the different learning methods: $F(2, 57) = 8.313, p < .05, f^2 = .048$. and for the element interactivity level: $F(1, 177) = 101.297, p < .05, f^2 = .467$. The post-hoc test results showed that the confidence question score for the test tasks was significantly lower for the control system in comparison with the familiar narrative version: $t(57) = -3.563, p < .05, d = 0.46$, also, the unfamiliar narrative version was significantly lower than the familiar narrative version: $t(57) = -3.495, p < .05, d = 0.451$. However, there was no significant difference between the control version and the unfamiliar narrative version: $t(57) = -0.068, p > .05, d = 0.008$.

The interaction effect analysis showed a significant element interactivity by group interaction: $F(2, 177) = 7.132, p < .05, f^2 = .073$ and the simple effects of the learning

methods for the high element interactivity task showed a significant difference between the control version and the familiar narrative version: $t(38) = -3.814$, $p < .05$, $d = 0.492$, also, between the unfamiliar narrative and the familiar narrative versions: $t(38) = -5.03$, $p < .05$, $d = 0.649$. However, there was no significant difference between the control version and the unfamiliar narrative version: $t(38) = 1.216$, $p > .05$, $d = 0.156$. For the low element tests there was no significant difference between the control version and the familiar narrative version: $t(38) = -1.99$, $p > .05$, $d = 0.257$, nor between the control and the unfamiliar narrative versions: $t(38) = -1.327$, $p > .05$, $d = 0.171$, nor between the unfamiliar narrative and the familiar narrative versions: $t(38) = -0.663$, $p > .05$, $d = 0.086$. The significant differences using high but not low element interactivity materials explains the significant element interactivity by group interaction.

Regarding, the Stress Scale (hypotheses 1F and 2F), the main effect was not significant for the different learning methods: $F(2, 57) = 1.697$, $p > .05$, however, the main effect was significant for the element interactivity level: $F(1, 177) = 64.725$, $p < .05$. The interaction effect analysis between the learning methods and element interactivity level was not significant: $F(2, 177) = .834$, $p > .05$ as well.

4.12. Discussion

In this study we investigated interactions between the narrative and element interactivity levels of the learning content, on the cognitive load of learners while learning software through e-learning platforms. We compared the value of including a familiar, and unfamiliar narrative versus no-narrative. The results showed a positive effect on the user's learning performance by the inclusion of an appropriate narrative that can be explained based on the environmental organizing and linking principle of cognitive load theory. Domain-specific, biologically secondary knowledge stored in long-term memory

determines how we perceive information and determines our actions based on that information (Bransford & Johnson, 1972; Kirschner et al., 2018; Pichert & Anderson, 1977). From the current results, a narrative-based teaching approach could help learners to link new domain-specific, biologically secondary knowledge to their existing knowledge.

4.12.1. Effect of familiar context narrative on high and low interactivity teaching materials

There was not any significant difference between the time duration of reading the familiar narrative, no-narrative and unfamiliar narrative systems, neither for the high element interactivity materials nor for the low element interactivity materials which shows that learners spent a similar amount of time to learn the concepts in all 3 methods.

Although, based on hypothesis 1A we predicted that for high element interactivity materials, a familiar context narrative will reduce the reading time, the results did not support this prediction, therefore, hypothesis 1A is rejected, however, hypotheses 2A is validated which predicted that for the low interactivity teaching materials, a familiar context narrative will not lead to a significant reduction in reading time.

Regarding the Likert-scale questionnaire, for the high interactivity teaching materials, participants did not report less/more difficulty and stress during the learning phase, however, they reported more confidence while learning the teaching materials with the use of the familiar context narrative system. However, for the low interactivity teaching materials, there was not any significant difference between the groups.

Therefore, hypothesis 1B which predicted that for the high interactivity test materials, in the familiar context narrative system, learners will report less difficulty, more confidence

and less stress during the learning phase in comparison with both unfamiliar narrative and no-narrative systems is partially rejected as learners only reported more confidence. Also, the results supported hypothesis 2B which stated that for the low interactivity learning materials the familiar context narrative will not affect cognitive load and learners will not report more/less difficulty, confidence and stress.

While the results of this study did not show a positive effect for the familiar narrative on the time duration of learning and participants just reported more confidence in learning phase, the user's learning performance and test marks were improved.

This issue will require further investigation as no related literature could be found to support why the familiar narrative could not positively affect the learning phase timing, but it affected the test phase significantly. One reason could be the presence of additional concepts used in the narratives (i.e. concepts related to hotel or mortgage management systems). In fact, the hotel narrative caused learners to have more in depth learning which is reflected on their test phase however, since learners needed to process extra content related to hotel during learning, their reading time and the difficulty level that they felt during learning did not change. The interesting point here is that this extra information did NOT increase learning times, which is further evidence that the information provided in fact supported the learning phase.

4.12.2. Effect of familiar context narrative on high and low interactivity test tasks

For test task performance, results showed that test task marks increased for the test tasks of both low and high element interactivity in comparison with the no-narrative and unfamiliar context systems. Therefore, hypothesis 1C is supported which predicted that for the high interactivity test materials, a familiar context narrative will lead to reduced

difficulty levels and improved test performance marks, relative to the no-narrative and unfamiliar narrative groups. However, hypothesis 2C is rejected as it predicted that for the low interactivity test materials, familiar context narrative will not have a significant effect on the test performance marks.

These findings are in accord with studies indicating that by decreasing cognitive load, learners will experience less difficulty and so their test marks will be increased (Brünken, Plass, & Leutner, 2003; DeLeeuw, & Mayer, 2008; Mayer, 2001; Paas, Ayres, & Pachman, 2008; Van Mierlo et al., 2012). In our study, the familiar narrative enabled learners to place the target software application into a familiar context, and so it could facilitate learning which supports the way we learn based on the environmental organizing and linking principle (Sweller, Ayres, & Kalyuga, 2011a). The results showed that the familiar narrative helped learners to link the new knowledge of the software to their existing knowledge that is stored in their long-term memory which facilitated recall of information (Bransford, & Johnson, 1972; Kirschner et al., 2018; Pichert, & Anderson, 1977). Not only did it impact on the test mark of high element interactivity content, it also affected the test mark of low element interactivity content. These findings suggest that the low element interactivity materials, may have been more complex and difficult to learn than initially predicted.

Mouse movement distance decreased, for the high element interactivity content, for both the familiar and unfamiliar narrative systems in comparison with the no-narrative system. Also, the number of left clicks decreased, for the familiar narrative, high element interactivity content, in comparison with the no-narrative and unfamiliar narrative systems. However, there was no significant difference for the right click. For the elements with low interactivity, these differences were not significant. These results suggest that

narrative was useful overall for learning, but the familiar narrative was most helpful for learning when the cognitive load of the materials was higher due to higher levels of interacting elements.

Therefore, hypothesis 1D is partially supported and hypothesis 2D is supported. Hypothesis 1D predicted that for the high element interactivity test materials, a familiar context narrative will lead to a decrease in the mouse movement distance, and number of left and right clicks in comparison with the no-narrative and unfamiliar context systems, and hypothesis 2D predicted that for the low interactivity test materials, a familiar context narrative, will not lead to a decrease in the mouse movement distance, and number of left and right clicks.

The mouse data is supported by the findings of Grimes and Valacich (2015), Khawaji, et al. (2014) and Rheem, Verma, and Becker (2018) regarding the effect of cognitive load on the human motor system and consequently on mouse movements. They found that using a dual task paradigm, mouse movements decrease with increasing cognitive load, since users had less resources to perform the tasks as load increased and so less resources left to move the mouse. We note that in these studies, the mouse movements were potentially redundant to the task at hand, and so reduced as the load increased, while in the current experiment the movements may have supported learning and so increased with task complexity where participants required more effort to find the solution and complete the task. Furthermore, the results are in line with related software usability studies that showed that mouse movement distance and number of clicks increased when users do not have the necessary knowledge to work with a software application (Kortum & Acemyan, 2016). Mouse movements may be a useful indicator of load, due to embodied cognition effects (Barsalou, 2008) where links between the mind and body allow movements to

support cognitive tasks. However, whether they increase or decrease as load increases depends on their purpose in the task at hand, and so they should be included with caution.

In addition to the above findings, for both high and low interactivity elements, test tasks performance speed increased for the familiar narrative system in comparison with the no-narrative system, due to a decrease in difficulty level as well as an associated decrease in mouse movement distance and number of left clicks. Therefore, hypothesis 1E which predicted that for the high element interactivity test materials, a familiar context narrative will lead to an increase in the test task performance speed in comparison with the no-narrative and unfamiliar context systems is partially supported. However, hypothesis 2E which predicted that for the low element interactivity test materials, test task performance speed will not be affected by a familiar context narrative, in comparison with the no-narrative and unfamiliar context systems, is rejected.

The reason that hypotheses 1D and 1E are partially supported is that the familiar narrative decreased the mouse movement distance, number of left clicks and test task performance speed, as predicted. However, as well as a familiar narrative leading to improved learning outcomes, an unfamiliar narrative also led to a significant decrease in mouse movement distance and left clicks and time duration in comparison with the no-narrative system for high element interactivity materials. This result suggests that the unfamiliar narrative may still have provided some benefits compared to the no-narrative condition (Booth et al., 2015).

Finally, participants reported less difficulty and more confidence in the familiar context narrative in comparison with the control and unfamiliar context systems that shows that the narrative with the familiar context could decrease the difficulty level of the test tasks for the learners. Therefore, hypothesis 1F which predicted that for the high interactivity

test materials, in the familiar context narrative system, learners will report less difficulty, more confidence and less stress during performing the test tasks in comparison with both unfamiliar narrative and no-narrative systems is partially approved as learners did not report less stress, however, they reported less difficulty and more confidence. Also, hypothesis 2F which predicted that for the low interactivity test materials, in the familiar context narrative system, learners will not report less/more difficulty, confidence and stress during performing the test tasks in comparison with both unfamiliar narrative and no-narrative systems is partially approved as learner reported less difficulty, however, they did not report less/more confidence and stress.

These results are supported based on the studies that proved that Likert scale questionnaire can be used as a direct measurement method of cognitive load and by increasing cognitive load, learners will express more difficulty (Ayres, 2006; De Jong, 2010; DeLeeuw, & Mayer, 2008; Gerjets et al., 2009; Kalyuga, Chandler, & Sweller, 1999; Paas et al., 2003).

Based on the sub hypotheses findings, the first main hypothesis that assumed that in order to learn high interactivity elements of productivity software applications, a familiar narrative can decrease the cognitive load of novice users in comparison with the no-narrative and unfamiliar narrative systems, is validated. The second main hypothesis that assumed that for elements with a low interactivity familiar narrative would not have any significant effect on cognitive load is rejected, as narrative had some positive effects on both elements with low and high interactivity.

4.12.3. Narrative to support learning

It can be concluded that e-learning systems with a familiar narrative led to significantly increased learning performance outcomes and decreased cognitive load in comparison with the no-narrative and unfamiliar narrative systems for both low and high interactivity materials. Although, the unfamiliar narrative, like the familiar narrative, improved mouse movement and duration of performing the test tasks, it was not efficient in increasing learning performance as it did not affect any of the other measured factors. However, these results show that even an unfamiliar narrative may be more efficient in learning in comparison with the no-narrative procedure. In fact, familiar and unfamiliar context narratives have similar functions, however the unfamiliar context of the narrative can increase cognitive load, since working memory resources will need to be allocated to processing the context, which can counteract the benefits of the narrative.

The findings are in line with the concept of schemas which states that people can learn new concepts more easily if they can integrate it with their existing schemas (Sweller, 1988). Since the learners had schemas for hotel related concepts, they could integrate the familiar narrative content with their existing schemas which led to better learning performance in comparison with the unfamiliar banking narrative or the no-narrative procedure (Bransford, & Johnson, 1972; Kirschner et al., 2018; Pichert, & Anderson, 1977). A narrative can decrease cognitive load and facilitate the formation of schemas by providing appropriate worked examples that provide a clear guideline for the problem in addition to showing the relations between different elements of the problem (Renkl, 2014a). A familiar narrative can thus serve to integrate related elements of different worked examples and reduce cognitive load that may be associated with understanding the context.

The results of the current study are different to other studies that primarily evaluated motivational aspects of narrative in, for example, gamified learning systems in that we examined the effects of the narrative on cognitive load (Bell, Sheth, & Kaiser, 2011; Calderón, Ruiz, & O'Connor, 2017; Caulfield, Veal, & Maj, 2011; Chaves et al., 2010; Eagle, & Barnes, 2009; Hailey et al., 2011; Jain, & Boehm, 2006; Li, Grossman, & Fitzmaurice, 2012; Srinivasan, & Lundqvist, 2007). Those studies provided evidence for the positive effect of narrative on learners' engagement with the learning content while we indicated its benefits in terms of decreasing cognitive load. The findings are also important because research in teaching software applications is very limited, and this study could provide some support for potential benefits of narrative for teaching software applications.

4.13. Conclusion, limitations, future directions

In summary we found that a familiar narrative can decrease cognitive load and facilitate the formation of schemas by providing worked-out examples using a familiar context (Renkl, 2014a). We also found cognitive load benefits associated with including a familiar context narrative when learning an unfamiliar software tool.

With respect to limitations and further work, since in this experiment we just assumed that the content of the everyday hotel narrative was more familiar than the more technical banking content, future studies could directly test this assumption.

Since, the results showed significant improvement for both elements with high and low interactivity, there is a chance to get different results for high versus low interactivity elements if we can make the low element test tasks easier or the high element test tasks

more difficult than they are, in future studies. It would also be good to include more test items to further differentiate between high and low element interactivity tasks.

Finally, in this experiment we just evaluated the effect of narrative using a text-based e-learning system. It is necessary to find the best approach of delivering narrative-based content among the common approaches that are used in e-learning systems including static content, animation and interactive animation. Therefore, in the second experiment of this research the effect of different ways of delivering narrative-based content was examined (see chapter 5).

Chapter 5

Experiment 2

5.1. Introduction

Experiments 1 evaluated how the cognitive load of novice users is affected by applying a narrative with a familiar and unfamiliar context to the tutorials of elements with low and high interactivity. Results showed that, overall, the familiar narrative versus no-narrative, and unfamiliar narrative contents could significantly increase test performance marks and the related factors for both low and high interactivity materials.

In this chapter, the second experiment which evaluated the effect of interactivity in order to deliver the narrative-based content, is discussed. Cognitive load of the learners is compared, while they learn software using narrative-based e-learning systems that deliver the teaching contents using either animation or interactive animation. Animation included motion and audio, and interactive animation is same as the animation, however, it also enables users to interact with the animation by clicking on the animation content, which provides a simulated software environment for teaching the target software (Price et al., 2008).

It should be noted that, the reason that in this experiment, just animation and interactive animation were compared, while, in the first experiment the teaching contents were presented using static content is that from the research design perspective, it was not possible to compare these three groups with each other simultaneously. Since, the static

content includes text and pictures, the animation includes motion and audio, and interactive animation includes motion, audio and click, therefore, these three groups were not comparable as more than one variable changes when comparing any of these three groups with the other groups. It would thus not be possible to tell which changes cause which effects. While the data for the static group was collected and analyzed, for the reasons described above and to ensure the running of a true randomized controlled experiment, these details are not included as part of this thesis.

We assume that interactive animation can facilitate learning based on embodied cognition effects where links between the mind and body allow movements to support cognitive tasks (Barsalou, 2008; Hung, & Chen, 2018). As explained in chapter 2, embodied cognition theory emphasizes on the role of entire body including the motor system, to achieve cognitive skills and the use of actions to support educational goals (Weisberg, & Newcombe, 2017).

There are many different studies in the area of teaching sciences which prove that interacting physically with the objects that are related to the learning content can enhance learning performance (Ceciliani, 2018; Enyedy et al., 2012; Gerofsky, 2011; Glenberg, 2015; Glenberg, 2010; Glenberg, Witt & Metcalfe, 2013; Herrera, & Riggs, 2013; Hung, Kinshukc, & Chen, 2018; Kontra et al., 2015; Nathan, & Walkington, 2017; Radford, 2009; Schiavio, et al., 2019; Shapiro, & Stolz, 2019; Zhu, 2018; Zudini, & Zuccheri, 2016) as there is a tight connection between cognitive processing and physical motion areas of our brain. These physical interactions can then serve to decrease the complexity of difficult cognitive tasks (Schulz, 2017; Calvo, & Gomila, 2008).

In addition to proving the positive effects of physical interaction with the learning content on cognitive load for teaching different subject areas, these positive effects are supported

in teaching computer software through gamified e-learning systems as well. These e-learning systems provided an interactive learning environment so that users can learn the target software through physical interaction and clicking on different tools in the simulated interface of the target software (Dong et al., 2012; Dontcheva et al., 2014; Li, Grossman, & Fitzmaurice, 2012; Shane, 2013).

Since, interactive animations enables learners to interact with the animation contents by moving their hand and clicking on the screen, therefore, it can potentially decrease cognitive load by engaging the motor system of the learners in addition to their visual and audio senses. Furthermore, based on modality effect, we have separate channels in our working memory for processing different sensory information, and engaging more sensory channels can decrease cognitive load by effectively expanding our working memory capacity (Mousavi, Low, & Sweller, 1995; Sweller, Ayres, & Kalyuga, 2011b).

We hypothesized that: 1) in order to learn high interactivity elements of productivity software applications, the e-learning system that delivers the teaching content using interactive-animation will decrease the cognitive load of novice users when compared to the animation system, due to embodied cognition effects where links between the mind and body allow movements to support cognitive tasks, (Barsalou, 2008; Skulmowski, & Rey, 2018;), 2) for the elements with low element interactivity, interactive-animation based e-learning system may not have any significant effect on cognitive load, when compared to the normal animation version, as the users' processing load is still manageable. Based on these overarching hypotheses, it is predicted that:

1A) For the high interactivity teaching materials, interactive animation will lead to a reduced cognitive load and consequently learning time duration will be reduced. We

predicted this result based on Brünken, Plass and Leutner (2003) who showed that by decreasing cognitive load, time duration of performing the target task can be decreased.

2A) For the low interactivity teaching materials, the interactive animation will not lead to a significant reduction in cognitive load and learning time duration will not be affected. We predicted this result because when the teaching materials are low in cognitive load due to low element interactivity, the users' processing load will still be manageable and learning time duration will not be significantly affected (Brünken, Plass, & Leutner, 2003).

1B) For the high interactivity teaching materials, the interactive animation will lead to less cognitive load, therefore, learners will report less difficulty, more confidence and less stress during the learning phase. We predicted this result because Likert scale questionnaire is a direct measurement method of cognitive load and by decreasing cognitive load, learners will feel less stress and they will express less difficulty (Ayres, 2006; Cranford et al., 2014; De Jong, 2010; DeLeeuw, & Mayer, 2008; Gerjets et al., 2009; Granholm et al., 1996; Kalyuga, Chandler, & Sweller, 1999; Paas et al., 2003).

2B) For the low interactivity teaching materials, the interactive animation will not lead to a significant reduction in cognitive load, therefore, learners will not report more/less difficulty, confidence and stress during the learning phase.

1C) For the high interactivity test materials, the interactive animation will lead to less cognitive load resulting in an increase in test performance marks (e.g. Brunken, Plass, & Leutner, 2003; DeLeeuw, & Mayer, 2008; Mayer, 2001; Paas, Ayres, & Pachman, 2008; Van Mierlo et al., 2012).

2C) For the low interactivity test materials, the interactive animation will not have a significant effect on the test performance marks. This prediction was made because the users' processing load will still be manageable, and consequently test performance marks will not be affected (e.g. Brünken, Plass, & Leutner, 2003; DeLeeuw, & Mayer, 2008; Mayer, 2001; Paas, Ayres, & Pachman, 2008; Van Mierlo et al., 2012).

1D) For the high interactivity test materials, the interactive animation will lead to a decrease in mouse movement distance and number of left and right clicks. This prediction is based on embodied cognition effects (see Barsalou, 2008), where less movements may be needed to support and improve learning outcomes when the cognitive load is lower. Furthermore, Kortum and Acemyan (2016) showed that by increasing the knowledge level of the users, mouse movement distance and number of clicks can be decreased.

2D) For the low interactivity test materials, interactive animation will not lead to a decrease in mouse movement distance and number of left and right clicks. We predicted this result because the users' processing load will still be manageable, and so mouse movement distance and number of clicks will not be affected (Barsalou, 2008; Kortum & Acemyan, 2016).

1E) For the high interactivity test materials, interactive animation will lead to less cognitive load and consequently test task performance speed will be increased. We predict this result based on Brünken, Plass, and Leutner (2003) who showed that by decreasing cognitive load, time duration of performing the target task can be decreased.

2E) For the low interactivity test materials, the interactive animation will not lead to a significant reduction in cognitive load and test task performance speed will not be affected. We predicted this result because when the test materials are low in element

interactivity, it is still manageable for the learners to process the information and test task performance speed will not be affected (Brunken, Plass, & Leutner, 2003).

1F) For the high interactivity test materials, the interactive animation will lead to less cognitive load, therefore, learners will report less difficulty, more confidence and less stress during performing the test tasks. We predicted this result because by decreasing cognitive load, learners will feel less stress and they will express less difficulty (Ayres, 2006; Cranford et al., 2014; De Jong, 2010; DeLeeuw, & Mayer, 2008; Gerjets et al., 2009; Granholm et al., 1996; Kalyuga, Chandler, & Sweller, 1999; Paas et al., 2003).

2F) For the low interactivity test materials, the interactive animation will not lead to a significant reduction in cognitive load, therefore, learners will not report more/less difficulty, confidence and stress during performing the test tasks.

5.2. Participants Recruitment Method

All the participants were selected from university students. Similar to the first experiment, in order to find the participants, the research was advertised on the UNSW Internship Facebook page and a \$20 voucher was offered to the students who participate in this study. The students who were interested in participating sent an email or a Facebook message to the researcher. They were then invited to come to the HCI lab or a consultation room for the experiment after approving their eligibility through asking them some basic questions about their computer background, university major, courses that they had passed and their familiarity with MS Access. In order to invite the participants an invitation email was sent to their email calendar.

5.3. Participants and Design

In total in this experiment 40 users participated:

- 20 participants in the control group (e-learning system with a familiar narrative that delivered the teaching content using normal animation).
- 20 participants in the experimental group (e-learning system with a familiar narrative that delivered the teaching content using interactive animation).

Participants had the characteristics below:

- They were above 18.
- They had a good English proficiency.
- They were not professional computer users.
- They were not expert in a great range of professional software or any programming languages.
- They did not have any prior experience or knowledge with MS Access.

In addition to the basic questions that were asked from the potential participants about their university major and courses that they had passed, the same computer skill placement test form (Singh & Dyer, 2002) similar to the first experiment was used for the selected participants to make sure that they are a relatively homogenous group.

5.4. Developing the e-learning systems

The e-learning systems of this study was developed using HTML 5 and JavaScript and the animations and interactive animations were recorded and edited using Camtasia Studio software which is a powerful platform to record, edit and make interactive videos/animation.

5.5. The e-learning systems contents and tasks

In order to align the teaching content of this experiment with the first experiment, Microsoft Access was selected as the experimental productivity software application to teach to the novice learners.

In order to teach MS Access, we used the same teaching content as the first experiment. In this experiment, just the first two topics and tasks of the first experiment were used (1 with low and 1 with high element interactivity) in order to decrease the study duration. See chapter 4, section 4.5 for more detail.

5.5.1. The detail of the e-learning systems content

In this experiment 2 e-learning systems were designed. In all the systems, the teaching content and the tasks were the same and the only independent variable was the way that the tutorials were presented. All the systems had the hotel story narrative.

5.5.1.1. E-learning system of the animation group

Same as the first experiment each tutorial started with explaining a request or a problem by the hotel owner and the software developer implemented the request using MS Access. The steps and the amount of content in each was exactly the same as the first experiment, however, the text and picture of each page were replaced by a short animation.

5.5.1.2. E-learning system of the interactive animation group

In this e-learning system the content was presented using interactive animation. As it was explained in the introduction, interactive animation enables users to interact with the video content. In contrast with the traditional animation, interactive animation does not have only play, pause, forward and rewind buttons. There are some transparent spots on

the animation and users should click on them to continue the animation, go to a specific part of the animation or open a specific window. An interactive animation, gives the users the ability to interact with the animation content itself through click, drag, scroll, hover, and gesture (Hung, Kinshukc, & Chen, 2018; Price et al., 2008).

In this e-learning system some hotspots were placed on the target software's parts that we wanted to teach to the participants and instead of clicking on the next button to go to the next page, learners were supposed to click on the software's parts with hotspots to see the next step of learning. For example, in the first tutorial, each step taught learners how to create a table column to store different data types, as an instance one of the steps was: "In order to store the price of each room click on the currency button". When the narrator said: "In order to store the price of each room click on the currency button" users should move the mouse and click on the currency button of the software interface in the animation to continue learning and watch the next step.

5.6. Time duration for watching the tutorials and performing the tasks

Each experiment took approximately 45 minutes, and same as the first experiment, there was not any time limit for watching the tutorials and performing the test tasks and participants could spend any amount of time for learning and performing the test tasks. Learning and performance times were measured for group comparison purposes.

5.7. Measurement method

Same as the first experiment, in order to measure cognitive load of the participants a mixture of objective and subjective measurement methods were used to increase the reliability of the measurement process. As the subjective part of the measurement, participants were asked to fill a self-reported difficulty 9-point Likert scale questionnaire

about their experience after each tutorial and task (Ayres, 2006; De Jong, 2010; DeLeeuw, & Mayer, 2008; Gerjets et al., 2009; Kalyuga, Chandler, & Sweller, 1999; Paas et al., 2003). The questions of the Likert scale were a combination of questions related to difficulty of the teaching materials, confidence, and stress level in order to evaluate cognitive load from different aspects. This questionnaire was adopted from Joseph (2013) and modified to fit the context of this study.

As the objective part of the measurement, 4 factors were measured. These factors are: a) time duration of watching each tutorial, b) whether participants could complete the tasks, c) the time duration that they spent to solve each task, and d) mouse move distance, and number of clicks to find the solution of the task (Brünken, Plass, & Leutner, 2003; Mayer, 2001). The details can be seen in section 4.7.

5.8. Ethics approval procedure

Although ethics approval has been granted for the first experiment, in order to get permission to collect data for conducting this experiment, the existing negligible risk research application was modified with detailed information of this experiment including problem statement, methodology, type of participants, and type of data that will be collected and submitted to UNSW Human Ethics Team. After reviewing the ethics application by the human research ethics committee and asking for some minor modifications, the existing ethics approval code (HC17074) of the first experiment was updated with the information of this experiment.

5.9. Data collection procedure

Same as the first experiment, the data is collected from the participants one by one. Each participant came to the experiment location, and a summary of the project was given to

them. Afterwards, in order to confirm the eligibility of the participant a computer skill placement form (Appendix H) was given to them, then the participant was asked to sign the project consent form (Appendix I).

The experiment was started by watching the first tutorial. During each tutorial time duration of reading was recorded (hypotheses 1A and 2A) and after finishing each tutorial a Likert scale questionnaire (Appendix F) with 3 questions was given to the participant (hypotheses 1B and 2B). The questionnaire items were same as in the first experiment (Appendix F).

After answering the Likert scale questionnaire, a test task related to the first tutorial was assigned to the participant. In order to measure participants performance while performing the test tasks, Mouse distance moved, Number of left and right clicks (hypotheses 1D and 2D) and performance speed (hypotheses 1E and 2E), were measured using Moustron Software. Also, after finishing each test task a Likert scale questionnaire (Appendix G) was given to the participant (hypotheses 1F and 2F).

After answering the Likert scale questionnaire of the test task, participant could watch the second tutorial, perform the second test task and the same measurement procedure was repeated. The test tasks were the same as the first two test tasks of the first experiment (Appendix D). Also, the questionnaires items were the same as the first experiment (Appendix G).

In order to calculate the test performance marks (hypotheses 1C and 2C), the MS Access files of the test tasks were saved on the computer during the experiment and the mark of each test task was calculated manually after the experiment.

At the end of the experiment a \$20 voucher was given to the participant to express our appreciation for their participation. A summary of the data collection procedure for each participant is presented in figure 5.1.



Figure 5.1: Summary of the research procedure

5.10. Results

A General Linear Model test with repeated measures was conducted in order to calculate the main effect of the experimental groups (i.e. Animation [Control], and Interactive Animation) and to check if there was an interaction between the experimental groups and task element interactivity levels of the teaching materials / test tasks for all the dependent variables including: test marks, mouse moves, left clicks, right clicks, duration, and Likert scale difficulty, confidence, and stress questions. For all the dependent variables where the general linear model test showed a significant interaction effect, simple effect tests were conducted to compare the effects on low and high element interactivity materials.

The means (with standard deviations in brackets) of the dependent variables can be seen in Tables 5.1 and 5.2.

Table 5.1: Test task means

Groups	Task type	Marks (out of 9)	Duration	Mouse movement	Left clicks	Right clicks	Difficulty question (out of 9)	Confidence question (out of 9)	Stress question (out of 9)
Animation	Low element	8.3 (0.8)	3.9 (1.2)	8.1 (2.7)	59.3 (22.9)	2.6 (2.7)	2.2 (1.3)	1.9 (0.9)	2.5 (1.8)
	High element	7.2 (1.6)	5.5 (2)	9.5 (3)	63 (25.2)	1.4 (1.5)	4 (1.9)	2.3 (1.3)	3.9 (2.2)
Interactive Animation	Low element	8.1 (0.9)	3.5 (1.4)	8.1 (4.6)	55 (23)	1.1 (1)	2 (1.1)	2 (1)	2 (1.3)
	High element	7.4 (1.9)	5.3 (1.6)	9.1 (3.2)	57.8 (27.3)	0.5 (0.9)	3.6 (1.6)	2.1 (1.2)	2.9 (1.4)

Table 5.2: Teaching materials means

Groups	Task type	Duration	Difficulty question	Confidence question	Stress question
Animation	Low element	7.6 (0.6)	2 (1.2)	1.8 (0.7)	1.9 (1.1)
	High element	6.4 (1)	4.6 (1.7)	3.3 (1.9)	3.3 (1.6)
Interactive Animation	Low element	7.2 (0.1)	1.8 (0.9)	1.7 (0.8)	1.7 (1)
	High element	5.7 (0.3)	3.4 (1.1)	2.2 (1.1)	2.1 (1)

5.10.1. Learning time duration

Regarding the duration of watching the teaching materials (hypotheses 1A and 2A), the main effect was significant for the different teaching methods: $F(1, 38) = 10.482$, $p < .05$, $\eta^2 = 0.216$ and for the element interactivity level: $F(1, 38) = 254.744$, $p < .05$, $\eta^2 = 0.870$. The interaction effect analysis showed a significant element interactivity by group interaction: $F(1, 38) = 4.263$, $p < .05$, $\eta^2 = 0.101$, and the simple effects of the teaching methods for the high element showed that the duration of watching the teaching materials decreased for the interactive animation in comparison with the animation version: $t(38) =$

3.167, $p < .05$, $d = 0.501$. Also, for the low element materials the duration of watching decreased for the interactive animation in comparison with the animation version: $t(38) = 2.752$, $p < .05$, $d = 0.435$.

5.10.2. Difficulty, stress and confidence questionnaires for the teaching materials

Regarding the Difficulty Scale of the teaching materials (hypotheses 1B and 2B), the main effect was significant for the different teaching methods: $F(1, 38) = 4.541$, $p < .05$, $\eta^2 = 0.107$ and for the element interactivity level: $F(1, 38) = 91.076$, $p < .05$, $\eta^2 = 0.706$. The interaction effect analysis showed a significant element interactivity by group interaction: $F(1, 38) = 5.163$, $p < .05$, $\eta^2 = 0.120$, and the simple effects of the teaching methods for the high element materials showed that participants reported more difficulty for the animation in comparison with the interactive animation version: $t(38) = 0.448$, $p < .05$, $d = 0.425$. For the low element teaching methods there was no significant differences between the animation and the interactive animation version: $t(38) = 0.593$, $p > .05$, $d = 0.094$. The significant differences using high but not low element interactivity materials explains the significant element interactivity by group interaction.

Regarding the Confidence Scale of the teaching materials (hypotheses 1B and 2B), the main effect was not significant for the different teaching methods: $F(1, 38) = 3.130$, $p > .05$ however, it was significant for the element interactivity level: $F(1, 38) = 19.025$, $p < .05$, $\eta^2 = 0.344$. The interaction effect analysis showed a significant element interactivity by group interaction: $F(1, 38) = 4.515$, $p < .05$, $\eta^2 = 0.106$, and the simple effects of the teaching methods for the high element materials showed that participants reported less confidence for teaching through the animation in comparison with the interactive animation version: $t(38) = 2.11$, $p < .05$, $d = 0.334$. For the low element tests there was

no significant differences between the animation and the interactive animation version: $t(38) = 0.395, p > .05, d = 0.062$.

Regarding the Stress Scale of the teaching materials (hypotheses 1B and 2B), the main effect was significant for the different teaching methods: $F(1, 38) = 4.890, p < .05, \eta^2 = 0.114$ and for the element interactivity level: $F(1, 38) = 20.692, p < .05, \eta^2 = 0.353$. The interaction effect analysis showed a significant element interactivity by group interaction: $F(1, 38) = 7.728, p < .05, \eta^2 = 0.169$, and the simple effects of the teaching methods for the high element materials showed that participants reported less stress for the interactive animation in comparison with the animation version: $t(38) = 2.990, p < .05, d = 0.473$. For the low element tests there was no significant differences between the animation and the interactive animation version: $t(38) = 0.464, p > .05, d = 0.073$.

5.10.3. Test performance marks

Regarding the test performance marks (hypotheses 1C and 2C), the main effect was not significant for the different teaching methods: $F(1, 38) = .000, p > .05$ however, it was significant for the element interactivity level: $F(1, 38) = 10.372, p < .05$. Also, The interaction effect analysis did not show a significant element interactivity by group interaction: $F(1, 38) = .288, p > .05$.

5.10.4. Mouse movement distance and number of clicks while performing the test tasks

Regarding the Mouse Movement distance (hypotheses 1D and 2D), the main effect was not significant for the different teaching methods: $F(1, 38) = .044, p > .05$ however, it was significant for the element interactivity level: $F(1, 38) = 4.485, p < .05$. Also, The

interaction effect analysis did not show a significant element interactivity by group interaction: $F(1, 38) = .089, p > .05$.

Regarding the Left Clicks (hypotheses 1D and 2D), the main effect was not significant for the different teaching methods: $F(1, 38) = .610, p > .05$ however, it was significant for the element interactivity level: $F(1, 38) = .442, p < .05$. Also, The interaction effect analysis did not show a significant element interactivity by group interaction: $F(1, 38) = .007, p > .05$.

Regarding the Right Clicks (hypotheses 1D and 2D), the main effect was significant for the different teaching methods: $F(1, 38) = 11.643, p < .05$ and for the element interactivity level: $F(1, 38) = 5.088, p < .05$. The interaction effect analysis did show a significant element interactivity by group interaction: $F(1, 38) = .565, p > .05$.

5.10.5. Test performance speed

Regarding the duration of performing the test tasks (hypotheses 1E and 2E), the main effect was not significant for the different teaching methods: $F(1, 38) = .333, p > .05$ however, it was significant for the element interactivity level: $F(1, 38) = 45.841, p < .05$. Also, The interaction effect analysis did not show a significant element interactivity by group interaction: $F(1, 38) = .197, p > .05$.

5.10.6. Difficulty, confidence and stress questionnaire results for the test tasks

Regarding the Difficulty Scale of the test tasks (hypotheses 1F and 2F), the main effect was not significant for the different teaching methods: $F(1, 38) = .532, p > .05$, however, it was significant for the element interactivity level: $F(1, 38) = 32.666, p < .05$. Also, The

interaction effect analysis did not show a significant element interactivity by group interaction: $F(1, 38) = .065, p > .05$.

Regarding the Confidence Scale of the test tasks (hypotheses 1F and 2F), the main effect was not significant for the different teaching methods: $F(1, 38) = .028, p > .05$ nor for the element interactivity level: $F(1, 38) = 2.557, p > .05$. Also, The interaction effect analysis did not show a significant element interactivity by group interaction: $F(1, 38) = .639, p > .05$.

Regarding, the Stress Scale of the test tasks (hypotheses 1F and 2F), the main effect was not significant for the different teaching methods: $F(1, 38) = 2.836, p > .05$ however, it was significant for the element interactivity level: $F(1, 38) = 14.646, p < .05$. Also, The interaction effect analysis did not show a significant element interactivity by group interaction: $F(1, 38) = .875, p > .05$.

5.11. Discussion

In this study we investigated interactions between the delivering approach (animation vs interactive animation) and element interactivity levels of the pedagogical content, on the cognitive load of learners while learning software through e-learning platforms. We compared the value of using an interactive animation versus normal animation to deliver the narrative-based e-learning systems.

5.11.1. Effect of interactive animation on high and low interactivity teaching materials

The results showed that the time duration of watching the animation system was higher in comparison with the interactive animation system, for both the high and the low

element interactivity materials. It shows that based on embodied cognition effects, interacting with the animation content could decrease cognitive load and facilitate learning, therefore, learners had less need to replay the tutorials' contents and their learning time decreased (Calvo, & Gomila, 2008; Glenberg, 2010; Schulz, 2017). These findings are in accord with the studies indicating that by decreasing cognitive load, learning duration will be decreased (Brünken, Plass, & Leutner, 2003; DeLeeuw, & Mayer, 2008; Mayer, 2001; Paas, Ayres, & Pachman, 2008; Van Mierlo et al., 2012).

Therefore, hypothesis 1a is supported which predicted that for the high interactivity teaching materials, interactive animation will lead to decrease learning time, relative to the normal animation group. However, hypothesis 2a is rejected as it predicted that for the low interactivity learning materials, interactive animation will not have a significant effect on the learning time.

Regarding the Likert-scale questionnaire, for the high interactivity teaching materials, the results showed that participants reported less difficulty, less stress and more confidence while learning the teaching materials with the use of the e-learning system that had the interactive animation. However, for the low interactivity teaching materials, there was not any significant difference between the groups. These findings are in line with the hypothesis 1b which predicted that for the high interactivity learning materials the interactive animation-based system can decrease cognitive load and learners will report less difficulty, more confidence and less stress during the learning process. Also, the results supported hypothesis 2b which stated that for the low interactivity teaching materials the interactive animation-based system will not affect cognitive load and learners will not report more/less difficulty, confidence and stress.

These findings are supported with studies indicating that by decreasing cognitive load, learners will feel less stress and they will report less difficulty (Cranford et al., 2014; DeLeeuw & Mayer, 2008; Granholm et al., 1996; Paas et al., 2003; Van Mierlo et al., 2012).

5.11.2. Effect of interactive animation on high and low interactivity test tasks

The results did not show any significant difference between the animation system and the interactive animation system for most of the measured factors of the test tasks including performance mark, mouse movement distance, number of left clicks, time duration of performing the test tasks, and the Likert-scale questionnaire, neither for the high interactivity elements nor for the low interactivity elements. The only factor that was significant is decreasing the number of right clicks for both the high and the low element interactivity test tasks.

Therefore, hypotheses 1c, 1e and 1f are rejected. Hypothesis 1c predicted that for the high element interactivity test task, test performance marks will be increased, hypothesis 1e predicted that test task speed will be increased and hypothesis 1f predicted that learners will report less difficulty, more confidence and less stress during performing the test task in the interactive animation system versus the animation system.

However, hypothesis 1d that predicted that for the high element interactivity test task, mouse movement distance, number of left and right clicks will be increased, in the animation system versus the interactive animation system, was partially rejected. Although, mouse movement distance and number of left clicks did not change, number of right clicks of performing both high and low element interactivity test tasks decreased significantly.

This finding is important as it can prove the efficiency of interactive animation and embodied cognition effects in avoiding unnecessary actions. Interacting with the animation content could teach the participants the correct form of click which is left click as when performing the test tasks, participants did not need to use any right clicks.

Furthermore, hypotheses 2c, 2e and 2f were approved. Hypothesis 2c predicted that for the low element interactivity test task, test performance marks will not be changed, hypothesis 2e predicted that test task speed will not be changed and hypothesis 2f predicted that learners will not report less/more difficulty, confidence and stress during performing the low element interactivity test task in the animation system versus the interactive animation system.

However, hypothesis 2d that predicted that for the low element interactivity test task, mouse movement distance, number of left and right clicks will not be changed, in the animation system versus the interactive animation system, was partially supported, since the number of right clicks decreased.

Based on the sub hypotheses findings, the first main hypothesis that assumed that in order to learn high interactivity elements of productivity software applications, interactive animation will decrease the cognitive load of novice users in comparison with the animation, is validated only for the learning phase and the right clicks of the test phase. The second main hypothesis which assumed that for elements with low interactivity, interactive animation will not have any significant effect on cognitive load is validated to a great extent, except for the time duration of watching the tutorials and number of right clicks that are decreased.

As it was predicted in the hypotheses, interactive animation decreased cognitive load during the learning phase for the high element interactivity teaching materials in addition

to the watching duration of the tutorials for low interactivity materials, which proves that when users' processing load is high, engaging body in learning can positively affect cognitive load. Moreover, in spite of the reduced learning times involved in interacting with the interactive animations compared to the regular animation, there were still equal learning outcomes, so students spent less time with equal learning benefits.

This study had three important findings, it found that interactive animation can: a) decrease cognitive load during the learning phase, b) decrease learning time duration, and c) avoid unnecessary actions during the test phase. These findings are important, as it shows that embodied cognition can facilitate learning software applications and learners can learn how to use the software with less mental effort and in less time. It can also help learners to understand what actions are not needed to complete the test tasks. It is the main reason that the number of right clicks decreased for both low and high interactivity test tasks as it was unnecessary action to complete the tasks.

These findings are in line with the studies regarding embodied cognition which proved involving learners physically with the objects that are related to the learning content can enhance learning performance (Ceciliani, 2018; Glenberg, 2015; Shapiro & Stolz, 2019). The findings are also supported by the studies related to the positive effect of interactive animation (Devinea, Gormley, & Doylec, 2015; Hung, Kinshukc, & Chen, 2018) and gamification studies that showed interactive e-learning platforms can increase learning performance (Dong et al., 2012; Dontcheva, et al., 2014; Li, Grossman, & Fitzmaurice, 2012; Shane, 2013).

5.11.3. Is interactive animation useful in practice

Based on the findings of this experiment, interactive animation could impact the teaching phase but not on the test phase except for one factor. The justification can be the difficulty level of the test tasks or the nature of the target software that was taught to the participants. It was possible, if we could increase the difficulty level of the test tasks or change the target software, some significant results could be reached in the test phase. There is a chance if interactive animation is used for teaching graphical software, we could get significant results for the test phase as learning graphical software involves drawing which means more body movements.

Although, MS Access is more complicated than graphical software applications in nature, however, embodied cognition can be more effective on graphical software as users need to use mouse and a combination of keyboard keys to draw or modify pictures in addition to moving the mouse to find the tools and click on them. Therefore, it can be said that the benefits of interactive animation to engage the motor system of the students during learning, depends on the type of software that we want to teach. The more we need hand movement in order to work with a software system, the more beneficial interactive animation is likely to be.

The benefits of promoting physical interaction with the learning content through interactive animation are also supported by different studies that evaluated the effects of physical interactions in learning of language and translation (Glenberg, Witt & Metcalfe, 2013; Zhu, 2018), science and physics (Kontra et al., 2015; Enyedy et al., 2012), music and sport (Schiavio et al., 2019), medical science (Kalet et al., 2012) and children education (Chandler, & Tricot, 2015). In all these studies teaching the target concept is

integrated with some sort of physical activities including interacting with the learning objects through touching, moving them or sketching by hand.

5.12. Conclusion, limitations, future directions

In this experiment, we compared the value of using animation versus interactive animation to deliver the narrative-based e-learning systems. The findings showed that, interactive animation could significantly decrease cognitive load in the learning phase, however, it did not have any significant effect on performing the test tasks. Decreasing the time duration of learning and the participants' response to the questionnaire showed that the interactive animation decreased the perceived difficulty level of the learning content compared to the animation version.

The findings of this research are important because there is no research, we are aware of regarding the application of interactive animation for teaching software applications through narrative-based e-learning systems. This study can help address this existing gap in the literature, and support potential benefits associated with interactive animations. In particular, they can decrease learning times with no detriment to learning outcomes.

With respect to limitations and further work, although the test tasks that were used in this study were the most difficult tests tasks that could be designed for the concepts we taught in MS Access, the findings did not show any significant results in the test phase. Therefore, testing the effect of interactive animation using a different software that has the potential for the test tasks to be more difficult and with more motor movement might yield some significant results. We could also endeavor to create larger differences in difficulty between the high and low element interactive tasks.

In this experiment we only compared animation with interactive animation, and it is not clear if any of them can improve learning performance in comparison with the static content. Therefore, in the future experiments comparing these two systems with a static system can show interesting results, however, as it is mentioned in the introduction from a research design perspective it is not scientific to change more than one variable at any given time when we are comparing two groups, so both groups would need to include either only narration or only text with the animated and static learning content.

Furthermore, in order to know more about users' feelings and how they perceived interacting with the animation content, some qualitative data using think-aloud protocol, or an interview could be collected in future studies.

Finally, in this experiment interactive animation is used to conduct the learning linearly, therefore, it would be interesting to evaluate its effects in an adaptive learning environment. In other words, the interactive animation in this study is used to engage learners with the software learning interface, by asking them to click on the software tools to continue learning. However, in an adaptive learning environment, by clicking on the targets in the interactive animation, different options would be offered to the learners, and they can choose the direction of learning based on what they want to learn next. This involves giving the learners control of their path through the learning content.

The next chapter will discuss the third experiment in which a talking avatar is added into the narrative-based e-learning system that uses interactive animation in order to see whether the talking avatar can affect the cognitive load of novice users while learning software applications.

Chapter 6

Experiment 3

6.1. Introduction

In the first experiment, we found that a familiar narrative can decrease learners' cognitive load and increase test performance marks compared to no-narrative and unfamiliar narrative conditions. The second experiment indicated that interactive animations led to less learning time, with similar performance-based learning outcomes when compared to a regular animation. This chapter describes the third experiment in which a talking avatar is added into the narrative-based e-learning system that uses interactive animation to see whether the talking avatar can affect the cognitive load of novice users while learning software applications. A talking avatar is an animated character that can read text and it has different gestures such as lip syncing, and body movement based on the content it is reading.

As discussed in chapter 3, there are a great number of studies in the area of avatar-based e-learning systems that can be grouped into the four categories including: a) increasing learning performance for mathematics, business, nursing, language, criminology, and marketing (Aikina & Zubkova, 2015; Cook et al., 2017; Flood, & Commendador, 2016; Hughes et al., 2015), b) increasing users' motivation to continue learning, brainstorming or expressing their opinion (Allmendinger, 2010; Ang et al., 2013; Chen et al., 2012; Theng, & Aung, 2012), c) helping people with mental and physical disorders such as deaf

people, people with depression, autistic children, and children with attention deficit hyperactivity disorder (Bouزيد, Khenissi, & Jemni, 2016; Fabio et al., 2019; Gilani et al., 2019; Wang, Xing, & Laffey, 2018), and d) evaluating the effect of an avatar on cognitive load during decision-making and in virtual reality environments (Gentile et al., 2017; Pan, & Steed, 2019; Pignatiello et al., 2019; Steed et al., 2016). The findings of all the mentioned studies showed positive impacts of using an avatar on knowledge acquisition, motivation, self-efficacy, and helping disabled people.

However, the findings might not demonstrate the whole picture as most of the studies just compared avatar-based systems with non-computerised situations such as a classroom, not with other e-learning systems that do not have an avatar. In fact, many different variables have been changed in the studies and it is not clear if the avatar itself was efficient or if a system without an avatar would be more efficient. Also, most of the studies just evaluated the effect of avatar-based e-learning systems on users' motivation and engagement with the use of surveys and questionnaires to gather users' opinions and it is not clear if the avatar had a positive effect on cognitive load and learning or not. Although, there are some studies on the effect of an avatar on cognitive load, they have not evaluated the effect of avatars on learning performance especially when the avatar is added to an e-learning system with different visual elements that learners should focus on.

Since, the only usage of talking avatar is making the e-learning environment more appealing, it is considered as a decorative graphic which can increase cognitive load based on the redundancy effect as the avatar is a redundant element for the audio of the animation that can shift the focus of learners (Bus, Takacs, & Kegel, 2015; Dewan, 2015; Jaeger, & Wiley, 2014; Knoop-van Campen, Segers, & Verhoeven, 2018; Mayer, 2014; Rey, 2012; Rey, 2014; Sung, & Mayer, 2012; Vössing, Stamov-Roßnagel, & Heinitz,

2016; Wang et al., 2017). Information that is redundant is not essential for learning and may use up valuable cognitive resources that could otherwise be directed towards learning outcomes.

Therefore, in order to address the contradiction between the existing studies on talking avatar and decorative graphic, in this experiment a talking avatar was added into the e-learning system as the only variable and compared with the same e-learning system without the talking avatar in order to find the effect of a talking avatar on the cognitive load of learners.

It is hypothesized that: 1) in order to learn high interactivity elements of productivity software applications, the e-learning system that uses a talking avatar will increase the cognitive load of novice users when compared to the no-avatar system as the avatar is redundant. 2) for the elements with low element interactivity, the avatar-based e-learning system may not have any significant effect on cognitive load, when compared to the no-avatar system, as the users' processing load is still manageable. Based on these overarching hypotheses, it is predicted that:

1A) For the high interactivity teaching materials, the talking avatar will lead to an increase in cognitive load that exceeds working memory capacity and consequently learning time will be increased. We predict this result since by increasing cognitive load, time duration of performing the target task can be increased (Brünken, Plass, & Leutner, 2003; Park et al., 2011).

2A) For the low interactivity teaching materials, the talking avatar will not lead to a significant increase in cognitive load that exceeds working memory capacity and reading time will not be affected. We predicted this result because when the teaching materials

are low in cognitive load due to low element interactivity, the users' processing load will still be manageable and reading duration will not be significantly affected (Brünken, Plass, & Leutner, 2003; Park et al., 2011).

1B) For the high interactivity teaching materials, the talking avatar will lead to more cognitive load that exceeds working memory capacity, therefore, learners will report more difficulty, less confidence and more stress during the learning phase. We predicted this result because the Likert scale questionnaire is a direct measurement method of cognitive load and by increasing cognitive load, learners will feel more stress and they will express more difficulty (Ayres, 2006; Cranford, et al., 2014; De Jong, 2010; DeLeeuw, & Mayer, 2008; Gerjets et al., 2009; Granholm, et al., 1996; Kalyuga, Chandler, & Sweller, 1999; Paas, et al., 2003).

2B) For the low interactivity teaching materials, the talking avatar will not lead to a significant increase in cognitive load that exceeds working memory capacity, therefore, learners will not report more/less difficulty, confidence and stress during the learning phase (Park et al., 2011).

1C) For the high interactivity test materials, the talking avatar will lead to more cognitive load that exceeds working memory capacity, resulting in a decrease in test performance marks (e.g. Brunken, Plass, & Leutner, 2003; DeLeeuw, & Mayer, 2008; Mayer, 2001; Paas, Ayres, & Pachman, 2008; Van Mierlo et al., 2012).

2C) For the low interactivity test materials, the talking avatar will not have a significant effect on the test performance marks. This prediction was made because the users' processing load will still be manageable, and so test difficulty level will not be changed and consequently test performance marks will not be affected (e.g. Brunken, Plass, &

Leutner, 2003; DeLeeuw, & Mayer, 2008; Mayer, 2001; Paas, Ayres, & Pachman, 2008; Park et al., 2011; Van Mierlo et al., 2012).

1D) For the high interactivity test materials, the talking avatar will lead to an increase in mouse movement distance and number of left and right clicks. This prediction is based on embodied cognition effects (see Barsalou, 2008), where more movements may be needed to support and improve learning outcomes when the cognitive load is higher.

2D) For the low interactivity test materials, the talking avatar will not lead to an increase in mouse movement distance and number of left and right clicks. We predicted this result because the users' processing load will still be manageable, and so mouse movement distance and number of clicks will not be affected (Barsalou, 2008; Kortum, & Acemyan, 2016; Park et al., 2011).

1E) For the high interactivity test materials, the talking avatar will lead to increased cognitive load and consequently test task performance speed will be decreased. We predict this result based on Brünken, Plass and Leutner (2003) who showed that by increasing cognitive load, time duration of performing the target task can be increased.

2E) For the low interactivity test materials, the talking avatar will not lead to a significant increase in cognitive load and test task performance speed will not be affected. We predicted this result because when the test materials are low in element interactivity, it is still manageable for the learners to process the information and test task performance speed will not be affected (Brünken, Plass, & Leutner, 2003; Park et al., 2011).

1F) For the high interactivity test materials, the talking avatar will lead to more cognitive load, therefore, learners will report more difficulty, less confidence and more stress during performing the test tasks. We predicted this result because by increasing cognitive load,

learners will feel more stress and they will express more difficulty (Ayres, 2006; De Jong, 2010; DeLeeuw, & Mayer, 2008; Gerjets et al., 2009; Kalyuga, Chandler, & Sweller, 1999; Paas, et al., 2003).

2F) For the low interactivity test materials, the talking avatar will not lead to a significant increase in cognitive load, therefore, learners will not report more/less difficulty, confidence and stress while performing the test tasks (Park et al., 2011).

6.2. Participants Recruitment Method

All the participants were selected from university students. In order to find the participants, the research was advertised on the UNSW Internship Facebook page and a \$20 voucher was offered to the students who participate in this study. The students who were interested in participating sent an email or a Facebook message to the researcher, then they were invited to come to a quiet room such as the HCI lab or a consultation room for the experiment, after approving their eligibility through asking them some basic questions about their computer background, university major, courses that they had passed and their familiarity with MS Access. In order to invite the participants an invitation email was sent to their email calendar.

6.3. Participants and Design

In total in this experiment 40 users participated:

- 20 participants in the control group (e-learning system with a familiar narrative that delivered the teaching content using interactive animation but without an avatar).
- 20 participants in the experimental group (e-learning system with a familiar narrative that delivered the teaching content using interactive animation including an avatar).

Participants had the characteristics below:

- They were above 18.
- They had a good English proficiency.
- They were not professional computer users.
- They were not expert in a great range of professional software or any programming languages.
- They did not have any prior experience or knowledge with MS Access.

In addition to the basic questions that were asked from the potential participants about their university major and courses that they had passed, the same computer skill placement test form (Singh, & Dyer, 2002) similar to the first experiment was used for the selected participants to make sure that they are a relatively homogenous group.

6.4. Developing the e-learning systems

The e-learning systems of this study were developed using HTML 5, the interactive animations were recorded and edited using Camtasia Studio software and the avatar was created using Site Pal service. The narration of the avatar was uploaded on Site Pal service, and after designing the avatar, the narration and the avatar were synced online. Then, the screen recorder was used to record the avatar when reading the narration. Finally, the recorded animation was broken down into the different sections based on the lessons and imported into Camtasia Studio software to be merged with the interactive animation.

6.5. The e-learning systems contents and tasks

In order to align the teaching content of this experiment with the first and the second experiments, Microsoft Access was selected as the experimental productivity software

application to teach to the novice learners. In order to teach MS Access, we used the same teaching content as the second experiment. See chapter 4, section 4.5 for more detail.

6.5.1. The detail of the e-learning systems content

In this experiment, two e-learning systems were designed. In both systems, the teaching content, the way that the content was presented, and the tasks were the same and the only independent variable was adding a talking avatar to the experimental system. Both systems had a hotel story narrative.

6.5.1.1. E-learning system of the control group

This e-learning system had the familiar narrative (hotel story) and the content were presented using interactive animation and there was no talking avatar in the system.

6.5.1.2. E-learning system of the experimental group

This e-learning system was the same as the control group, however, instead of just having a background audio to teach the learning content, a talking avatar was added (see figure 6.1). This talking avatar had body movement and lip syncing with the audio.

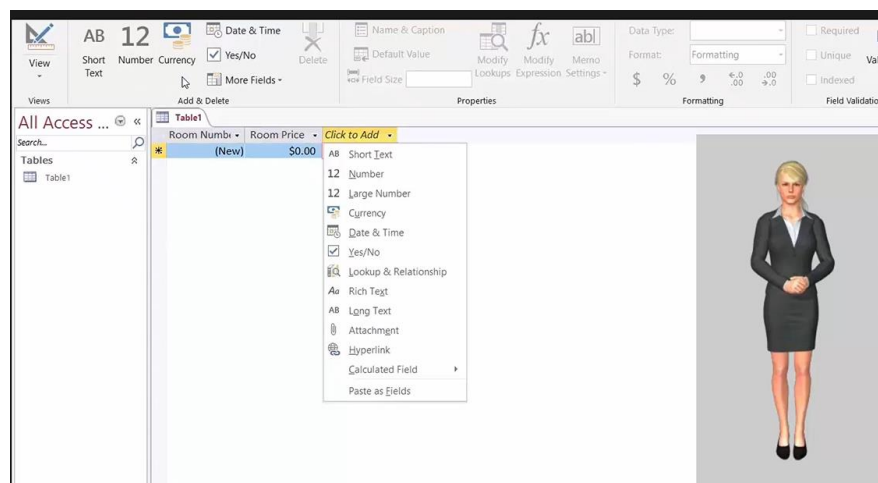


Figure 6.1: E-learning system with avatar

6.6. Time duration for watching the tutorials and performing the tasks

Each experiment took approximately 45 minutes, and same as the first and the second experiments, there was not any time limitation for watching the tutorials and performing the tasks. Learning and performance times were measured for group comparison purposes.

6.7.Measurement method

Same as the first and the second experiments, in order to measure the cognitive load of the participants a mixture of objective and subjective measurement methods was used to increase the reliability of the measurement process. In the subjective part of the measurement, participants were asked to fill a self-reported difficulty 9-point Likert scale questionnaire about their experience after each tutorial and task (De Jong, 2010; Ayres, 2006; Gerjets et al., 2009; Kalyuga, Chandler, & Sweller, 1999; Paas, et al., 2003; DeLeeuw, & Mayer, 2008). The questions of the Likert scale were combination of questions related to the difficulty of the teaching materials, confidence, and stress level in order to evaluate cognitive load from different aspects. This questionnaire was adopted from Joseph (2013) and modified to fit the context of this study.

As the objective part of the measurement, 4 factors were measured. These factors are: a) time duration of watching each tutorial, b) whether participants could complete the tasks, c) the time duration that they spent to solve each task, and d) mouse move distance, and number of clicks to find the solution of the task (Brünken, Plass, & Leutner, 2003; Mayer, 2001). The details can be seen in section 4.7.

6.8. Ethics approval procedure

Same as the other two experiments, in order to get permission to collect data for conducting this experiment an ethics application was lodged by modifying the existing negligible risk research application. The application was updated by the information of this experiment including problem statement, methodology, type of participants, and type of data that will be collected and submitted to UNSW Human Ethics Team. After the review of the ethics application by the human research ethics committee and asking for some minor modifications, the existing ethics approval code (HC17074) of the study was updated with the information of this experiment.

6.9. Data collection procedure

Same as the first and the second experiments, the data is collected from the participants one by one. Each participant came to the experiment location, and a summary of the project was given to them. Afterward, in order to confirm the eligibility of the participant a computer skill placement form (Appendix H) was given to them, then the participant was asked to sign the project consent form (Appendix I).

The experiment was started by watching the first tutorial. During each tutorial time duration of reading was recorded (hypotheses 1A and 2A) and after finishing each tutorial a Likert scale questionnaire (Appendix F) with 3 questions was given to the participant (hypotheses 1B and 2B).

After answering the Likert scale questionnaire, a test task related to the first tutorial was assigned to the participant. In order to measure participants performance while performing the test tasks, Mouse distance moved, Number of left and right clicks

(hypotheses 1D and 2D) and performance speed (hypotheses 1E and 2E), were measured using Moustron Software. Also, after finishing each test task a Likert scale questionnaire (Appendix G) was given to the participant (hypotheses 1F and 2F).

After answering the Likert scale questionnaire of the test task, participant could watch the second tutorial, perform the second test task and the same measurement procedure was repeated. In order to calculate the test performance marks (hypotheses 1C and 2C), the MS Access files of the test tasks were saved on the computer during the experiment and the mark of each test task was calculated manually after the experiment.

At the end of the experiment a \$20 voucher was given to the participant to express our appreciation for their participation. A summary of the data collection procedure for each participant is presented in figure 6.2.

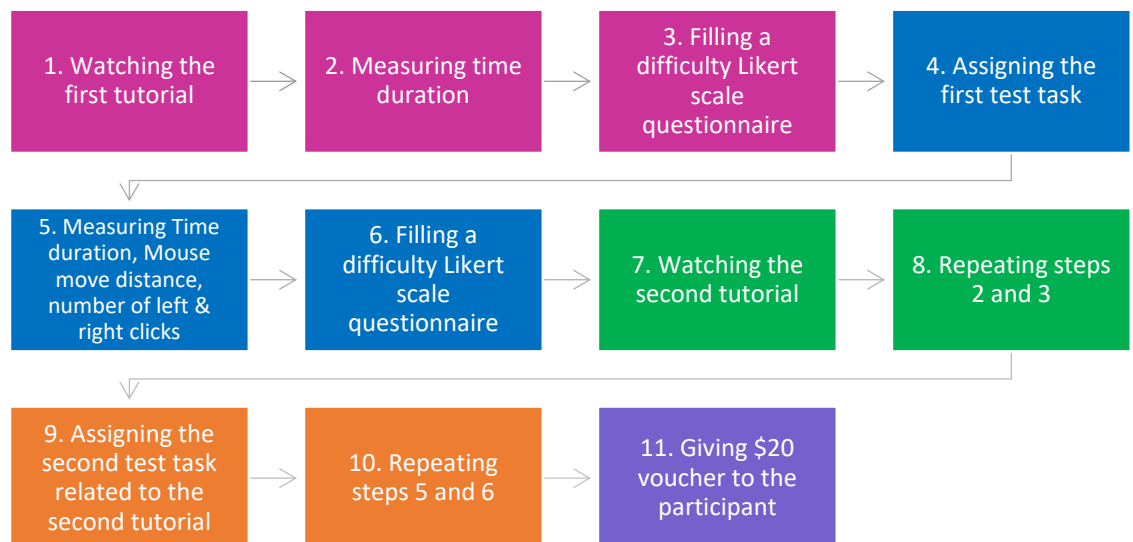


Figure 6.2: Summary of the research procedure

6.10. Results

A General Linear Model test with repeated measures was conducted in order to calculate the main effect of the experimental groups (i.e. no talking avatar [control], and talking avatar groups) and to check if there was an interaction between the experimental groups and element interactivity levels of the teaching materials / test tasks for all the dependent variables including: test marks, mouse moves, left clicks, right clicks, duration, and Likert scale difficulty, confidence, and stress questions. For all the dependent variables where the general linear model test showed a significant interaction effect, simple effect tests were conducted to compare the effects on low and high element interactivity materials.

The means (with standard deviations in brackets) of the dependent variables can be seen in Tables 6.1 and 6.2.

Table 6.1: Test task means

Groups	Task type	Marks (out of 9)	Duration	Mouse movement	Left clicks	Right clicks	Difficulty question (out of 9)	Confidence question (out of 9)	Stress question (out of 9)
No avatar (Control)	Low element	8 (0.9)	3.2 (0.9)	7.6 (2)	58.5 (27)	1 (0.9)	2.2 (1.2)	1.7 (1.2)	1.9 (1.3)
	High element	7.3 (1.6)	5 (1.3)	9.5 (5.2)	59.3 (23.4)	0.6 (0.8)	3.4 (2.1)	2.3 (1.8)	2.7 (1.8)
Avatar	Low element	7.8 (0.9)	3 (0.8)	8.5 (3.5)	65.1 (24.8)	1.4 (2)	2.3 (1.2)	2.4 (1.4)	2.1 (1.4)
	High element	6.9 (1.8)	6 (1.8)	10.2 (4.7)	66.9 (23.4)	0.9 (1.4)	3.9 (1.9)	2.8 (1.6)	3 (1.5)

Table 6.2: Teaching materials means

Groups	Task type	Duration	Difficulty question	Confidence question	Stress question
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No avatar (Control)	Low element	7.2 (0.1)	1.5 (0.5)	1.5 (0.8)	1.5 (0.9)
	High element	5.8 (0.4)	3.5 (1.9)	2.5 (1.9)	2.3 (1.4)
Avatar	Low element	7.2 (0.1)	1.7 (0.9)	1.9 (1)	1.7 (1.1)
	High element	6.6 (0.8)	4.9 (1.9)	3.4 (1.2)	3.5 (1.7)

6.10.1. Learning time duration

Regarding the duration of watching the teaching materials (hypotheses 1A and 2A), the main effect was significant for the learning methods: $F(1, 38) = 14.135$, $p < .05$, $\eta^2 = 0.271$ and for the element interactivity level: $F(1, 38) = 102.693$, $p < .05$, $\eta^2 = 0.730$. The interaction effect analysis showed a significant element interactivity by group interaction: $F(1, 38) = 12.586$, $p < .05$, $\eta^2 = 0.249$. Simple effects testing of the teaching methods for the high element showed that the duration of watching the teaching materials increased for the avatar version in comparison with the no-avatar version: $t(38) = -3.716$, $p < .05$, $d = -0.587$. However, for the low element tests, there was no significant difference between the no-avatar and the avatar version: $t(38) = -1.530$, $p > .05$, $d = -0.239$. The significant differences using high but not low element interactivity materials explains the significant element interactivity by group interaction.

6.10.2. Difficulty, stress and confidence questionnaires for the teaching materials

Regarding the Difficulty Scale of the teaching materials (hypotheses 1B and 2B), the main effect was significant for the different learning methods: $F(1, 38) = 5.373$, $p < .05$, $\eta^2 = 0.124$ and for the element interactivity level: $F(1, 38) = 86.027$, $p < .05$, $\eta^2 = 0.694$. The interaction effect analysis showed a significant element interactivity by group interaction: $F(1, 38) = 4.877$, $p < .05$, $\eta^2 = 0.114$, and the simple effects of the teaching methods for

the high element showed that the participants reported more difficulty in the avatar version in comparison with the no-avatar version: $t(38) = -2.407$, $p < .05$, $d = -0.380$. However, for the low element tests, there was no significant difference between the no-avatar and the avatar version: $t(38) = -0.890$, $p > .05$, $d = -0.141$.

Regarding the Confidence Scale of the teaching materials (hypotheses 1B and 2B), the main effect was not significant for the different learning methods: $F(1, 38) = 3.595$, $p > .05$, however, it was significant for the element interactivity level: $F(1, 38) = 24.806$, $p < .05$. Also, the interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 38) = 1.250$, $p > .05$.

Regarding the Stress Scale of the teaching materials (hypotheses 1B and 2B), the main effect was significant for the different learning methods: $F(1, 38) = 4.274$, $p < .05$, $\eta^2 = 0.101$ and for the element interactivity level: $F(1, 38) = 36.184$, $p < .05$, $\eta^2 = 0.488$. The interaction effect analysis showed a significant element interactivity by group interaction: $F(1, 38) = 5.681$, $p < .05$, $\eta^2 = 0.130$, and the simple effects of the teaching methods for the high element showed that the participants reported more stress in the avatar version in comparison with the no-avatar version: $t(38) = -2.551$, $p < .05$, $d = -0.403$. However, for the low element tests, there was no significant difference between the no-avatar and the avatar version: $t(38) = -0.623$, $p > .05$, $d = -0.099$.

6.10.3. Test performance marks

Regarding the test performance marks (hypotheses 1C and 2C), the main effect was not significant for the different learning methods: $F(1, 38) = 1.315$, $p > .05$, however, it was significant for the element interactivity level: $F(1, 38) = 7.670$, $p < .05$. Also, the

interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 38) = .113, p > .05$.

6.10.4. Mouse movement distance and number of clicks while performing the test tasks

Regarding the Mouse Movement distance (hypotheses 1D and 2D), the main effect was not significant for the different learning methods: $F(1, 38) = .606, p > .05$, however, it was significant for the element interactivity level: $F(1, 38) = 5.227, p < .05$. Also, the interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 38) = .018, p > .05$.

Regarding the Left Clicks (hypotheses 1D and 2D), the main effect was not significant for the different learning methods: $F(1, 38) = 1.182, p > .05$, however, it was significant for the element interactivity level: $F(1, 38) = .097, p < .05$. Also, the interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 38) = .015, p > .05$.

Regarding the Right Clicks (hypotheses 1D and 2D), the main effect was not significant for the different learning methods: $F(1, 38) = 1.791, p > .05$, however, it was significant for the element interactivity level: $F(1, 38) = 1.619, p < .05$. Also, the interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 38) = .050, p > .05$.

6.10.5. Test performance speed

Regarding the duration of performing the tasks (hypotheses 1E and 2E), the main effect was not significant between the learning methods: $F(1, 38) = 1.741, p > .05$, however,

there was a significant difference for the element interactivity level: $F(1, 38) = 100.601$, $p < .05$, $\eta^2 = 0.726$. Also, the interaction effect analysis showed a significant element interactivity by group interaction: $F(1, 38) = 7.016$, $p < .05$, $\eta^2 = 0.156$, and the simple effects of the test task for the high elements showed that the test performance speed decreased in the avatar version in comparison with the no-avatar version: $t(38) = -2.129$, $p < .05$, $d = -0.337$. However, for the low element tests, there was no significant difference between the no-avatar and the avatar version: $t(38) = 0.800$, $p > .05$, $d = 0.126$.

6.10.6. Difficulty, confidence and stress questionnaire results for the test tasks

Regarding the Difficulty Scale of the test tasks (hypotheses 1F and 2F), the main effect was not significant for the different learning methods: $F(1, 38) = .514$, $p > .05$, however, it was significant for the element interactivity level: $F(1, 38) = 19.345$, $p < .05$. Also, the interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 38) = .395$, $p > .05$.

Regarding the Confidence Scale of the test tasks (hypotheses 1F and 2F), the main effect was not significant for the different learning methods: $F(1, 38) = 2.346$, $p > .05$, however, it was significant for the element interactivity level: $F(1, 38) = 3.074$, $p < .05$. Also, the interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 38) = .123$, $p > .05$.

Regarding, the Stress Scale of the test tasks (hypotheses 1F and 2F), the main effect was not significant for the different learning methods: $F(1, 38) = .367$, $p > .05$, however, it was significant for the element interactivity level: $F(1, 38) = 12.905$, $p < .05$. Also, the interaction effect analysis did not show a significant element interactivity by group interaction: $F(2, 38) = .000$, $p > .05$.

6.11. Discussion

In this study we investigated interactions between the talking avatar and element interactivity levels of the pedagogical content, on the cognitive load of learners while learning software through e-learning platforms. We compared the value of including a talking avatar versus no-avatar in the narrative-based e-learning systems.

6.11.1. Effect of talking avatar on high and low interactivity teaching materials

The results showed that the time duration of watching the interactive-animation in the talking avatar system was higher in comparison with the no-avatar system, for the high element interactivity materials which supports the suggestion that the talking avatar was redundant and distracted learners. Therefore, hypothesis 1A is supported which predicted that for the high interactivity teaching materials, the talking avatar will distract learners and increase learning time, relative to the no-avatar group. Furthermore, hypothesis 2A which predicted that for the low interactivity learning materials, the talking avatar will not have a significant effect on the learning time was supported. These findings are in accord with the studies indicating that by increasing cognitive load, learning duration will be increased for high element interactive materials (Brünken, Plass, & Leutner, 2003; DeLeeuw, & Mayer, 2008; Mayer, 2001; Paas, Ayres, & Pachman, 2008; Van Mierlo et al., 2012) and redundant elements such as decorative elements and background music do not have a significant effect on learning of low element interactivity materials (Park et al., 2011).

Regarding the Likert-scale questionnaire, for the high interactivity teaching materials, the results showed that participants reported more difficulty and more stress while learning the teaching materials with the use of the e-learning system that had the talking avatar.

However, for the low interactivity teaching materials, there was not any significant difference between the groups. These findings are partially supported with the hypothesis 1B which predicted that for the high interactivity learning materials the avatar-based system can increase cognitive load and learners will report more difficulty, less confidence and more stress during the learning process. We mentioned partially as the confidence level did not change. Also, the results validated hypothesis 2B which stated that for the low interactivity learning materials the avatar-based system will not affect cognitive load and learners will not report more/less difficulty, confidence and stress. These findings are supported with studies indicating that by increasing cognitive load, learners will report more difficulty and their stress will be increased (Cranford, et al., 2014; DeLeeuw, & Mayer, 2008; Granholm, et al., 1996; Paas et al., 2003; Van Mierlo et al., 2012).

6.11.2. Effect of talking avatar on high and low interactivity test tasks

The results did not show any significant difference between the no-avatar system and the talking avatar system for most of the measured factors of the test tasks including test marks, mouse movement distance, number of left and right clicks, and the Likert-scale questionnaire, neither for the high interactivity elements nor for the low interactivity elements. The only factor that significantly affected was time duration of performing the high element interactivity test task.

Therefore, hypotheses 1C, 1D and 1F are rejected. Hypothesis 1C predicted that for the high interactivity test materials, the test performance marks will be decreased in the talking avatar system versus the no-avatar system, hypothesis 1D predicted that for the high interactivity test materials, the talking avatar will lead to an increase in mouse movement distance and number of left and right clicks, and hypothesis 1F predicted that

for the high interactivity test materials, the talking avatar will lead to more cognitive load, therefore, learners will report more difficulty, less confidence and more stress during performing the test tasks.

However, hypothesis 1E which predicted that for the high element interactivity test task, performance speed will be decreased was supported. A possible reason why the performance speed decreased despite the mouse movements and number of clicks being unaffected, can be because of the more time that participants spent on the formula part of the test task, where the test task asked them to type a formula to calculate the discount amount. Since when performing that part of the test task, participants did not need to use the mouse, only the time duration was affected.

Furthermore, hypotheses 2C, 2D, 2E and 2F were approved. They predicted that, for the low interactivity teaching materials, the avatar-based e-learning system will not affect the test performance marks, mouse movement distance and number of clicks, time duration of performing the test tasks and Likert-scale results.

Based on the sub hypotheses findings, the first main hypothesis that assumed that in order to learn high interactivity elements of productivity software applications, talking avatar will increase the cognitive load of novice users in comparison with the no-avatar system, is validated only during the learning phase for difficulty and stress questionnaire, in addition to the duration of the learning phase and the test task performance speed. The second main hypothesis which assumed that for elements with low interactivity talking avatar would not have any significant effect on cognitive load is validated completely, as the talking avatar did not affect either the learning phase nor the test phase. The significant difference between the no-avatar and avatar groups for high element interactivity materials but not for the low element interactivity materials shows a significant element

interactivity by group interaction for the difficulty and stress questionnaire, and for the duration of the learning phase in addition to the test task performance speed.

As was predicted in the hypotheses, the talking avatar only increased cognitive load for the high element interactivity teaching materials but not for the elements with low interactivity during the learning phase which indicates that when users' processing load is high and learners need to integrate different parts to learn a concept, the decorative elements can distract learners and significantly affect cognitive load. In fact, participants spent more time on learning, and they felt more difficulty and experienced more stress because of the redundancy effect of the avatar as they needed more working memory resources to learn high element interactivity materials. Also, the redundancy effect of the avatar during learning, could affect the test phase, as test task performance speed increased which shows that participants could not remember the location of the software tools and coding syntax of MS Access as efficiently as the no avatar group.

Therefore, when it is necessary to use a talking avatar to increase learners' motivation or engagement, the element interactivity of the teaching materials and learners background knowledge should be considered. Since the participants of this study were novice learners without any background knowledge about MS Access, their cognitive load increased for the high element interactivity materials. These findings are supported by the studies which found that the negative effects of the decorative elements depends on the type of learners and the difficulty level of the teaching contents (Lenzner, Schnotz, & Müller, 2013; Morrison, Ross, & Kemp, 2001; Park et al., 2015; Schneider et al., 2018). When the background knowledge of the learners is low and the teaching materials are more difficult, decorative elements can have more negative effects on the learning performance (Park et al., 2011), however for the expert learners decorative elements can increase learners

motivation and have positive effect on learning (Lenzner, Schnotz, & Müller, 2013; Magner et al., 2014; Shangguan et al., 2020; Wang & Adesope, 2016). However, when there is not any other visual element such as video or picture on the screen that learners need to focus on, utilizing talking avatar may be benign for both teaching materials with high and low interactivity. Further research would be needed to clarify these ideas.

It can be concluded that the talking avatar is a redundant element and can increase cognitive load during the learning phase for high element interactivity materials without any benefit for the test phase. The reason that the participants experienced more difficulty and stress during the learning phase but their test task marks have not changed can be due to the extra time duration that the participants spent on the learning phase and for solving the test tasks which could potentially compensate for the redundancy effect of the avatar to some extent. This claim is in line with Wang et al., (2017), Vössing Stamov-Roßnagel, and Heinitz (2016) and Jaeger and Wiley (2014) who found that the detrimental effects of the decorative pictures can be decreased if the learning process is facilitated through for example giving learners more time, allowing learners to take note or using metacognitive strategies (Muller, Lee, & Sharma, 2008; Wang et al., 2016). However, if we could increase the difficulty level of the test tasks in this study, it might be possible to get some significant results for the test phase.

6.11.3. Is a talking avatar always detrimental?

There is a contradiction between the results of this experiment and the existing studies that evaluated the effect of avatar. Most of the previous studies, proved the efficiency of the avatar in different contexts such as motivation and learners engagement, however, the results of this experiment indicated that a talking avatar can decrease learning performance and increase learning time and test task duration, due to the redundancy

effect and an increase in cognitive load. However, it should be noted that the increased learning time and test duration did not lead to reduced performance outcomes and so these results should be considered with caution.

The difference between this experiment and many of the other studies that evaluated the effect of avatar on learning performance is that, in most of the studies avatar is used as the only teaching element and there was not any other visual element such as text, picture or animation on the screen in contrast with our experiment. Also, a couple of studies, compared avatar-based systems with non-computerised situations such as a classroom, not with another e-learning system that does not have the avatar which can affect the accuracy of the results (Aikina, & Zubkova, 2015; Commendador & Chi, 2013; Flood, & Commendador, 2016; Rueda, Estupiñán, & García, 2016; Ward, 2010; Yasin et al., 2010). The other group of studies, only measured learners' feeling about avatar and the extent that avatar could increase learners' motivation and engagement with the learning content not the cognitive load (Allmendinger, 2010; Ang et al., 2013; Chen et al., 2012; Theng & Aung, 2012). Finally, the studies that evaluated the impact of avatar on cognitive load, only found the benefits of avatar on cognitive load during the decision-making process (Pignatiello et al., 2019) and when users can see their own avatar in the virtual reality-based systems (Gentile et al., 2017; Pan, & Steed, 2019; Steed et al., 2016), not learners' cognitive load during learning phase.

Therefore, it can be said that an avatar is not always beneficial, and its effectiveness depends on the context and the purpose for which it is utilized. When it comes to increasing motivation and engagement, avatars can be helpful, however, when it is used in conjunction with different visual elements especially learning videos, an avatar can

increase cognitive load due to the redundancy effect, especially if the learning content is high in intellectual complexity.

The results of this experiment are in line with many of the studies that demonstrated that decorative elements that are redundant can use up limited working memory resources and increase cognitive load (Bus, Takacs, & Kegel, 2015; Dewan, 2015; Jaeger, & Wiley, 2014; Jonassen et al., 2008; Jonassen, & Driscoll, 2003; Kalyuga, 2009; Knoop-van Campen, Segers, & Verhoeven, 2018; Mayer, 2014; Moreno, & Mayer, 2000b; Rey, 2012; Rey, 2014; Sanchez, & Wiley, 2006; Sung & Mayer, 2012; Vössing, Stamov-Roßnagel, & Heinitz, 2016; Wang et al, 2017).

6.12. Conclusion, limitations, future directions

In this experiment, we evaluated the effect of a talking avatar on the cognitive load of novice users while learning software applications in the narrative-based e-learning system that used interactive animation. In contrast with the existing studies that proved the positive effects of talking avatar on motivation, knowledge acquisition, and self-efficacy, the results of this experiment showed that when the talking avatar is used in conjunction with the other visual elements such as picture or interactive animation, this can distract learners and increase cognitive load especially during the learning phase of materials high in element interactivity.

The findings of this research are important because there is no research, we are aware of regarding the application of avatars for teaching software applications using interactive animation-based e-learning systems. This study helps address this existing gap in the literature and provides some support for when and how it should be used to be beneficial for the learners.

With respect to limitations and further work, although the test tasks that were used in this study were the most difficult tests tasks that was possible to be designed for MS Access, the findings did not show any significant results in the test phase. Therefore, testing the effect of avatar using a different software application or a programming language that has the potential for more difficult test tasks can be beneficial.

Furthermore, since we evaluated the effect of avatar using an interactive animation-based system it could potentially decrease the redundancy effect of avatar, therefore, in the future experiments adding avatar in a text-based or a normal animation-based system can lead to more significant results.

In order to know more about the users' feelings and how they perceived the talking avatar, some quantitative data using a Likert-scale questionnaire and qualitative data using think-aloud protocol, or an interview could be collected. Also, eye-tracking devices could be used to track the eye movement of the users between the avatar and the video, in order to get a better picture of how the avatar could distract the users.

In this study the avatar was a human full body with different body gestures which could increase the distraction for the learners, therefore, in future studies just a talking head might be used in order to see if just showing the avatar head can result in any significant differences on learners' cognitive load. Since some studies indicated that showing the face of the instructor while watching a video tutorial does not have any effect on cognitive load, the results of showing just the avatar head may reveal interesting results about how the avatar should be used in a benign fashion (Díaz, Ramírez & Hernández-Leo, 2015; Kizilcec, Papadopoulos & Sritanyaratana, 2014).

Finally, in this experiment avatar is just used to read the learning content. In the future studies it would be interesting to use avatar as a complementary teaching material so that users can ask their questions from it and get feedback.

The next chapter will discuss how the results of all the three experiments of this thesis can be applied in designing e-learning systems and teaching software applications. Finally, the limitations of the experiments along with the possible future studies will be presented.

Chapter 7

Discussion and conclusion

7.1. Introduction

In this chapter a summary and a critical analysis of all the three experiments findings are discussed. Then the findings are tied into the existing literature and their implication for cognitive load theory, gamified e-learning systems, and teaching software applications are presented. Finally, the limitations and future directions of this study are listed.

7.2. Analysis of the findings

In this research thesis three elements of gamification including narrative, interactivity and talking avatar are added into an e-learning system in order to find their effects on cognitive load of novice learners while learning software applications. The main findings will now be summarized.

In the first experiment, the effect of including a familiar versus unfamiliar context for learning, in the form of a familiar and unfamiliar narrative was evaluated. The results showed that familiar narrative led to superior performance when compared to an unfamiliar narrative and no narrative. Test task marks increased for both elements with low and high interactivity. Number of left and right clicks and mouse movement distance decreased for elements with high interactivity, which indicates that learners could find the solution with the increased performance and less need for supporting mouse input. Time duration to perform the test tasks decreased for both elements with low and high

interactivity and participants reported less difficulty, and more confidence in the familiar context narrative in comparison with the control and unfamiliar context systems. However, the results did not show a significant difference between the participants performance in the control versus the unfamiliar narrative group.

In the second experiment, the effect of interactivity on delivering narrative-based content was evaluated by comparing an e-learning system with animation versus interactive animation. The findings revealed that the interactive animation was superior to the animation-based version. Time duration for watching the tutorials decreased for both elements with low and high interactivity and participants reported less difficulty, less stress and more confidence in the interactive animation version in comparison with the animation version for the high element interactivity teaching materials. Although, the interactive animation had a significant impact on the learning phase, it did not affect the test phase results, except for one factor (right clicks). The findings demonstrated that interactive animations can reduce learning times, with no negative outcomes in terms of performance.

Finally, the last experiment evaluated the effect of a talking avatar versus plain audio on the cognitive load of learners in narrative-based e-learning systems that used interactive animation. The finding revealed that the talking avatar increased cognitive load during learning. Time duration for watching the tutorials increased for both elements with low and high interactivity materials and participants reported more difficulty, and more stress in the talking avatar version in comparison with the no-avatar version for the high element interactivity teaching materials. Although, the talking avatar impacted the learning phase times significantly, it did not affect test performance measures, except for one factor namely, the test performance speed.

While strong results were obtained for the first experiment, the differences in performance outcomes were less obvious in the 2nd and 3rd experiments, where results only showed significant differences in the learning phase. The main reason may be that in the first experiment, the learning content was improved using narrative, however, in experiments 2 and 3 the narrative was still a part of the instructional design, and the delivery approach was further updated by adding either an interactive animation or a talking avatar. In fact, since experiments 2 and 3 already included a familiar narrative in the design of the learning content, therefore the integrated worked examples, may have helped compensate for any other weaknesses in how the updated content was delivered leading to similar performance-based learning outcomes.

It can be said that, in the context of teaching software, when effective teaching content is designed based on cognitive load effects such as worked-examples, the further updating of the delivery approach of the teaching materials (which in this case involved interaction animations and a talking avatar) may not have a significant effect on the test task performance, as the teaching content may already transfer the necessary knowledge to learners. Moreover, the software interface may provide visual cues and remind learners where the tools are. This means that the software interface could provide visual reminders to learners of where they should click, and so implicitly guide them in how to complete the test tasks. The test tasks then rely more on recognition memory rather than recall, and so become harder to design with high levels of difficulty. This is different from domains such as mathematics or chemistry where students should rely entirely on their memory and rather solve the problems based on what they are able to recall.

It can be concluded that, when teaching software applications, either one or a combination of the gamified elements including narrative, interactive animations and talking avatar may impact the learning phase significantly, however, when combining these elements, it may no longer have a significant impact on the test phase. Narrative can facilitate learning through providing integrated worked-examples (especially if they are familiar), interactive animations through interacting with the software during learning (which is supported based on embodied cognition effects), and a talking avatar may make learning more difficult based on the fact that the avatar is not essential to the learning task and so may be a distraction during learning how to use the software (due to redundancy effects). Whether gamified elements increase or decrease learning times or impact performance measures, can be understood and predicted based on our understanding of our cognitive architecture.

7.3. Implication of the findings for cognitive load theory

In this research thesis, the impact of three cognitive load theory effects including worked examples through narrative, embodied cognition through interactive animation and redundancy through talking avatar are evaluated with reference to learning software applications.

7.3.1. Worked examples effect

The efficiency of Worked examples has been proven in teaching different concepts including geometry, mathematics, physics, law, and English (Kyun et al., 2013; Nievelstein et al., 2013; Paas, & Van Merriënboer, 1994; Retnowati, Ayres, & Sweller, 2010; Saw, 2017; Schwonke et al., 2009; Van Gerven et al., 2002; Van Gog, Kester, & Paas, 2011; Van Loon-Hillen, Van Gog, & Brand-Gruwel, 2012). In this study the

benefits of Worked examples are demonstrated within the context of teaching software applications as well.

A new form of worked examples was proposed by integrating worked examples and providing a similar theme to them using a familiar context narrative which could reduce cognitive load that may be associated with understanding the context of each worked example. Furthermore, the familiarity of the narrative content could help learners to integrate the new information to their existing schema that is supported based on the information linking principle (Sweller, 2008; Sweller, 1988).

The study showed that when learners, learn the usages of a new software with the use of integrated and familiar examples, they can connect the usages of the software tools with the information that is stored in their long-term memory, therefore, they can recall the usages of different tools easier and use the software for solving different problems.

In fact, narrative could facilitate learning of software tools by helping learners to use their working memory more efficiently and allocate their free working memory space to more advanced learning. Narrative, also, helped to automate learning the necessary steps to complete different tasks using the software tools which means that it could form the necessary schemas in the long-term memory of the learners (Van Merriënboer & Sweller, 2005). Therefore, appropriate worked examples that can integrate concepts related to the usage of software features and demonstrate the necessary processes to solve real-world problems, can decrease cognitive load and facilitate software applications learning (Sweller & Cooper 1985).

7.3.2. Embodied cognition effect

Engaging the motor system during learning to achieve cognitive skills is supported by different studies that integrate some physical activities including interacting with the learning objects, gesturing, moving, sketching, or mapping to enhance learning of the concepts that need some physical activities. For example, making the shape of letters by hand in order to learn a new language, playing with educational toys to help children learn the names of animals or geometric shapes, playing with musical instruments instead of just reading instructions, learning physics and chemistry concepts using lab tools instead of textbooks, are all instances of embodied cognition effects (Chandler, & Tricot, 2015; Enyedy et al., 2012; Glenberg, Witt, & Metcalfe, 2013; Kontra et al., 2015; Schiavio, et al., 2019; Zhu, 2018).

This study verified the positive effects of engaging the motor system and interacting with the teaching content during learning software applications. The interactive animation tutorial used in this study engaged hand movements to move the mouse and click on the software tools in the learning platform. The integration of hand movement with the animation during watching the tutorials, could facilitate learning based on embodied cognition effects (Shapiro, 2019; Weisberg, & Newcombe, 2017; Wilson & Foglia, 2017) which state that engaging the motor system of students during learning can decrease the complexity level of the difficult cognitive tasks (Calvo, & Gomila, 2008; Schulz, 2017).

The reason for the positive effects of embodied cognition in the context of teaching software is integrating learning and practicing using human movements at the same time. Moving a mouse and clicking different tools are a kind of practice for the users during learning that can engage them with the software environment and make the learning process more practical and embodied.

However, it should be considered that the efficiency of the interactive animation tutorial depends on the type of software that we want to teach to the students. Embodied cognition effect can be more effective for teaching software applications such as graphical or animation software that involve more mouse movement for drawing objects. For example, when teaching drawing and editing tools in Photoshop, 3D Max, or AutoCAD one can show learners how they should click, hold or move a mouse in order to draw the desired shapes or objects with the use of different tools.

It should be noted that in addition to the effects of embodied cognition, signalling is another factor that can affect the efficiency of the animations. However, in the context of this study the difference between the control and the experimental groups can be only the result of embodied cognition, since in both the animation and the interactive animation groups the same animation and signalling method (mouse cursor indicated the target tool that should be clicked in both versions) were used and the only difference was the physical interaction with the interactive video through mouse. Furthermore, if moving mouse and clicking the tools could play the role of signalling, this signalling has occurred by moving the mouse through hand movement which in itself, is the result of embodied cognition.

7.3.3. Redundancy effect

The negative effects of redundant elements, such as additional text, background audio, decorative graphics or videos that aim to make a teaching environment aesthetically appealing, on cognitive load during learning through e-learning systems is supported by different studies. As some examples Cheah and Leong (2019) found that adding additional text for teaching C++ programming language will increase cognitive load when there are screenshots and a narrator, Jaeger and Wiley (2014) showed that decorative images can lead to poor comprehension accuracy while reading science text, and Sanchez

and Wiley (2006) and Sung and Mayer (2012) found that although any kind of graphics can increase learners satisfaction, when the graphics are decorative and are not related to the teaching materials, they can increase cognitive load. In particular, having redundant elements while there is an animation can significantly increase cognitive load (Arslan, 2012; Mayer & Moreno, 2003; Moreno & Ortegado-Layne, 2008).

On the other hand, there are some studies which proved that when the decorative graphics increase learners' motivation, they can be harmless, and in some cases they increase learning performance through inducing a better mood and making learning more engaging (Lenzner, Schnotz, & Müller, 2013; Magner et al., 2014; Morrison, Ross, & Kemp, 2001; Park et al., 2015; Schneider et al., 2018; Shangguan et al., 2020; Wang, & Adesope, 2016). However, most of the studies found that the decorative illustrations are beneficial for the learners with a high prior knowledge level or for elements with low interactivity, but did not benefit novice learners (Magner et al., 2014; Park et al. 2011; Wang, & Adesope, 2016).

The third experiment of this thesis addressed the contradiction between these two groups of studies by showing the effects of decorative elements during learning of software applications. This experiment indicated that, based on the redundancy effect, decorative elements such as a talking avatar can take up working memory resources and increase cognitive load, especially when the learners are novice and they do not have enough background knowledge and when the learning content is high in intellectual complexity. Furthermore, this study showed that since a talking avatar is an attractive decorative element for the users, it can distract them from the main learning content and increase the learning time. This is supported by other studies which found that the detrimental effect of the decorative elements can be increased when they are attractive for the users as it can

change the focus of their concentration (Mayer et al., 2008; Park et al. 2011; Sung, & Mayer, 2012).

The reason that the talking avatar was only detrimental for learning the contents with high element interactivity can be the higher demands on working memory. Since, in order to learn the elements with high interactivity, learners need to connect different parts of contents and process them simultaneously, any distracting element can affect their learning performance. In particular an animated character that narrates the learning content can shift the focus of learners' attention from the learning video to itself.

Therefore, when e-learning systems include visual learning content such as a diagram or a video that learners need to focus on, decorative elements can be detrimental, especially if the learning content is of high intellectual complexity. Moreover, the negative effects can be increased when the learners have a lack of background knowledge about the target teaching content, and the decorative elements are attractive for them and thus especially distracting.

7.4. Implication of the findings for the gamified e-learning systems

The experiments in this thesis provided evidence of the positive effects of including a familiar narrative and interactivity in e-learning systems and the potential negative effects of an animated talking avatar, on the cognitive load of learners. All these components are common elements of gamified e-Learning systems (Darejeh & Salim, 2016; Dontcheva, et al., 2014; Li, Grossman, & Fitzmaurice, 2012; Shane, 2013). Therefore, based on the findings of the first and the second experiments, using narrative and interactive animation in the gamified e-learning systems can decrease learners' cognitive load. Although, the motivational effects of narrative and interactive animation are not measured in this study,

based on the existing literature, they can have positive effects on learners' motivation as well as the cognitive load.

The positive effect of narrative on motivation is supported by different studies (Bell, Sheth, & Kaiser, 2011; Calderón, Ruiz, & O'Connor, 2017; Caulfield, Veal, & Maj, 2011; Chaves et al., 2010; Eagle, & Barnes, 2009; Hainey et al., 2011; Jain, & Boehm, 2006; Li, Grossman, & Fitzmaurice, 2012; Srinivasan, & Lundqvist, 2007) and the first experiment of this study evaluated narrative from a different aspect and demonstrated its positive effects on cognitive load.

As for interactivity, the second experiment showed that interacting with the learning content is not only benign, but it is also beneficial by decreasing cognitive load which is in line with the findings of the previous studies that found positive effects of interactive learning environments on learners' motivation (Dong et al., 2012; Dontcheva et al., 2014; Li, Grossman, & Fitzmaurice, 2012; Shane, 2013) and their cognitive load (Hung, Kinshuk & Chen 2018; Price et al., 2008). Therefore, if interactivity is included in gamified e-learning systems appropriately, not only can it increase the attractiveness of the system but can also potentially decrease the cognitive load of the learners.

Regarding the talking avatar, based on the findings of the third experiment, it can only be benign when it is not used in conjunction with the other on-screen learning contents or if the learning materials are low in element interactivity and the learners have the necessary background knowledge. When element interactivity is high and there is a text or a video, in order to decrease the redundancy effect, instead of the graphics that are just decorative such as comic pictures that only decorate the page or talking avatars that are redundant to the audio of the animation, explanatory images could be used. Explanatory images can make the e-learning systems engaging in addition to helping learners to learn the key

concepts more easily and increase learning performance (Garner, & Alley, 2011). Some examples of explanatory images are representational graphics to show an object shape, relational graphics to show relationship among two objects, organizational graphics to show different categories of the objects, transformational graphics to show the changes in an object over time, interpretive graphics to show invisible relationships among the objects (Clark, & Mayer, 2016).

As the findings of these three experiments suggest, when a game element is added to make an e-learning system more engaging and authentically appealing, it is important to consider the cognitive load effects of the element in addition to its motivational effects to assure that the learning performance will not be affected negatively. Although, some studies indicated that increasing the motivational level of learners can increase learning performance through encouraging them to increase their mental effort (Homer, 2012; Paas & van Merriënboer, 2020), it is not always the case. For example, based on the literature all the three elements that were evaluated in this study have positive effect on motivation (Aikina & Zubkova, 2015; Calderón, Ruiz & O'Connor, 2017; Denning, Kohno & Shostack, 2012; Devinea, Gormley & Doylec, 2015; Dong et al., 2012; Falloon, 2010; Hung, Kinshuk & Chen, 2018; Kleftodimos & Evangelidis, 2016; Li, Grossman & Fitzmaurice, 2012; Rueda, Estupiñán, & García, 2016), however, the study results showed that avatars have a negative effect on cognitive load which can lead to lower learning performance. There is a chance that the other elements of gamification such as point, badge, leaderboard, progress and challenge that have positive effect on motivation (Fotaris et al., 2016; Hasegawa, Koshino & Ban, 2015; Li, Grossman, & Fitzmaurice, 2012) can promote mental effort and consequently have a positive effect on learning performance, however, they should be evaluated to find out if it is indeed the case.

7.5. Implication of the findings for teaching software applications

In order to enable users to work with software applications efficiently, it is important to teach the context that the software can be used and different usage of software tools in practice. Therefore, based on the findings of this study, a familiar narrative can be an appropriate approach for teaching software applications practically, as narrative provides a package of integrated examples that can be used to turn the learning into a practical project. This is similar to the inquiry-based learning (IBL) learning method where students learn in a practical environment with the use of a scenario or a project (Dostál, 2015). The difference between IBL and narrative is that IBL generally is used in minimally guided learning methods such as problem-based or project-based methods, however, narrative can be applied in both fully or minimally guided methods (Brookfield, 2009; Loyens, Magda & Rikers, 2008).

Based on the literature, IBL methods are efficient teaching methods to motivate and provide practical knowledge to learners as they learn the content through solving a sample real-world scenario (Al-Abdeli & Bullen, 2005; Balim, 2010; Bunch, 2009; Rojter, 2011; Yusof, et al., 2005). However, since IBL methods are minimally guided, and learners should find the solution with the use of their own knowledge and trial and error (Schmidt, Rotgans & Yew, 2011; Savery, 2006), they can have negative effects on the cognitive load of novice learners and prevent formation of an appropriate schema and so should be used with caution (Clark, Kirschner, & Sweller, 2012; Kirschner, Sweller, & Clark, 2006).

Narrative can potentially solve the minimally guided issue of the IBL methods, by providing a sample real-world scenario, but in a fully guided learning environment which is more appropriate for novice learners. Minimally guided methods are more appropriate

for the expert learners, as if learners do not have the necessary background knowledge, their cognitive load will be increased during problem solving process (Brown, & Campione, 1994; Dean & Kuhn, 2007; Mayer, 2004). A familiar narrative can make the narrative more efficient by providing a familiar context to the worked-examples of the narrative so that novice learners can link the new content into their prior knowledge and so support the learning of new and unfamiliar content.

Another factor that can facilitate learning of software applications is interacting with the software interface through interactive animations, that can teach learners the correct clicks and gestures in addition to decreasing their cognitive load. Specifically, it can help to learn how to use the tools of graphical software applications such as how to draw, how to change the brush size, how to use stamp, or patch tools for repairing a photo. Since for using these tools users need to use a combination of keyboard keys and mouse movement, interacting with the software interface can increase learning performance by giving users practical activities during the learning of how to use the mouse and keyboard in order to use different tools. Also, this interaction can help learners to more easily remember the location of different tools within an interface, as instead of just watching a video, they watch and click on software tools which can increase learning performance based on embodied cognition effects, where mind body interactions can be used to support cognition (Shapiro, 2019; Weisberg, & Newcombe, 2017; Wilson, & Foglia, 2017). Combining narrative with interactivity can further increase the power of a narrative and has a strong positive effect on learning.

Finally, since when teaching software applications using e-learning systems there is always a picture of the software interface or a video that shows the procedure of working with different tools, we should avoid using extra graphics or sounds that can shift learners'

working memory resources from the main learning content. Elements such as background sounds, blinking elements, crowded background pictures, comic pictures, and animated graphics that are not related to the learning content can increase learners cognitive load (Bus, Takacs & Kegel, 2015; Craik, 2014; Jaeger & Wiley, 2014; Jonassen & Driscoll, 2003; Jonassen et al., 2008; Kalyuga, 2009; Knoop-van Campen, Segers & Verhoeven, 2018; Mayer, 2014; Moreno & Mayer, 2000b; Rey, 2012; Rey, 2014; Sanchez & Wiley, 2006; Sung & Mayer, 2012; Vössing, Stamov-Roßnagel, & Heinitz, 2016; Wang et al, 2017).

7.6. Limitations and future directions

The participants' age in this research was limited to young people between 18-30 years old, therefore, it would be interesting to expand this scope to different age ranges especially children and elderly people to see if similar results are achieved. Furthermore, due to limitations in time we used 20 participants in each experimental group. Using more participants could improve the reliability of the results.

Another limitation of this research is just using quantitative measurement methods and not collecting any data about users' perception of the independent variables. Although, most of the cognitive load studies are quantitative, it would be interesting to collect some qualitative data using interviews to get a better picture of how narrative, interactivity and avatar could affect learning performance and motivation. It could help to find the potential relationship between motivation and cognitive-load or vice versa. Also, some additional quantitative data using a Likert-scale questionnaire could be collected to know how users perceived the narrative, interactive animation and talking avatar. This additional data could be used to conduct a manipulation check and increase the reliability of the results.

Furthermore, adding physiological and real-time measures such as eye gaze, heart rate, muscle response measure, functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and electroencephalography (EEG) may help to measure cognitive load from different perspectives (Antonenko, et al., 2010; Paas, Ayres, & Pachman, 2008). However, installing these devices, such as eye-trackers, EEGs, and GSRs, can have some negative effects on learners including the potential to distract them from the learning task (Korbach, Brünken, & Park, 2017).

Since, after finding the positive effects of familiar narrative in the first experiment of this study, the second and the third experiments were designed to find the best way of delivering narrative-based materials, interactive animation and talking avatar were added to a narrative-based system and their effect was evaluated in conjunction with narrative. Therefore, in future studies, the effect of interactive animations and talking avatars are worth evaluating in isolation in order to see whether they can make any significant difference in the test phase.

In the second experiment, we only compared animation with interactive animation, and it is not clear if animation can improve learning performance in comparison with static content. Therefore, future experiments could compare an animation-based system with a static system. Since from a research design perspective it is not scientific to change more than one variable at any given time when we are comparing two groups, so either only narration or only text with the animated content, should be compared with equivalent static learning content.

The scope of this study was limited to examine the effect of gamification elements on software applications. In order to find if narrative, interactivity and avatars can be used in different computer related courses, it is worth evaluating their effects on teaching

programming languages as well. Also, the effect of these elements can be evaluated in teaching other courses such as engineering, science, mathematics, sport, architecture, and human science that have a different nature in comparison with software teaching courses.

In the future studies, the effect of gamification elements can be evaluated on adaptive learning systems that adjust the learning content based on the knowledge of the learners and their preferred learning style (Truong, 2016; Yang, Hwang & Yang, 2013) to see whether adapting the content of the narrative and avatar based on the learners' knowledge and preferences can affect their cognitive load.

Since a group of studies have already proved that by increasing motivation, learning performance can be increased (Betts, Bal, & Betts, 2013; Campos et al., 2015; Magner et al., 2014; Shangguan et al., 2020; Todor, & Pitică, 2013), motivational elements of gamification could be added into the e-learning systems to see whether increasing users' motivation could affect their cognitive load. Also, although, the motivational effects of narrative, interactive animation, and talking avatar are already measured in different studies, the motivational effects in conjunction with the cognitive load effects could be measured in the future studies.

Finally, it may be useful to investigate if motivational elements such as the allocation of points and badges that are given to users during learning result in an increase in cognitive load. Any relationships between levels of motivation and mental effort in gamified systems (Homer, 2012; Paas & van Merriënboer, 2020) should be investigated.

7.7. Conclusion

This study showed that gamification elements not only can affect motivation, they can also have positive or negative effects on cognitive load. The first experiment indicated

that narrative can provide practical knowledge to software learners in addition to decreasing cognitive load through providing a familiar theme to worked-examples so that novice learners can link the new content with their prior knowledge. The second experiment found that interactivity can facilitate the learning of software applications through enabling learners to interact with the software interface by mouse moving and clicking which can integrate learning and practicing at the same time. Increasing learning performance through interaction with the software interface is suggested based on embodied cognition research where interaction between mind and body can support learning. Finally, the third experiment showed that a talking avatar can increase cognitive load during learning but only for the high element interactivity materials. This result is due to the redundancy effect as the avatar is a redundant element for the audio of the animation which can shift the focus of learners. However, a talking avatar can be benign when it is not used in conjunction with other on-screen learning content or when the learning materials are low in element interactivity and the learners have the necessary background knowledge. Based on the findings of these three experiments, it can be concluded that when a game element is added to make an e-learning system more engaging and authentically appealing, it is important to consider the cognitive load effects of the element in addition to its motivational effects to ensure that learning performance will not be negatively impacted.

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Appendix A: No-narrative e-learning system

Introduction

What is Access? Access is a database management system (DBMS) which combines Microsoft Jet Database Engine with a graphical user interface and software-development tools in order to create systems for storing information in tables.

Lesson 1

As the first lesson, you will learn how to create a table. We will create a table with 8 columns for storing different information.

What is a table? A table is a database object that we use to store data about a particular subject, all data in access are stored in tables. A table consists of rows that are called records and columns that are called fields.

Step 1

As the first step, you should create a new database in Access so that you can create your table. What is a database? Database is a file which consists of some tables.

In order to create a new database, follow the steps below.

1. Click 'Blank' database.
2. Type your database name.
3. Click 'Create' button.

Step 2

After creating a database, Access opens table editor. By using this editor, you can create your table to store information. By default, there is one column in every new table called ID, so, you can start creating the table by renaming this column. In order to edit ID column, follow the steps below.

1. Double click 'ID' column.
2. Change the name to 'Column1'.

Step 3

Now you should create the other columns of your table. In order to create the other columns, open the 'Fields' tab, select the data type that will be stored in the column and then type the column name. What is data type? Data type shows the type of content and its length that we want to store in each column of a table. Data type can be text, number, Boolean (Yes / No), Date, etc. If we select text for data type, we can enter everything in the column, however, if we select other types like number we can only enter that data type.

As the second column, we want to create a column to store only number values. In order to create this column, follow the steps below.

1. Click 'Fields' tab.
2. Click 'Number' button.

3. Type the column title which is 'Column2'.

Step 4

As the third column, we want to create a column to store currency values. In order to create this column, follow the steps below.

1. Click 'Currency' button.
2. Type the column title which is 'Column3'.

Step 5

As the fourth column, we want to create a column to store date. In order to create this column, follow the steps below.

1. Click 'Date & Time' button.
2. Type the column title which is 'Column4'.

Step 6

As the fifth column, we want to create a column to store date, similar to the fourth column. In order to create this column, follow the steps below.

1. Click 'Date & Time' button.
2. Type the column title which is 'Column5'.

Step 7

As the sixth column, we want to create a column to store Yes or no values. In order to create this column, follow the steps below.

1. Click 'Yes/No' button.
2. Type the column title which is 'Column6'.

Step 8

As the seventh column, we want to create a column to store number, similar to the second column. In order to create this column, follow the steps below.

1. Click 'Number' button.
2. Type the column title which is 'Column7'.

Step 9

As the last column, we want to create a column to store some pictures and documents. For this purpose, we should use Attachment type. This data type can store any type of file including picture, audio, video, and document. In order to create this column, follow the steps below.

1. Click 'More fields'.
2. Click 'Attachment' button.

Lesson 2

In this lesson, you will learn how to update the values of a column automatically based on some conditions. We want to update the value of Column3 based on a condition of Column2 and a condition of Column7. We want to add \$5 to the value of Column3 if the value of Column2 is greater than 100 and the value of column7 is equal to 10, otherwise just \$2 will be added to the value of Column3. Therefore, you should create a query to calculate the value of Column3 based on the values of Column2 and Column7.

What is a query? A query is a request for data results. We can use a query to answer very specific questions about our data that would be difficult to answer by looking at table data directly or by using normal filtering feature. Queries can be used to filter our data, to perform calculations with our data, and to summarize our data and combine data from different tables, or even to add, change, or delete table data. Queries that we use to filter data of a table are called select queries. Queries that add, change, or delete data are called action queries.

Step 1

For creating this query follow the steps below.

1. Click 'Create' tab.
2. Click 'Query Design'.

Step 2

In order to select the table that you want to create a query based on, follow the steps below.

1. Select the 'Table1' from show table window.
2. Click 'Add'.
3. Click 'Close'.

Step 3

We should create an action query to update the value of Column3. For this purpose, we should use Update query.

1. Click 'Design' tab.
2. Click 'Update' button.

Step 4

Use the editor to create your query.

1. Select 'Column3' from the fields part.
2. Click 'Update to' part of 'Column3'.
3. Click 'Expression builder' button.

Step 5

By using builder window, you can type your expression.

What is an expression? An expression is a combination of mathematical or logical operators, functions and table fields that are used to calculate values, validate data, and set a default value for a column. Operators include: Plus, minus, multiply, division (+, -, *, /), greater than, or less than (>, <), and functions include: Math, Date / Time, Financial, or Program Flow that is used for defining calculations' conditions.

We need to use IIF function as we want to calculate the value of column 3 after checking the value of column 2 and the value of column 7. Follow the steps below to enter IIF function.

1. Click 'Built in functions'.
2. Click 'Program flow' category.
3. Double click 'IIF' function.

Step 6

Now, we should fill IIF function parts. In the expression part, we should type our conditions and in the true and false parts we should type what we want to get based on the conditions.

1. Replace the <<expression>> part with [Column2]>100 And [Column7]=10
2. Replace the <<true part>> with [Column3]+5
3. Replace the <<false part>> with [Column3]+2
4. Click OK.

This expression checks if the value of Column2 is greater than 100 and value of column7 is equal to 10. It then adds 5 to the value of Column3 otherwise adds 2 to the value of Column3.

Hint: You should put the columns names between [].

Step 7

In order to update the values of Column3 based on the defined conditions, follow the steps below.

1. Click 'Run' button.
 2. Click 'Yes' to update Column3 based on the defined condition.
-

Lesson 3

In this lesson, you will learn how to use action query to delete some rows from a table based on two conditions. We want to delete the rows that the value of their Column2 is greater than 500 and the value of their Column6 is unchecked.

Step 1

For creating this query follow the steps below.

1. Click 'Create' tab.
2. Click 'Query' design.

Step 2

In order to select the table that you want to create a query based on, follow the steps below.

1. Select the 'Table1' from show table window.
2. Click 'Add'.
3. Click 'Close'.

Step 3

Since we want a query to delete the records that the value of their Column2 is greater than 500 and the value of their Column6 is unchecked, we should use "Delete" query.

1. Click 'Design' tab.
2. Click 'Delete' button.

Step 4

Use the editor to create your query.

1. Select 'Column2' from the fields part.
2. Select 'Column6' from the fields part.
3. Click the Criteria part of 'Column2' and type '>500'.
4. Click the Criteria part of 'Column6' and type '=False'.

Step 5

In order to delete the rows that the value of their Column2 is greater than 500 and the value of their Column7 is unchecked, follow the steps below.

1. Click 'Run'.
 2. Click 'Yes' to delete the rows based on the defined condition.
-

Lesson 4

In this lesson, we want to create a report to see the records with two conditions. As the first condition the value of Column2 should be less than 10 and as the second condition the date in Column5 should be in the past 3 days (3 days from the current date). In order to do this, you need to use query again.

Step 1

For creating this query follow the steps below.

1. Click 'Create' tab.
2. Click 'Query Design'.

Step 2

In order to select the table that you want to create a query based on, follow the steps below.

1. Select the 'Table1' from show table window.
2. Click 'Add'.

3. Click 'Close'.

Step 3

Since we want a query to see only some specific data (the records that the value of their Column2 is less than 10 and the date of their Column5 is in the past 3 days), we should use "Select" query.

1. Click 'Design' tab.
2. Click 'Select' button.

Step 4

Use the editor to create your query.

1. Select 'Column1' from the fields part.
2. Select 'Column2' from the fields part.
3. Select 'Column5' from the fields part.

Step 5

In the criteria part of the columns you should write the conditions. For viewing only, the records that the value of their Column2 is less than 10 follow the step below.

1. Click the Criteria part of 'Column2' and type '<10'.

Step 6

Now you should type the second condition to see the records that the value of their Column5 is in the past 3 days. For entering this condition, you need one of the date functions to calculate the difference between current date and the value of Column5. For entering this condition follow the steps below.

1. Click the Criteria part of 'Column5'.
2. Click 'Expression builder' button.

Step 7

In order to calculate the difference between the current date and the date in Column5 you should use DateDiff function. In the interval part, we should type the measurement unit between the dates, it can be day, month, or year. In date1 and date 2, we should enter the dates that we want to calculate their difference. For using DateDiff follow the steps below.

1. Click 'Built in functions' button.
2. Click 'Date/Time' category.
3. Double click 'DateDiff' function.

Step 8

In order to use DateDiff function to calculate the difference between value of Column5 and the current date follow the steps below.

1. Replace the <<interval>> part with 'd' which means that you want to calculate the number of days between two dates.

2. Replace <<date1>> with [Column5].
3. Replace <<date2>> with Now() which is a function to return the current date.
4. Type <= 3 which means that you want to see the records that DateDiff result of their 'Column5' shows a value in the past 3 days.
5. Click 'OK'.

Step 9

In order to see the records that the value of their Column2 is less than 10 and the date of their Column5 is in the past 3 days, follow the step below.

1. Click 'Run'.

Appendix B: Familiar narrative e-learning system

Introduction

John is a new hotel owner and he is looking for a computer-based system to manage his hotel rooms and guests. He employed you for a short period of time to help him implement a computer-based system for his hotel using Access.

What is Access? Access is a database management system (DBMS) which combines Microsoft Jet Database Engine with a graphical user interface and software-development tools in order to create systems for storing information in tables.

Lesson 1

John explains that he needs a table for storing rooms' information including: Room Number, Number of Beds, Room Price, Occupancy Status, Last Cleaned Date, Time to Clean, Room picture, and Room Class.

What is a table? A table is a database object that we use to store data about a particular subject, all data in access are stored in tables. A table consists of rows that are called records and columns that are called fields.

Step 1

As the first step, you should create a new database in Access so that you can create the room table. What is a database? Database is a file which consists of some tables.

In order to create a new database, follow the steps below.

1. Click 'Blank' database.
2. Type your database name which is 'Hotel management system'.
3. Click 'Create' button.

Step 2

After creating a database, Access opens table editor. By using this editor, you can create room table to store hotel rooms information. By default, there is one column in every new table called ID, so, you can start creating the table by using this column. We want to use this column to identify each room by storing its numbers. In order to edit ID column, follow the steps below.

1. Double click 'ID' column.
2. Change the name to 'Room number'.

Step 3

Now you should create the other columns of room table. In order to create the other columns, open the 'Fields' tab, select the data type that will be stored in the column and then type the column name. What is data type? Data type shows the type of content and its length that we want to store in each column of a table. Data type can be text, number,

Boolean (Yes / No), Date, and etc. If we select text for data type, we can enter everything in the column, however, if we select other types like number we can only enter that data type.

As the second column, we want to create a column for storing price of each room. Therefore, we should create a column called “Room Price” as currency data type. In order to create this column, follow the steps below.

1. Click ‘Fields’ tab.
2. Click ‘Currency’ button.
3. Type the column title which is ‘Room price’.

Step 4

As the third column, we want to create a column for storing number of beds of each room. Therefore, we should create a column called “Number of Beds” as number data type. In order to create this column, follow the steps below.

1. Click ‘Number’ button.
2. Type the column title which is ‘Number of beds’.

Step 5

As the fourth column, we want to create a column to store if the room is occupied or not. Therefore, we should create a column called “Occupancy Status” as Yes/No data type. In order to create this column, follow the steps below.

1. Click ‘Yes/No’ button.
2. Type the column title which is ‘Occupancy Status’.

Step 6

As the fifth column, we want to create a column for storing the date that room is cleaned. Therefore, we should create a column called “Last cleaned” as date & time type. In order to create this column, follow the steps below.

1. Click ‘Date & Time’ button.
2. Type the column title which is ‘Last cleaned’.

Step 7

As the sixth column, we want to create a column for storing the date that the room should be cleaned. Therefore, we should create a column called “Time to clean” as date & time type. In order to create this column, follow the steps below.

1. Click ‘Date & Time’ button.
2. Type the column title which is ‘Time to clean’.

Step 8

As the seventh column, we want to create a column to store the picture of the hotels' rooms. For this purpose, we should use attachment data type. This data type can store any

types of file including picture, audio, video, and document. In order to create this column, follow the steps below.

1. Click 'More fields'.
2. Click 'Attachment' button.

Step 9

Based on the decoration of each room, they are divided into the different classes (first class, second class, and third class). Therefore, as the eighth column create a column called "Room Class" to store the class number of each room.

1. Click 'Number' button.
 2. Type the column title which is 'Room class'.
-

Lesson 2

Based on the hotel policies each room should be cleaned every 3 days, however, rooms with 3 beds which cost more than \$100 should be cleaned every 2 days. John asked you to make this calculation process automatic, so that he does not need to calculate and enter the value of Time to Clean column manually (the default value of Time to clean column is always the current date). Therefore, you should create a query to calculate the value of Time to Clean column based on the values of Number of beds and Room price columns.

What is a query? A query is a request for data results. We can use a query to answer very specific questions about our data that would be difficult to answer by looking at table data directly or by using normal filtering feature. Queries can be used to filter our data, to perform calculations with our data, and to summarize our data and combine data from different tables, or even to add, change, or delete table data. Queries that we use to filter data of a table are called select queries. Queries that add, change, or delete data are called action queries.

Step 1

For creating a query follow the steps below.

1. Click 'Create' tab.
2. Click 'Query Design'.

Step 2

In order to select the table that you want to create a query based on, follow the steps below.

1. Select the 'Hotel table' from show table window.
2. Click 'Add'.
3. Click 'Close'.

Step 3

We should create an action query to update 'Time to clean' column data. For this purpose, we should use Update query.

1. Click 'Design' tab.
2. Click 'Update' button.

Step 4

Use the editor to create your query.

1. Select the 'Time to clean' column from the fields part.
2. Click 'Update to' part of 'Time to clean' column.
3. Click 'Expression builder' button.

Step 5

By using builder window, you can type your expression.

What is an expression? An expression is a combination of mathematical or logical operators, functions and table fields that are used to calculate values, validate data, and set a default value for a column. Operators include: Plus, minus, multiply, division (+, -, *, /), greater than, or less than (>, <), and functions include: Math, Date / Time, Financial, or Program Flow that is used for defining calculations' conditions.

We should use 'IIF' function as we want to calculate the cleaning date after checking the number of beds and room price. Follow the steps below to enter IIF function.

1. Click 'Built in functions'.
2. Click 'Program flow' category.
3. Double click 'IIF' function.

Step 6

Now, we should fill 'IIF' function parts. In the expression part we should type our conditions and in the true and false parts we should type what we want to get based on the conditions.

1. Replace the <<expression>> part with [Number of beds]=3 And [Room Price]>100
2. Replace the <<true part>> with [Time to clean]+2
3. Replace the <<false part>> with [Time to clean]+3
4. Click OK.

This expression checks if the value of number of beds column is equal to 3 and the value of room price is greater than 100. It then adds 2 days to the date of 'Time to clean' column, otherwise adds 3 days to the date of 'Time to clean' column.

Hint: You should put the columns names between [].

Step 7

In order to update the dates of 'Time to Clean' column, follow the steps below.

1. Click 'Run' button.
 2. Click 'Yes' to update 'Time to Clean' column based on the defined condition.
-

Lesson 3

John is renovating the first-class rooms with the rent price of less than \$100 per night. Since after the renovation most of the room information will be changed, he prefers to delete all of these rooms from the room table and enter them again after the renovation. He asked you to delete all the first-class rooms whose rent price is less than \$100. In order to do this task, you need to use an action query.

Step 1

For creating this query follow the steps below.

1. Click 'Create' tab.
2. Click 'Query' design.

Step 2

In order to select the table that you want to create a query based on, follow the steps below.

1. Select the 'Hotel table' from show table window.
2. Click 'Add'.
3. Click 'Close'.

Step 3

Since we want to create a query to delete the first-class rooms whose rent price is less than \$100, we should use "Delete" query.

1. Click 'Design' tab.
2. Click 'Delete' button.

Step 4

Use the editor to create your query.

1. Select 'Room price' column from the fields part.
2. Select 'Room class' column from the fields part.
3. Click the Criteria part of 'Room price' column and type '<100'.
4. Click the Criteria part of 'Room class' column and type '=1'.

Step 5

In order to delete the first-class rooms whose rent price is less than \$100, follow the steps below.

1. Click 'Run'.
 2. Click 'Yes' to delete the rooms based on the defined condition.
-

Lesson 4

John needs a report to only see the room numbers that are occupied and were cleaned in the past 2 days. In order to do this, you need to use query again.

Step 1

For creating this query follow the steps below.

1. Click 'Create' tab.
2. Click 'Query Design'.

Step 2

In order to select the table that you want to create a query based on, follow the steps below.

1. Select the 'Hotel table' from show table window.
2. Click 'Add'.
3. Click 'Close'.

Step 3

Since we want a query to see only some data (room numbers that are occupied and were cleaned in the past 2 days), we should use "Select" query.

1. Click 'Design' tab.
2. Click 'Select' button.

Step 4

Use the editor to create your query.

1. Select 'Room number' column from the fields part.
2. Select 'Occupancy status' column from the fields part.
3. Select 'Last cleaned' column from the fields part.

Step 5

In the criteria part of the columns you should write the conditions. For viewing only, the occupied rooms follow the steps below.

1. Click the Criteria part of 'Occupancy status' column and type '=Yes'.

Step 6

Now you should type the second condition to see if the cleaning date was in the past 2 days or not. For entering this condition, you need one of the date functions to calculate the difference between current date and the date of last cleaned column. For entering this condition follow the steps below.

1. Click the Criteria part of 'Last cleaned' column.
2. Click 'Expression builder' button.

Step 7

In order to calculate the difference between current date and the date of 'Last Cleaned' column, you should use DateDiff function. In the interval part, we should type the measurement unit between the dates, it can be day, month, or year. In date1 and date 2, we should enter the dates that we want to calculate their difference. For using DateDiff follow the steps below.

1. Click 'Built in functions' button.
2. Click 'Date/Time' category.
3. Double click 'DateDiff' function.

Step 8

In order to use DateDiff function to calculate the difference between value of 'Last Cleaned' column and the current date follow the steps below.

1. Replace the <<interval>> part with 'd' which means that you want to calculate the number of days between two dates.
2. Replace <<date1>> with [Last cleaned].
3. Replace <<date2>> with Now() which is a function to return the current date.
4. Type <= 2 which means that you want to see the room numbers that DateDiff result of their 'Last cleaned' column shows a value in the past 2 days.
5. Click 'OK'.

Step 9

In order to see list of the room numbers that are occupied and were cleaned in the past 2 days, follow the step below.

1. Click 'Run'.

Appendix C: Unfamiliar narrative e-learning system

Introduction

John works in the mortgage department of a bank. He is looking for a computer-based system to manage the mortgage data of the customers. He employed you for a short period of time to help him implement a computer-based system using Microsoft Access.

What is Access? Access is a database management system (DBMS) which combines Microsoft Jet Database Engine with a graphical user interface and software-development tools in order to create systems for storing information in tables.

Lesson 1

John explains that he needs a table, for storing customers mortgage information including: Account Number, Principal, Interest Rate, Term, Standing Order, Standing Order Start Date, Collateral, and Appraisal.

What is a table? A table is a database object that we use to store data about a particular subject, all data in access are stored in tables. A table consists of rows that are called records and columns that are called fields.

Step 1

As the first step, you should create a new database in Access so that you can create the mortgage table. What is a database? Database is a file which consists of some tables. In order to create a new database, follow the steps below:

1. Click 'Blank' database.
2. Type your database name which is 'Mortgage management system'.
3. Click 'Create' button.

Step 2

After creating a database, Access opens table editor. By using this editor, you can create mortgage table to store customers' mortgage information. By default, there is one column in every new table called ID, so, you can start creating the table using this column. We want to use this column to store customers account numbers. In order to edit ID column, follow the steps below:

1. Double click 'ID' column.
2. Change the name to 'Account number'.

Step 3

Now you should create the other columns of mortgage table. In order to create the other columns, open the 'Fields' tab, select the data type that will be stored in the column, then type the column name. What is data type? Data type shows the type of content and its length that we want to store in each column of a table. Data type can be text, number, Boolean (Yes / No), Date, etc. If we select text for data type, we can enter everything in

the column, however, if we select other types like number, we can only enter that data type.

As the second column, we want to create a column to store the amount that customers want to borrow. This column is called 'Principal' and should be defined as currency type. In order to create Principal column, follow the steps below.

1. Click 'Fields' tab.
2. Click 'Currency' button.
3. Type the column title which is 'Principal'.

Step 4

As the third column, we want to create a column to store Interest rate of the mortgage. Therefore, you should create a new column called 'Interest rate' as number type. In order to create Interest rate column, follow the steps below.

1. Click 'Number' button.
2. Type the column title which is 'Interest rate'.

Step 5

As the fourth column, we want to create a column to store the number of years that customers should repayment their mortgage. Therefore, you should create a new column called 'Term' that only accepts numbers. In order to create Term column, follow the steps below.

1. Click 'Number' button.
2. Type the column title which is 'Term'.

Step 6

As the fifth column, we want to create a column to store the fixed amount that the customer is willing to pay each month. This column is called 'Standing order' and should be defined as currency type. In order to create Standing order column, follow the steps below.

1. Click 'Currency' button.
2. Type the column title which is 'Standing order'.

Step 7

As the sixth column, we want to create a column to store the date that customers want to start standing order. Therefore, we should create a column called 'Standing order start date' as date type. In order to create this column, follow the steps below.

1. Click 'Date & Time' button.
2. Type the column title which is 'Standing order start date'.

Step 8

As the seventh column, we want to create a column to store scan of collateral documents. For this purpose, you should create a column as Attachment type. This data type can store

any types of file including picture, audio, video, and document. In order to create this column, follow the steps below.

1. Click 'More fields'.
2. Click 'Attachment' button.

Step 9

As the last column, we want to create a column to show if the appraisal result was acceptable for the bank. Therefore, you need to create a column called 'Appraisal' as Yes/No type. In order to create this column, follow the steps below.

1. Click 'Yes/No' button.
2. Type the column title which is 'Appraisal'.

Lesson 2

Based on the bank policies if principal value is greater than \$500,000 and standing order is less than \$2000, 5 years should be added to the default term otherwise just 1 year should be added to the default term. John asked you to make this calculation process automatic, so that he does not need to calculate and enter the value of term column manually. Therefore, you should create a query to calculate the term based on the values of principal and standing order columns.

What is a query? A query is a request for data results. We can use a query to answer very specific questions about our data that would be difficult to answer by looking at table data directly or by using normal filtering feature. Queries can be used to filter our data, to perform calculations with our data, and to summarize our data and combine data from different tables, or even to add, change, or delete table data. Queries that we use to filter data of a table are called select queries. Queries that add, change, or delete data are called action queries.

Step 1

For creating this query follow the steps below.

1. Click 'Create' tab.
2. Click 'Query Design'.

Step 2

In order to select the table that you want to create a query based on, follow the steps below.

1. Select the 'Mortgage table' from show table window.
2. Click 'Add'.
3. Click 'Close'.

Step 3

We should create an action query to update the values of 'Term' column. For this purpose, we should use Update query.

1. Click 'Design' tab.
2. Click 'Update' button.

Step 4

Use the editor to create your query.

1. Select 'Term' column from the fields part.
2. Click 'Update to' part of Term column.
3. Click 'Expression builder' button.

Step 5

By using builder window, you can type your expression.

What is an expression? An expression is a combination of mathematical or logical operators, functions and table fields that are used to calculate values, validate data, and set a default value for a column. Operators include: Plus, minus, multiply, division (+, -, *, /), greater than, or less than (>, <), and functions include: Math, Date / Time, Financial, or Program Flow that is used for defining calculations' conditions.

We should use 'IIF' function as we want to calculate the term after checking the principal and the standing order values. Follow the steps below to enter IIF function.

1. Click 'Built in functions'.
2. Click 'Program flow' category.
3. Double click 'IIF' function.

Step 6

Now, we should fill 'IIF' function parts. In the expression part we should type our conditions and in the true and false parts we should type what we want to get based on the conditions.

1. Replace the <<expression>> part with [Principal]>500000 And [Standing order]<2000
2. Replace the <<true part>> with [Term]+5
3. Replace the <<false part>> with [Term]+1
4. Click OK.

This expression checks if the value of principal column is greater than \$500,000 and the value of standing order column is less than \$2000. It then adds 5 to the value of term column otherwise adds 1 to the term value.

Hint: You should put the columns names between [].

Step 7

In order to update the values of 'Term' column based on the defined conditions, follow the steps below.

1. Click 'Run' button.
 2. Click 'Yes' to update 'Term' column based on the defined condition.
-

Lesson 3

Bank rejects the mortgage request, when the appraisal estimation is not acceptable by the bank and the mortgage principal is higher than 500000. John asked you to create a query to delete all the account numbers that the value of their principal column is greater than \$500000, and Appraisal column is unchecked.

Step 1

For creating this query follow the steps below.

1. Click 'Create' tab.
2. Click 'Query' design.

Step 2

In order to select the table that you want to create a query based on, follow the steps below.

1. Select the 'Mortgage table' from show table window.
2. Click 'Add'.
3. Click 'Close'.

Step 3

Since we want a query to delete the account numbers whose Principal value is greater than \$500000, and Appraisal column is unchecked, we should use 'Delete' query.

1. Click 'Design' tab.
2. Click 'Delete' button.

Step 4

Use the editor to create your query.

1. Select 'Principal' column from the fields part.
2. Select 'Appraisal' column from the fields part.
3. Click the 'Criteria' part of 'Principal' column and type '>500000'.
4. Click the 'Criteria' part of 'Appraisal' column and type '=False'.

Step 5

In order to delete the account numbers that the value of their principal column is greater than \$500000, and Appraisal column is unchecked, follow the steps below.

1. Click 'Run'.
 2. Click 'Yes' to delete the customers based on the defined condition.
-

Lesson 4

John needs a report to see the account numbers of the customers whose standing order is more than \$3,000 and standing order start date was in the past 3 days (3 days from the current date). In order to do this, you need to use query again.

Step 1

For creating this query follow the steps below.

1. Click 'Create' tab.
2. Click 'Query Design'.

Step 2

In order to select the table that you want to create a query based on, follow the steps below.

1. Select the 'Mortgage table' from show table window.
2. Click 'Add'.
3. Click 'Close'.

Step 3

Since we want a query to see only some specific data (customers whose standing order are more than \$3,000 and their standing order start date was in the past 3 days), we should use 'Select' query.

1. Click 'Design' tab.
2. Click 'Select' button.

Step 4

Use the editor to create your query.

1. Select 'Account numbers' column from the fields part.
2. Select 'Standing order' column from the fields part.
3. Select 'Standing order start date' column from the fields part.

Step 5

In the criteria part of the columns you should write the conditions. For viewing only, the customers whose standing order is more than \$3,000 follow the step below.

1. Click the 'Criteria' part of 'Standing Order' column and type '>3000'.

Step 6

Now you should type the second condition to see the customers whose standing order start date was in the past 3 days. For entering this condition, you need one of the date functions to calculate the difference between the current date and the date of 'Standing order start date' column. For entering this condition follow the steps below.

1. Click the 'Criteria' part of 'Standing order start date' column.
2. Click 'Expression builder' button.

Step 7

In order to calculate the difference between the current date and 'Standing order start date' column you should use 'DateDiff' function. In the interval part, we should type the measurement unit of the dates, it can be day, month, or year. In date1 and date 2, we should enter the dates that we want to calculate their difference. For using DateDiff follow the steps below.

1. Click 'Built in functions' button.
2. Click 'Date/Time' category.
3. Double click 'DateDiff' function.

Step 8

In order to use DateDiff function to calculate the difference between value of 'Standing order start date' column and current date follow the steps below.

1. Replace the <<interval>> part with 'd' which means that you want to calculate the number of days between two dates.
2. Replace <<date1>> with [Standing order start date].
3. Replace <<date2>> with Now() which is a function to return the current date.
4. Type <= 3 which means that you want to see the account numbers that DateDiff result of their 'Standing order start date' column shows a value in the past 3 days.
5. Click 'OK'.

Step 9

In order to see list of customers whose standing orders are more than \$3,000 and standing order start date was in the past 3 days, follow the step below.

1. Click 'Run'.

Appendix D: Test tasks of the experiments

Task 1

A travel agency company wants to develop an Access based software to manage their customers' information. Create a table for storing customers' information with the fields below. Please select appropriate data type for each field.

Passport Number	Full name	Date of birth	Nationality	Arrival	Departure	Travel Duration	Discount	Photo

Task 2

The travel agency wants to see the customers who are eligible for getting an extra discount. Based on the company policy only customers who are Australian and their travel duration is more than 5 days are eligible for extra \$15 discount, otherwise they can only get extra \$5 discount. So, you should create a query and check whether the nationality of the guest is Australian and travel duration is greater than 5 days, If the condition is correct then update Discount column value by adding \$15 to the current value, otherwise just \$5 should be added to the current value.

Task 3

A group of travelers from China reserved a tour with the company. They are supposed to arrive after 1/1/2017, however, they have canceled their reservation. Therefore, you need to delete their name from the table. You should create a query to delete all the travelers whose nationality is Chinese, and their arrival date is after 1/1/2017.

Task 4

The company needs a report to see the travelers' name who are older than 18, and their arrival is after 1/2/2017. Since we only have date of birth, you should use one of the date functions to calculate guests age by deducting the current date from their birth date.

Appendix E: marking rubric of the test tasks

Tasks	Description	Total Mark
1	1 mark for creating each column and selecting the right data type.	9
2	1 mark for finding the query feature. 1 mark for selecting the correct query type (update). 1 mark for typing the expression in the right place (update to). 1 mark for typing discount column. 1 mark for selecting the correct function (IIF). 2 marks for defining the conditions correctly (expression part). 2 marks for defining the correct outcome (true and false parts).	9
3	1 mark for finding the query feature. 1 mark for selecting the correct query type (delete). 1 mark for typing the expression in the right place (criteria). 2 marks for defining the first condition (nationality = chines). 2 marks for defining the second condition (arrival > 1/1/2017).	7
4	1 mark for finding the query feature. 1 mark for selecting the correct query type (select). 1 mark for typing the expression in the right place (criteria). 1 mark for selecting date of birth column. 1 mark for selecting the correct function (datediff). 3 marks for entering values in datediff correctly (datediff). DateDiff("y",[Date of birth],Now()) 1 mark for identifying how to return the current date (Now function) 2 marks for defining the second condition (arrive > 1/2/2017).	11

Appendix F: Self-reported difficulty Likert-scale questionnaire for the tutorials



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Self-reported difficulty Likert scale questionnaire

Tutorials related questions

1. I found learning the materials to be:

Extremely easy	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Extremely difficult
	1	2	3	4	5	6	7	8	9	
					Neither easy nor difficult					

2. How confident are you that you can learn other software with the use of the same teaching approach?

Extremely confident	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Not at all confident
	1	2	3	4	5	6	7	8	9	
					Neither certain nor uncertain					

3. How relaxed were you while reading/watching the tutorials?

Extremely relaxed	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	Not at all relaxed
	1	2	3	4	5	6	7	8	9	
					Neutral					

Appendix G: Self-reported difficulty Likert-scale questionnaire for the tasks



School of Computer Science and Engineering

Self-reported difficulty Likert scale questionnaire

Tasks related questions

1. How easy or difficult was the task to solve?

Extremely easy 1 2 3 4 5 6 7 8 9 Extremely difficult

Neither easy nor difficult

2. How confident are you that you can solve more tasks like the task that you have solved?

Extremely confident 1 2 3 4 5 6 7 8 9 Not at all confident

Neutral

3. How relaxed were you while solving the task?

Extremely relaxed 1 2 3 4 5 6 7 8 9 Not at all relaxed

Neutral

Appendix H: Computer skill placement test form



School of Computer Science and Engineering

Computer Skill Placement Test

Name:	Student ID:
Email:	Phone:

1. To what extent are you familiar with database concept?

I am ☐ ☐ ☐ ☐ ☒ ☐ ☐ ☐ ☐ I am
Novice 1 2 3 4 5 6 7 8 9 Expert
Neither an expert
nor a novice

2. To what extent are you familiar with database tables concepts including fields data types and relational tables?

I am ☐ ☐ ☐ ☐ ☒ ☐ ☐ ☐ ☐ I am
Novice 1 2 3 4 5 6 7 8 9 Expert
Neither an expert
nor a novice

3. To what extent are you familiar with SQL query codes to take report from your database?

I am ☐ ☐ ☐ ☐ ☒ ☐ ☐ ☐ ☐ I am
Novice 1 2 3 4 5 6 7 8 9 Expert
Neither an expert
nor a novice

4. How you are familiar and expert in using Microsoft Access?

I am ☐ ☐ ☐ ☐ ☒ ☐ ☐ ☐ ☐ I am
Novice 1 2 3 4 5 6 7 8 9 Expert
Neither an expert
nor a novice

5. Which of the following best describes your expertise with computers?

Novice with very little computer experience and knowledge ☒

Good with one type of software packages (such as Microsoft Office, Adobe Products) ☐

Good with several software packages ☐

Can program in one language and use several software packages ☐

Can program in several languages and use several software packages ☐



School of Computer Science and Engineering

6. What is your level of English proficiency?

- | | |
|----------------------------------|----------------------------------|
| Limited working proficiency | <input checked="" type="radio"/> |
| Elementary proficiency | <input type="radio"/> |
| Proficiency | <input type="radio"/> |
| Professional working proficiency | <input type="radio"/> |
| Full Professional proficiency | <input type="radio"/> |
| Native or bilingual proficiency | <input type="radio"/> |

Appendix I: Participant Information Statement and Consent Form



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PARTICIPANT INFORMATION STATEMENT AND CONSENT FORM

The effect of content gamification on novice users' cognitive load in E-learning platforms for learning software applications

Chief Investigator: Dr. Nadine Marcus

1. What is the research study about?

You are invited to take part in this research study. This study is an attempt to examine the effect of game thinking strategies such as narrative on the amount of mental effort of novice users in order to learn difficult software applications through e-learning systems.

2. Who is conducting this research?

The study is being carried out by *Ali Darejeh* as a part of his PhD thesis under supervision of *Dr. Nadine Marcus*, and *Prof. John Sweller*.

3. Inclusion/Exclusion Criteria

Before you decide to participate in this research project, we need to ensure that it is ok for you to take part. The research study is looking recruit people who meet the following criteria:

- Above the age of 18.
- Have filled in the computer skilled placement test form and are determined as novice users in Microsoft Access.

4. Do I have to take part in this research study?

Participation in any research project is voluntary. If you do not want to take part, you do not have to. If you decide to take part and later change your mind, you are free to withdraw from the project at any stage.

If you decide you want to take part in the research study, you will be asked to:

- Read the information carefully (ask questions if necessary);
- If you would like to participate, sign the consent form and;
- Take a copy of this form home with you to keep.

5. What does participation in this research require, and are there any risks involved?

If you decide to take part in the research study, you will be asked to use an e-learning system to learn Microsoft Access then perform 2 tasks accordingly and fill out a Likert-scale questionnaire after each tutorial and task regarding your learning experience. Participation in this research project will take a total of approximately 45 minutes to complete. At the end of the experiment, we will reimburse you a \$20 gift voucher for your participation.

You are free to withdraw from the research at any time. If you withdraw from the research we will destroy any information that has already been collected.

6. What are the possible benefits to participation?

We hope to use results we get from this research can contribute to discover the solutions to decrease cognitive load of novice users for learning productivity applications through e-learning platforms. In other words, the results of this study would facilitate learning difficult software for novice users and increase the learning performance while it decreases the amount of mental effort on learners' part.

7. What will happen to information about me?

By signing the consent form, you consent to the research team to collect and use the collected data for the research study. We will store information about you in a non-identifiable format on UNSW servers. Your information will only be used for research, presentation and publication purposes and the data collected from the participants will not be identifiable and individual information will remain confidential.



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8. How and when will I find out what the results of the research study are?

The research team intend to publish and/ report the results of the research study in a variety of ways. All information published will be done in a way that will not identify you. If you would like to receive a copy of the results you can let the research team know by adding your email or postal address within the consent form. We will only use these details to send you the results of the research. The results will also be made available via the schools' website <https://education.arts.unsw.edu.au/>.

9. What if I want to withdraw from the research study?

If you do consent to participate, you may withdraw at any time during the experiment. You can do so by completing the 'Withdrawal of Consent Form' which is provided at the end of this document. If you decide to leave the research study, the researchers will not collect additional information from you. Your decision not to participate will not affect your relationship with UNSW Australia.

10. What should I do if I have further questions about my involvement in the research study?

The person you may need to contact will depend on the nature of your query. If you want any further information concerning this project or if you have any problems which may be related to your involvement in the project, you can contact the following member/s of the research team:

11. Research Team Contact Details

Name	<i>Ali Darejeh</i>
Position	<i>PhD student</i>
Telephone	<i>0451684545</i>
Email	<i>ali.darejeh@unsw.edu.au</i>

Name	<i>Nadine Marcus</i>
Position	<i>Senior Lecturer in Human Computer Interaction</i>
Telephone	<i>9385-5173</i>
Email	<i>nadinem@unsw.edu.au</i>

What if I have a complaint or any concerns about the research study?

If you have any complaints about any aspect of the project, the way it is being conducted, then you may contact:

Complaints Contact

Position	Human Research Ethics Coordinator
Telephone	+ 61 2 9385 6222
Email	humanethics@unsw.edu.au
HC Reference Number	<i>HC17074</i>



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Consent Form – Participant providing own consent

Declaration by the participant

- ☒ I understand I am being asked to provide consent to participate in this research project;
- ☒ I understand the purposes, study tasks and risks of the research described in the project.
- ☒ I understand that the research team will record the screen.
- ☒ I provide my consent for the information collected about me to be used for the purpose of this research study and publication only.
- ☒ I have had an opportunity to ask questions and I am satisfied with the answers I have received.
- ☒ I freely agree to participate in this research study as described and understand that I am free to withdraw at any time during the project and withdrawal will not affect my relationship with any of the named organisations and/or research team members.
- ☐ I would like to receive a copy of the study results via email or post, I have provided my details below and ask that they be used for this purpose only.

Email Address: _____

- ☐ I understand that I will be given a signed copy of this document to keep;

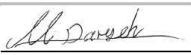
Participant Signature

Name of Participant (please print)	
Signature of Research Participant	
Date	

Declaration by Researcher*

- ☒ I have given a verbal explanation of the research study, its study activities and risks and I believe that the participant has understood that explanation.

Researcher Signature*

Name of Researcher (please print)	Ali Darejeh
Signature of Researcher	
Date	

*An appropriately qualified member of the research team must provide the explanation of, and information concerning the research study.

Note: All parties signing the consent section must date their own signature.



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Form for Withdrawal of Participation

I wish to **WITHDRAW** my consent to participate in the research proposal described above and understand that such withdrawal **WILL NOT** affect my relationship with The University of New South Wales. In withdrawing my consent, I would like any information which I have provided for the purpose of this research project withdrawn.

Participant Signature

Name of Participant (please print)	
Signature of Research Participant	
Date	

The section for Withdrawal of Participation should be forwarded to:

CI Name:	Nadine Marcus
Email:	nadinem@unsw.edu.au
Phone:	+61 2 9385 5173 (Internal: x55173)
Postal Address:	401B, K17, School of Computer Science and Engineering, The University of New South Wales, 2052.