Integrating Multiple Individual Differences in Web-Based Instruction

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BY

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ABSTRACT

There has been an increasing focus on web-based instruction (WBI) systems which accommodate individual differences in educational environments. Many of those studies have focused on the investigation of learners' behaviour to understand their preferences, performance and perception using hypermedia systems. In this thesis, existing studies focus extensively on performance measurement attributes such as time spent using the system by a user, gained score and number of pages visited in the system. However, there is a dearth of studies which explore the relationship between such attributes in measuring performance level. Statistical analysis and data mining techniques were used in this study. We built a WBI program based on existing designs which accommodated learner's preferences. We evaluated the proposed system by comparing its results with related studies. Then, we investigated the impact of related individual differences on learners' preferences, performance and perception after interacting with our WBI program.

We found that some individual differences and their combination had an impact on learners' preferences when choosing navigation tools. Consequently, it was clear that the related individual differences altered a learner's preferences. Thus, we did further investigation to understand how multiple individual differences (Multi-ID) could affect learners' preferences, performance and perception. We found that the Multi-ID clearly altered the learner's preferences and performance. Thus, designers of WBI applications need to consider the combination of individual differences rather than these differences individually. Our findings also showed that attributes relationships had an impact on measuring learners' performance level on learners with Multi-ID.

The key contribution of this study lies in the following three aspects: firstly, investigating the impact of our proposed system, using three system features in the design, on a learner's behavior, secondly, exploring the influence of Multi-ID on a learner's preferences, performance and perception, thirdly, combining the three measurement attributes to understand the performance level using these measuring attributes.

DECLARATION

I declare that this research, its idea, analysis, findings and conclusions that are included in this PhD dissertation are entirely developed by me for the purpose of this program only and have not been submitted for another qualification.

RANA ALHAJRI

DEDICATION

I dedicate this work to my dear family for their continuous support and encouragement which helped me to accomplish this work. I am very grateful to their unlimited care.

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PUBLICATIONS

The following publications have resulted from the research conducted related to the investigation undertaken in this thesis.

Journal Paper

[1] Alhajri, Rana A; Counsell, Steve; Liu, Xiaohui (2013). Investigating attributes affecting the performance of WBI users. *Computers and Education*, ISSN 0360-1315, Volume 68, pp. 117 – 128 (5-years, impact factor: 3.305).

Conference Papers

[1] Alhajri, Rana A; Counsell, Steve; Liu, Xiaohui (2013). The effect of individual difference on learning performance using web-based instruction. *10th IFIP World Conference on Computers in Education (IFIP-WCCE 2013)*, Poland, 1-7 July, Volume 3, pp. 189-190.

[2] Alhajri, Rana A; Counsell, Steve; Liu, Xiaohui (2013). Accommodating Individual Differences in Web Based Instruction (WBI) and Implementation. *10th International conference on E-Business (ICE-B 2013)*, Iceland 29-31 July. pp. 281-289.

[3] Alhajri, Rana A; Counsell, Steve; Liu, Xiaohui (2013). The Influence of Multiple Human Factors on Learner Preferences Using Hypermedia Systems. *2013 IEEE Conference on e-Learning, e-Management and e-Services (IC3e 2013)*, Malaysia 2 – 4 December.

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LIST OF ABBREVIATIONS

EFD	Expert Field-Dependent
EFI	Expert Field-Independent
FD	Field-Dependent
FE	Female Expert
FFD	Female Field-Dependent
FFDE	Female Field-Dependent Expert
FFDN	Female Field-Dependent Novice
FFI	Female Field-Independent
FFIE	Female Field-Independent Expert
FFIN	Female Field-Independent Novice
FI	Field-Independent
FN	Female Novice
HITN	The Higher Institute of Telecommunication and Navigation
ME	Male Expert
MFD	Male Field-Dependent
MFDE	Male Field-Dependent Expert
MFDN	Male Field-Dependent Novice

MFI	Male Field-Independent
MFIE	Male Field-Independent Expert
MFIN	Male Field-Independent Novice
MN	Male Novice
MN	Male Novice
Multi-ID	Multiple Individual Differences
NFD	Novice Field-Dependent
NFI	Novice Field-Independent
WBI	Web-based instruction

CHAPTER ONE

INTRODUCTION

1.1. Overview

Hypermedia systems have received much attraction for the aims of teaching and learning (Chen, 2002a; Chen & Liu, 2008; Chen & Macredie, 2004; Graf, et al., 2009; Khalifa & Lam, 2002; Mitchell, et al., 2005a). These systems provide users with freedom of navigation, allowing them to develop learning pathways. Empirical evidence indicates that not all learners can benefit from hypermedia learning systems. In order to develop a learning environment, individual differences need to be taken into account to ensure they impact on student achievement. Thus, many research studies have attempted to find ways of building systems to be robust and which can also accommodate preferences of individual differences.

There has been an increasing focus on web-based instruction (WBI) systems which accommodate individual differences in educational environments (Chen, 2002a; Chen & Liu, 2008; Chen & Liu, 2008; Chen & Macredie, 2004; Dillon & Zhu, 1997; Khan, 1998; Pituch & Lee, 2006; Minetou, et al., 2008) . Many of those studies have focused on the investigation of learners' behaviour to understand their preferences, behaviours and perception using hypermedia systems (Chen, et al., 2006; Chen & Liu, 2008; Chen & Macredie, 2010; Lee, et al., 2009; Minetou, et al., 2008; Pituch & Lee, 2006).

In this thesis, we present a WBI system specifically designed to accommodate learners' needs using the three system features of navigation tools, content scope and display options. In particular, three individual differences, i.e., cognitive style, prior knowledge and gender differences, are examined. Additionally, the system features and their effect on learners' preferences and performance are investigated. Furthermore, traditional statistics and data mining techniques and their use in answering research questions are introduced.

1.2. Research Problem

Unlike a linear structure which presents information like books and traditional computer-assisted learning, hypermedia systems provide users with freedom of navigation, which allows them to develop learning pathways. Hypermedia learning systems are known as a technology that helps to present information in a non-linear format (Khalifa & Lam, 2002; Mitchell, 2005a). Thus, hypermedia offers advancement over traditional computer-based learning systems because it allows users to choose their own paths to navigate through the material available.

Empirical evidence shows that not all learners benefit from hypermedia learning systems, where some learners faced problems when interacting with non-linear learning systems (Chen, 2002a). Therefore, it is essential for designers to realise learners' needs and what factors affect the ways in which they learn from hypermedia learning systems. In the research presented, we will provide those factors that have been known as influential variables affecting the learning approach using hypermedia learning systems.

Web-based instruction (WBI) has been described as: "a hypermedia based instructional programme which utilises the attributes and resources of the World Wide Web to create a meaningful learning environment where learning is fostered and supported" (Khan, 1998). WBI design can provide flexible navigational tools for teaching and learning in a non-linear learning approach (Minetou, et al., 2008; Pituch & Lee, 2006); examples include a main menu, a hierarchical map or an alphabetical index and a search option. The ability to match the design of a WBI program with a learner's preferences is vital in ensuring that users can interact with the WBI tool in an effective, efficient and satisfying way (Dillon & Zhu, 1997). Therefore, it is important for designers to understand how learners learn and what factors may affect the ways in which they learn. Thus, if a learner's preferences are successfully met, they will have a more beneficial interaction with a WBI program and complete their tasks in a more efficient and effective way.

There are many different factors that influence the preferences and performance of learners. The different individual differences are known to be the most basic distinction between learners' preferences. As well as effective design, WBI programs tend to have an influential impact on learner's interaction.

1.2.1. Individual Differences

Cognitive style refers to the preferred way that the learners may process information (Triantafillou, et al., 2003). More specifically, *field-dependent* and *field-independent* users refer to their analytical or global approach of learning. These are probably the most well-known divisions of cognitive styles (Witkin, et al., 1977). Field-independent learners are generally analytical in their approach, whereas field-dependent learners are more global in their perceptions. *Prior knowledge* is one of the individual differences that have been shown to influence users' preferences for interacting with WBI programs (Chen, et al., 2006; Ford & Chen, 2000; Gauss & Urbas, 2003; Minetou, et al., 2008; Möller & Müller-Kalthoff, 2000). Learners with different levels of prior knowledge, from experts to novices, benefit differently from hypermedia learning systems (Calisir & Gurel, 2003; Wildemuth, 2004).

Additionally, *gender* is the most obvious individual difference between users. Many studies have been conducted on gender differences and hypermedia systems, and indicate that gender is a significant variable in the learning process. Males and females tend to show different navigation patterns and different preferences in using hypermedia systems (Chen & Macredie, 2010; Gunn, et al., 2003; Large, et al., 2002; Mustafa, 2005; Ono & Zavodny, 2003; Roy, et al., 2003).

1.2.2. The Design of WBI Program and Learners' Preferences

The design of usable and effective web-based programs relies upon the design being compatible with a learner's characteristics (Dillon & Zhu, 1997). We have relied in our design on three major elements of the findings of Chen, et al., (2006): display options, content scope and navigation tools. Their findings suggested that these three features were important to hypermedia learning systems in order to be effective. Thus, in this thesis, we investigate the preferences of learners using such system features. Learners are identified by using one of the individual differences and by identifying learners according to the combination of three individual differences (prior knowledge, cognitive style and gender). Combined individual differences will be known as *multiple individual differences* (Multi-ID).

1.2.3. Data Analysis

Data collected from log files of web-based learning applications often contain valuable information for in-depth understanding of users' needs and behaviours (Zhao & Luan, 2006). This has become a critical and essential aspect for researchers to extract valuable information from large amounts of data. Our web-based program is able to record learning behaviours of each user and then provide a large amount of learning records to be analysed using traditional statistics or data mining techniques, which are analytical approaches of data analysis to uncovering the knowledge existing in data.

Traditional statistics are used to determine if there are statistically significant differences among the tested data, where data mining, also known as knowledge discovery (Fayyad & Uthurusamy, 1996) uses data to find unexpected relationships and patterns (Wang, et al., 2002). By doing so, hidden relationships and interdependencies can be discovered and predictive rules generated (Gargano & Raggad, 1999; Hedberg, 1995).

1.3. Thesis Aim and Objectives

Our aim is to understand learners' preference and performance after interacting with our WBI program which accommodates their needs using three system features presented by existing work (Chen, et al., 2006; Chen & Liu, 2008). In particular, we investigate the influence of combined individual differences, i.e., cognitive style, prior knowledge and gender on learners' preferences and performance in using web-based applications in addition to exploring the effect of the system features on learners' preferences and performance. Moreover, we will investigate the influence of the combined individual differences on a learner's performance using three measurement attributes after interacting with our WBI system, and how these attributes induce learners' performance level. The three measurement attributes are time spent using the system by a user, gained score, and number of pages visited in the system.

In order to achieve our aim, the research has the following six objectives:

Objective One: To understand whether our developed WBI program affects a learner's behaviour.

Objective Two: To investigate whether a learner's performance is affected by relating individual differences.

Objective Three: To investigate whether Multi-ID have an influence on learners' preferences using the navigational tools of our WBI program.

Objective Four: To investigate which factor of the Multi-ID has a significant impact on learners' preferences in using navigation tools of our WBI program.

Objective Five: To understand relationships between attribute values in measuring the performance level of the individual differences.

Objective Six: To understand the influence of the individual differences on learners' performance using three performance measurements attributes.

1.4. Research Methodology Outline

In this thesis, we use experimental methods and questionnaires to collect our data. An experimental method is used "to determine if a specific treatment influences an outcome" (Creswell, 2009). A questionnaire provides a quantitative or numeric description of trends, or opinions of participants (Creswell, 2009). Using existing designs (Chen, et al., 2006; Chen & Liu, 2008) helped us to build an agile WBI program, and this should be flexible enough to offer multiple options tailored to the distinctive individual differences; cognitive style and prior knowledge, in addition to gender. Our proposed WBI program will focus on the structure of three key design elements: navigation tools, display options and content scope. To investigate learners' preferences and performance we use different measuring factors, including those factors collected from a log file such as time and visited pages by each learner, gain score obtained by subtracting pre-test from post-test, and finally, a questionnaire used to collect data about learners' perception and satisfaction.

1.5. Research Questions

In Table 1-1, we provide our research questions, where they are investigated, and how we will answer them to achieve our objectives.

Research question	Investigated in	Question context	Achieving our objectives
RQ1	Chapter Four	Does the design of our developed WBI program affect learners' behaviour?	To achieve Objective One, we investigated and evaluated the effect of using our WBI program on learners' behaviour by comparing our findings to existing studies. We studied three important individual differences (gender, cognitive style and prior knowledge) as well as their interactions in the resulting learning performances. On the other hand, we investigated three system features (navigation tools, display options and content scope) to see how they could help users acquire information to meet their individual needs, thereby resulting in an improvement in the learning performance.

RQ2		How is a learner's performance affected by relating individual differences?	To achieve Objective Two, we investigated whether a learner's performance is affected by relating individual differences, and we investigate whether the interaction between individual differences had an impact on the learner's performance.
RQ3	Chapter Five	Does Multi-ID have an influence on learners' preferences using the navigational tools of our WBI program?	To achieve Objective Three and Objective Four, we studied the preferences of three individual differences (cognitive style, prior knowledge, and gender) individually. Then, we analysed several combinations of individual differences (Multi-ID) to investigate how each combination influences the learning preferences based on our individual tests. This was done in order to evaluate the effect of Multi-ID on user preferences while acquiring knowledge.
RQ4		How do the factors of Multi-ID affect learners' preferences in using the navigation tools of our WBI program?	
RQ5	Chapter Six	What are the relationships between attribute values in measuring the performance level of the individual differences?	To achieve Objective Five, we investigated the relationships between measurement attributes (gain scores, number of pages visited in a WBI program and time spent on such pages) to explore the performance level.

RQ6		How does the behaviour of individual differences influence a learner's performance using three performance measurement attributes?	To achieve Objective Six, we investigated the effect of individual differences on learning performance level by exploring relationships between measurement attributes that affect the performance level.

Table 1-1: Research questions and how they will be answered to achieve our objectives

1.6. Thesis Contribution

The main contribution of this our thesis lies in the following three aspects:

1. We investigated the impact of our proposed system using three system features (navigation tools, display options and content scope) in the design, on a learner's behaviour. We adapted the models resulting from Chen et al., (2006) and Chen and Liu (2008) to design a hypermedia system where cognitive style and prior knowledge will be analysed and gender will be incorporated.
2. We explored the influence of the combined Multi-ID on a learner's preferences, performance and perception.
3. We combined the three measurement attributes (gain score, number of visited pages and time spent on these pages) to understand the performance level using these measuring attributes.

1.7. Thesis Outline

The remainder of this thesis is illustrated in Figure 1-1 and is structured as follows:

In Chapter Two, we present a review of the previous literature investigating the effect of individual differences on users' preferences and performance in the use of web-based applications. Three individual differences are identified: cognitive style, prior knowledge and gender differences. Also, the feature design of WBI applications and their impact on the learners' interaction are highlighted. More specifically, individual differences and system features are reviewed and a number of significant links identified to understand their influence on the learners' performance level of learning behaviour. Additionally, suitable data mining tools are identified for analysis.

Chapter Three outlines the methodology used in our investigation. This chapter describes the nature of the experiment conducted, detailing design, materials used and the sample used. Additionally, this chapter describes the pilot studies conducted, the data analysis used, and our proposed framework.

Our objective in Chapter Four is two-fold. Firstly, models resulting from Chen and Liu (2008), and Chen, et al., (2006) are adapted to design a hypermedia system where cognitive style and prior knowledge will be analysed and gender incorporated. Secondly, we combine three attributes to measure performance (gain score, number of visited pages and time spent on these pages) of the three interacting individual differences. To do this, two studies are presented where we compare results from our program with previous studies, thus evaluating its design in one, while a data mining approach is used to investigate the effect of the interacted individual differences and how that could influence learner performance in the other. The aim of this chapter is to examine the gender, prior knowledge and cognitive style as individual differences in learning behaviour while using hypermedia systems. We built a WBI program to be used for data collection from the participants in the experimental study. Our findings demonstrate that such individual differences have an impact on learners' behaviour. Additionally, we have found that the relationship between individual differences had an even higher impact on learners' performance. Few previous studies have been carried out to investigate system features (navigation tools, display options and content scope) to see how they can help users acquire information to meet their individual needs.

In Chapter Five, we investigate learners' preferences and perception using our WBI program. Firstly, we analyse the preferences of individual differences individually using navigation tools and compare our findings with previous studies. We then analyse several combinations of individual differences to investigate how each combination influences the learning preferences based on our individual tests.

In Chapter Six, we investigate how differences between individuals influenced learners' performance using our WBI program which accommodates individuals' preferences. Performance focuses extensively on measurement attributes, such as time spent using the system by a user, gained score, and number of pages visited in the system. Moreover, we investigate the influence of combined individual differences on a learner's performance using such measurements and after interacting with our WBI system.

Finally, Chapter Seven summarises the investigations and findings, contributions made in this thesis, and limitations of the experiment conducted, and presents ideas for future research.

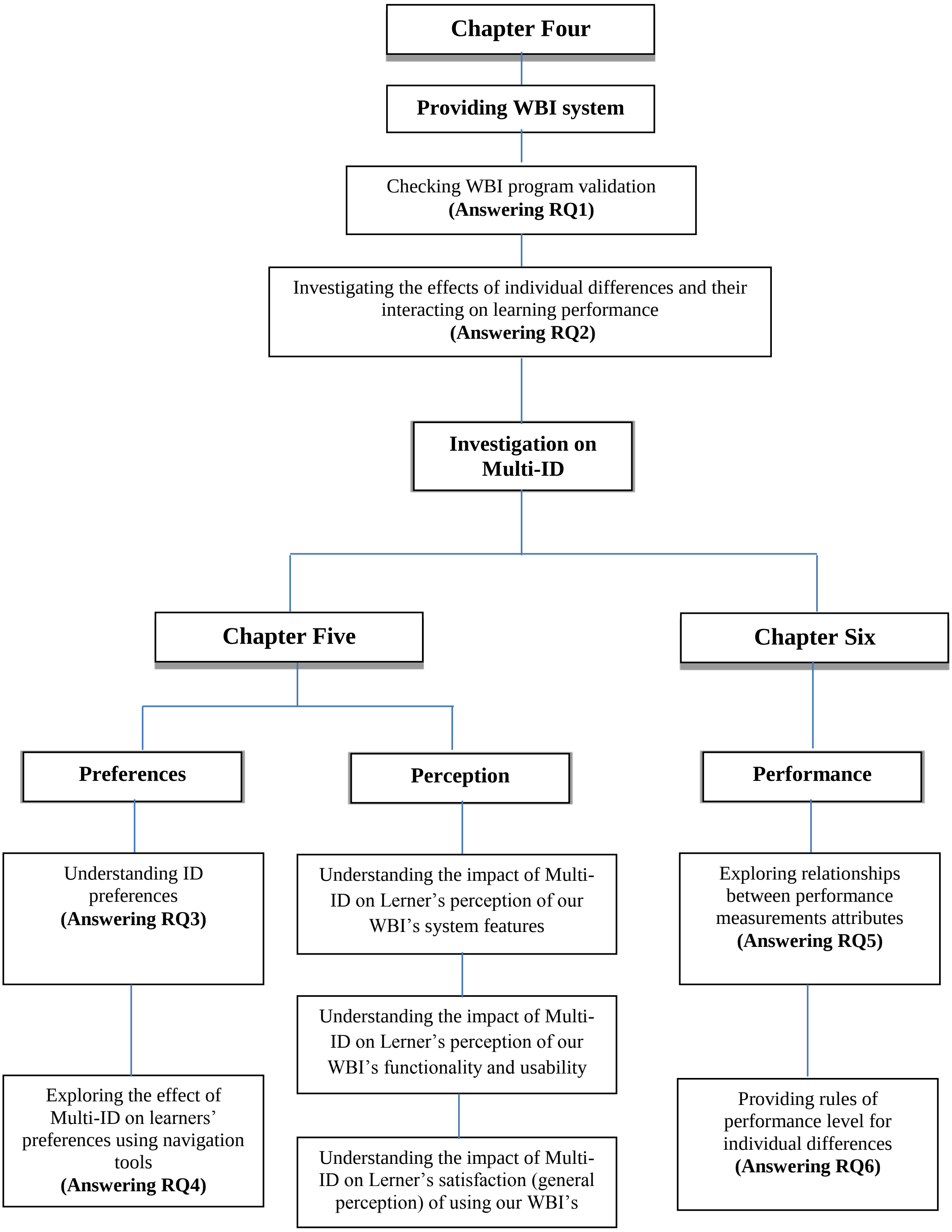


Figure 1-1: Illustration for the Thesis structure using our research questions

CHAPTER TWO

LITERATURE REVIEW

2.1. Introduction

In this chapter, we present a detailed review of past research regarding the influence of individual differences on users' preferences and performance in using web-based applications. In particular, three individual differences, i.e., cognitive style, prior knowledge and gender differences, will be examined. Additionally, system features in designing web-based applications, i.e., content scope, navigation tools and additional support, and their effect on learners' preferences and performance, are included. Furthermore, traditional statistics and data mining techniques and their use in answering our questions will be introduced.

This chapter is organised as follows. Firstly, the chapter starts by defining hypermedia learning systems, web-based applications in teaching and learning, and definitions of individual differences. We also provide a rationale and description for why these factors were chosen and that of the performance measures. Then, how individual differences could affect learners' learning will be presented. More specifically, it describes the challenges faced by designers in understanding user preferences in using web-based applications. Subsequently, the design of web-based applications is explored. Gaps in existing studies regarding individual differences, preferences and performance are presented. Finally, we present different data mining techniques that could be used in the analysis stage to bridge the gaps and to solve our research questions stated in Chapter One.

2.2. Hypermedia Systems and Learning Approaches

The world wide web is known as a development of information technology which contains a various amount of information (Ford & Chen, 2001; Liaw & Huang, 2006), produces fundamental changes in business, education, government and entertainment (Wang, et al., 2002), and has a considerable quantity of instructional materials (Yen & Li, 2003).

It is useful to understand learners' preferences in both teaching and learning (Graf, et al., 2009). Unlike the linear structure which presents information like books and traditional computer-assisted learning, hypermedia systems provide users with freedom of navigation which allows them to develop learning pathways. Hypermedia learning systems are known as a technology that helps to present information in a non-linear format (Khalifa & Lam, 2002; Mitchell, et al., 2005a). Thus, hypermedia is an advancement over traditional computer-based learning systems because they allow users to choose their own path to navigate through the material available. Hypermedia also allows non-linear access to large amounts of information and provides users with greater navigational control to browse that information, and provides a flexible approach; this helps users to work with the information from different points of view (Barua, 2001; Chen, 2002a; Farrell & Moore, 2001).

Empirical evidence shows that not all learners benefit from hypermedia learning systems, as some learners face problems when interacting with non-linear learning systems (Chen, 2002a). Therefore, it is essential for designers to realise learners' needs and what factors affect the ways in which they learn from hypermedia learning systems. In the next section, we will provide those factors that have been known as influential variables affecting the learning approach using hypermedia learning systems.

Web-based instruction (WBI) has been described as: "a hypermedia based instructional programme which utilises the attributes and resources of the Web to create a meaningful learning environment where learning is fostered and supported" (Khan, 1998). WBI tools have become a popular alternative to the traditional classroom teaching methods because these virtual learning spaces are far more accessible to a wide range of learners (Khan, 2005). Increasingly, WBI has become attractive to educational settings both for financial and technological reasons (Brotherton & Abowd, 2004), as well as in companies responsible for providing training in online learning programmes.

Furthermore, students expect educational and training establishments to employ the latest technologies to provide high quality instruction and 24/7 support (Khan, 2005). The online mode of learning is highly attractive for many reasons: they have easily updated materials, are widely available, are cheap (or free), are accessible at any time and are regularly updated (Scarsbrook, et al., 2005); remote access is possible from everywhere and at any time (Anido, et al., 2001), and presentations with multiple media such as text, graphics, audio, video and animation are possible (Masiello, et al., 2005).

WBI design can provide flexible navigational tools for teaching and learning in a non-linear learning approach (Minetou, et al., 2008; Pituch & Lee, 2006); examples include a main menu, a hierarchical map or an alphabetical index and search option. The ability to match the design of a WBI program with a learner's preferences is vital in ensuring that users can interact with the WBI tool in an effective, efficient and satisfying way (Dillon & Zhu, 1997). Therefore, it is important for designers to understand how learners learn and what factors may affect the ways in which they learn.

In summary, it is clear that successful web applications rely upon the ability of the application to meet the needs and preferences of each learner. Thus, if a learner's preferences are successfully met, they will have a more beneficial interaction with a WBI program and complete their tasks in a more efficient and effective way. There are many different factors that influence the preferences and performance of learners. The different individual differences are known to be the most basic distinction between learners' preferences. As well as effective design, WBI programs tend to have an influential impact on learner's interaction. Discussion about different individual differences and web-based systems designs are provided in the forthcoming sections.

2.3. Individual differences

Previous studies demonstrated the importance of individual differences in the design of web-based instruction (Chen & Macredie, 2010). Such differences can have a considerable effect on user learning in web-based instruction, which may affect the way users learn from, and interact with, hypermedia systems. These range from cognitive styles (Calcaterra, et al., 2005; Chen, 2010; Chen & Liu, 2008; Chen & Macredie, 2002; Chen & Macredie, 2004; Kim, 2001; Workman, 2004), to prior knowledge (Calisir & Gurel, 2003; Chen, et al., 2006; Hölscher & Strube, 2000; Mitchell, et al., 2005a), to gender differences (Beckwith, et al., 2005; Roy, et al., 2003; Schumacher & Morahan-Martin, 2001), to age differences (Ford, et al., 2001; Large, et al., 2002; Weiser, 2000). These individual differences are the most commonly studied in research related to WBI programs and how such individual differences may affect learning. As individual differences are of great interest in a research environment, it is essential to look at each of them and their effects on learning to better understand their impact on the use of a WBI program. In this way, a WBI program may be developed according to the users' needs to help improve their learning performance and to increase their satisfaction. The individual differences identified in our research to influence the learner's performance are cognitive styles: field-dependent vs. field-independent, prior knowledge: novice vs. expert and gender.

2.3.1. Cognitive Styles

Cognitive style refers to the preferred way that the learners may process information (Triantafillou, et al., 2003). Research into individual differences suggests that a learner's cognitive style has considerable effect on their learning in hypermedia systems. Many studies use statistical methods to analyse learners' preferences (Chen, et al., 2006; Chen & Liu, 2008; Lee, et al., 2009). Simply stated, cognitive style is known as an important factor that influences learners' preferences.

There are many dimensions to cognitive styles, such as field-dependent versus field-independent, visualised versus verbalised, or holistic-global versus focused-detailed. Field-dependent and field-independent are probably the most well-known division of cognitive styles (Chen & Macredie, 2004; Ford & Chen, 2000; Kim, 2001). These cognitive styles reflect how a learner is able to restructure information based on the use of relevant cues and field arrangements (Weller, et al., 1994).

Field-independent (FI) learners have impersonal behaviour. They are not interested in others and show both physical and psychological distance from people. They tend not to need external referencing methods to process information and are capable of restructuring their knowledge and developing their own internal referencing methods. Thus, field-independent learners are generally analytical in their approach (Chen & Liu, 2008).

Field-dependent (FD) learners demonstrate inter-personal behaviour in that they show strong interest in others and prefer to be physically close to people. They make greater use of external social influences for structuring their information. Field-dependent learners are more attentive to social cues than field-independent learners. Thus, field-dependent learners are more global in their perceptions (Chen & Liu, 2008; Witkin, et al., 1977).

Many experimental studies have assessed the impact of field-dependent and field-independent on the learning process. Differences between field-dependent and field-independent categories are shown in Table 2-1.

Field-dependent learners	**Field-independent learners**
More likely to face difficulties in restructuring new information and forging links with prior knowledge	Able to reorganise information to provide a context for prior knowledge
Their personalities show a greater social orientation	They are influenced less by social reinforcement
Experience surroundings in a relatively global fashion, passively conforming to the influence of the prevailing field or context	Experience surroundings analytically, with objects experienced as being discrete from their backgrounds
Demonstrate fewer proportional reasoning skills	Demonstrate greater proportional reasoning skills
Prefer working in groups	Prefer working alone
Struggle with individual elements	Good with problems that require taking elements out of their whole context
Externally directed	Internally directed
Influenced by salient features	Individualistic
Accept ideas as presented	Accept ideas strengthened through analysis

Table 2-1: Field-independent and field-independent categories (Chen & Macredie, 2002).

2.3.2. Prior Knowledge

Prior knowledge is one of the individual differences that have been shown to influence users' preferences for interacting with WBI programs (Chen, et al., 2006; Ford & Chen, 2000; Gauss & Urbas, 2003; Minetou, et al., 2008; Möller & Müller-Kalthoff, 2000). Prior knowledge of learners can be made up of both system experience and domain knowledge (Hölscher & Strube, 2000; Mitchell, et al., 2005a; Mitchell, et al., 2005b). Learners with different levels of prior knowledge, from experts to novices, benefit differently from hypermedia learning systems (Calisir & Gurel, 2003; Wildemuth, 2004). Many studies argue that there are different levels of perception in using hypermedia learning systems requiring different ways to navigate (Alexander, et al., 1994; Brusilovsky, et al., 1998; Calisir & Gurel, 2003; McDonald & Stevenson, 1998; Shin, et al., 1994). Table 2-2 shows a summary of the key differences between experts and novices suggested by Chen, et al., (2006), who argue that it is necessary to integrate prior knowledge into the design of hypermedia learning systems.

Experts	**Novices**
Global mental models	Local mental models
Directed search	Undirected search (trial and error)
Deep structures	Surface features
Mental simulation of integrated functions and whole application	Mental simulation of isolated functions
Complete analysis deferring details	Incomplete analysis
Depth-first strategies	Breadth-first strategies
Design whole and add pieces	Design pieces
Integrated whole throughout the process	Failure to integrate pieces into a whole
Find the best solution	Find a (any) solution

Table 2-2: Differences in learning characteristics of experts and novices (Chen, et al., 2006).

2.3.3. Gender

Differences of gender between males and females are the most obvious individual difference between users. Many studies have been conducted on gender differences and hypermedia systems, indicating that gender is a significant variable in the learning process. Males and females tend to show different navigation patterns and different preferences in using hypermedia systems (Chen & Macredie, 2010; Gunn, et al., 2003; Large, et al., 2002; Mustafa, 2005; Ono & Zavodny, 2003; Roy, et al., 2003).

Many studies focus on relationships between gender differences and navigation patterns (Ford, et al., 2001; Hupfer & Detlor, 2006; Large, et al., 2002; Liu & Huang, 2008; Lorigo, et al., 2006; Reed & Oughton, 1998; Roy, et al., 2003; Weiser, 2000). In navigating the hypermedia systems, these studies noted that female students preferred to take more linear steps while males preferred the non-linear approach to browse for information they required. Additionally, male students were faster in reaching their learning goals than females. Other findings revealed that there was no relationship between gender differences and search frequency (Hupfer & Detlor, 2006). Furthermore, other findings have shown that males and females have tended to use computers and the web for different reasons. For example, males use the web to search for information, entertainment and leisure, whereas women tend to use it for interpersonal communication and for educational purposes (Weiser, 2000). Additionally, females reported more computer anxiety and less computer self-efficacy than males, based on a general model of web use (Jackson, et al., 2001). A study that examined the effect of gender differences on information search behaviour found that males tended to rely on their own opinions to make faster decisions, while females followed a more exhaustive search pattern and relied more on a broad variety of information from a wide range of external sources (Meyers-Levy, 1988). Furthermore, males were shown to process information to a superficial level, whilst females processed information to a much deeper level (Riding & Rayner, 1998). Some studies have found that males more actively engage in browsing than females because they tended to perform more page jumps per minute (Large, et al., 2002; Roy, et al., 2003). Thus the majority of previous research findings have shown that females experience more anxiety and feelings of fear than males, who show more confidence and interest in interacting with web applications (Gunn, et al., 2003;

Shashaani, 1994). In terms of navigational patterns (Chen, et al., 2006; Chen & Liu, 2008), several studies have found that males tend to navigate in a much broader, non-linear way and tend to be more actively involved than female users, as they had more page jumps and spent less time viewing pages. Table 2-3 shows the different learning characteristics of males and females found from previous studies (Chen & Macredie, 2010; Ford, et al., 2001; Jackson, et al., 2001; Large, et al., 2002; Liu & Huang, 2008; Schumacher & Morahan-Martin, 2001) .

Male	**Female**
Broad understanding	Deep understanding
Actively involved	Passively involved
High confidence and interests	Low confidence and fears
Non-linear navigating	Linear navigating
Superficial search	Exhaustive search

Table 2-3: Differences in learning characteristics of males and females. Adapted from (Chen & Macredie, 2010; Ford, et al., 2001; Jackson, et al., 2001; Large, et al., 2002; Liu & Huang, 2008; Schumacher & Morahan-Martin, 2001)

Such different approaches to information processing mean that males and females might need different levels of support when they interact with the web. The literature suggests that major gender differences lie within navigation patterns, attitudes and perceptions (Chen & Macredie, 2010).

2.4. Design Elements of Web-based Program and Individual Differences' Need

The design of usable and effective web applications relies upon the design being compatible with a learner's characteristics (Dillon & Zhu, 1997). In this section, we discuss previous studies examining designs of web-based instruction programs and how individual differences interacted with such design. Suggested design elements will also be provided.

Chen, et al., (2006) developed a framework to help users with various levels of prior knowledge. The aim of their framework was to integrate users' prior knowledge into the design of hypermedia learning systems based on the analysis of previous research. This framework includes four elements: disorientation problems, content scope, navigation tools and additional support.

2.4.1. Disorientation Problems

Many studies argued that not all learners were able to manage the high level of links accessed by hypermedia systems. Such studies indicated that a learner’s prior knowledge is an important factor with significant influence. In particular, "novice hypermedia users met more disorientation problems and needed analogies with conventional structures if they were to learn successfully" (Chen, et al., 2006). McDonald and Stevenson (1998) examined the effects of prior knowledge on hypermedia navigation, and showed that users who lacked sufficient prior knowledge demonstrated more disorientation problems because they tended to open more additional notes, which suggested firstly that they could not remember where they had been, and secondly that they had difficulties in finding the information they required. These findings agreed with Mohageg (1992), who asserted that knowledgeable users might avoid disorientation in navigating in a hypermedia system because they already have a mental representation of the concepts in the domain that they are searching. Thus, non-knowledgeable users need to have navigational support to reduce their disorientation problems.

Furthermore, Last, et al., (2001) conducted a qualitative study of 12 undergraduates. They found that students with limited domain knowledge often suffered from disorientation. Additionally, they found that students with ample domain knowledge were able to navigate easily, remember where they had been and decide how to get to where they wanted to go. Moreover, in investigation of gender disorientation problems, they found that female students leant towards being more nervous, experienced more disorientation problems, and were less confident with web-based instructions than males (Jackson, et al., 2001). The study of Chen and Macredie (2010) identified and reviewed three important individual differences of gender differences, prior knowledge and cognitive styles. Table 2-4 shows those findings.

Individual difference	Summary
Gender differences	Some studies found that there are no gender differences in navigation patterns and attitudes toward web-based interaction, but the majority of studies indicated that females and males showed different behaviour and demonstrated different perceptions and attitudes. In particular, females encountered more disorientation problems and had more negative attitudes than males.
Prior knowledge	Regarding web-based instruction, studies suggest that flexible paths are more beneficial to experts, while structured content is more useful to novices, who can get more benefits from a hierarchical map. Regarding web searching, experts and novices used different types of search strategies, spent different amounts of time in doing broader tasks and reading documents, and show different perceptions.
Cognitive styles	Regarding web-based instruction, studies suggest that field-dependent and field-independent users demonstrate different learning preferences, but results remain inconclusive in terms of learning performance. Regarding web searching, studies suggest that field-dependent and field-independent users prefer to use different search strategies, especially in terms of the use of embedded links and Boolean searching.

Table 2-4: Summary of how individual differences affected users' interactions with the web. Source is Chen and Macredie (2010).

2.4.2. Additional Support and Display Options

Many studies argue that hypermedia learning seems to be more suitable for expert users. Conversely, novice users experience more disorientation problems, so it is essential to provide them with additional support through mechanisms such as advisement (Shin, et al., 1994), graphical overviews (de Jong & van der Hulst, 2002) and structural cues (Hsu & Schwen, 2003). Chen, et al., (2006) argued that research in this area shows that additional support can be provided to help novices in hypermedia learning. Advisement, which provides learners with visual aids and recommended navigation paths, is helpful in preventing disorientation in non-linear hypermedia learning. As novice learners cannot rely on their prior knowledge to help them structure the text, graphical overviews and structural cues are powerful and beneficial in providing navigation guidance so as to ease disorientation problems. The results in Chen and Liu’s (2008) study also have shown that "*different cognitive style groups tend to favour different display options*". Moreover, the study of Chen and Liu (2008) showed that field-independent students are capable of extracting relevant information from the detailed description because they have a tendency to use their own internal references. However, field-dependent students rely more heavily on external cues and they prefer to get concrete examples. Thus, field-dependent users look at examples, while field-independent users frequently examine the detailed descriptions.

2.4.3. Content Scope

In Chen, et al., (2006), participants were asked to look for medical information with search engines. Their findings indicated that experts focused on locating detailed information by using depth-first strategies, started from the first link on the initial site, then followed links provided by the site from one site to another, until they found a suitable site. Conversely, novices tended to get an overview by using breadth-first strategies, following the first link of the initial site, then going back to the initial site and following the second link without browsing any links in depth.

Many studies have argued that breadth-first and depth-first (also known as ‘Matching’ and ‘Mismatching’) instructional styles have a significant impact on individual styles. Ford and Chen (2001) present results of a research project which explored the relationship between breadth-first and depth-first instructional styles with users' cognitive style (field-dependent and field-independent) in a computer-based learning environment. Ford and Chen (2001) developed two websites with two different navigation paths. One used a depth-first path and the other one used a breadth-first path. In the depth-first path, each topic is presented in detail before the next topic, while a breadth-first path presents an overview of all material prior to introducing detail. Field-dependent users perform better using the breadth-first path. In contrast, field-independent users out-perform the depth-first path. The results of Chen and Liu (2008) concluded that field-independent users tended to browse fewer pages than field-dependent users. Field-independent subjects are good at analytical thought, whereas field-dependent subjects have global perceptions (Goodenough, 1976; Witkin, et al., 1977).

2.4.4. Navigation Tools

Navigation tools are used in current hypermedia learning systems, most commonly hierarchical maps and alphabetical indices, each of which provides different functions for information access. For example, hierarchical maps provide an overview of the global structure of the context, while alphabetical indices are useful for locating specific information (Chen & Macredie, 2002).

Carmel et al., (1992) found that experts were more interested in using tools that could facilitate the location of detailed information related to specific entities. Also, Pazzani (1991) found that experts profited most from a flexible path, whereas novices benefited most from a structured path. Moreover, in the study of Möller and Müller-Kalthoff (2000), novices appeared to benefit from hierarchical maps, which can facilitate the integration of individual topics. Minetou, et al., (2008) conducted two empirical studies to investigate how students' prior knowledge affected their use of navigation facilities. Sixty-five learners participated in Study One and sixty-nine learners in Study Two. In both studies they found that hierarchical maps were favoured by users with low prior knowledge. A possible explanation for these findings is that the hierarchical map not only reveals the document structure (i.e., the physical arrangement of a document), but also reflects the conceptual structure (i.e., the relationships between different concepts). In other words, the hierarchical map can help novices incorporate document structure into the conceptual structure, which helps them to integrate their knowledge.

The results of Lee, et al., (2009) also indicated that prior knowledge was an important factor influencing the use of navigation tools. Thus, the results show that experts preferred the alphabetical index, whereas novices favoured the hierarchical map. The researchers clarified that novices may lack the prior knowledge, but the hierarchical map presents the content in a structured format and can help novices categorise content. However, experts have more prior knowledge and are more able to use structure on content, which helps them find specific information.

The research of Chen, et al., (2006) showed that experts and novices had different preferences concerning, and derive different benefits from, navigation support. Expert learners need to have navigation tools which provide them with free navigation and find specific information that they need. Index tools, content lists and search tools are shown to be helpful for them. However, navigation tools such as map and menu tools are beneficial for novice learners in hypermedia learning systems.

In Table 2-5, we describe the results of the study by Chen, et al., (2006), which can be considered as a framework to help designers develop WBI programs by accommodating novice and expert preferences. Lee, et al., (2009) investigated the relationship between cognitive styles and users' learning behaviour in web-based learning programs. The findings in this study showed that "field-independent learners frequently use backward/forward buttons and spent less time for navigation. On the other hand, field-dependent learners often use a main menu and have more repeated visiting". One of the conclusions drawn from this study is that: "cognitive style is an important factor that determines users' learning behaviour".

	Additional support and display options	Content scope	Navigation tool
Novices	Need graphical display and structural cues	Overview by using breadth-first strategies	Map and main menu
Experts	Not shown to be essential	Detailed information by using depth-first strategies	Index tools, content lists and search tools

Table 2-5: Results from Chen, et al., (2006) framework

Field-independent users often prefer the alphabetical index, which provides users with the means to locate particular information without going through a fixed sequence (Chen & Macredie, 2002). On the contrary, field-dependent users often use the hierarchical map to illustrate the relationships among different concepts (Turns, et al., 2000), which reflects the conceptual structure of the display options (Nilsson & Mayer, 2002). Figure 2-1 shows the model presented by Chen and Liu (2008) which can be considered as a mechanism to help designers develop WBI programs; it achieved this by accommodating the preferences of both field-independent (FI) and field-dependent (FD) learners.

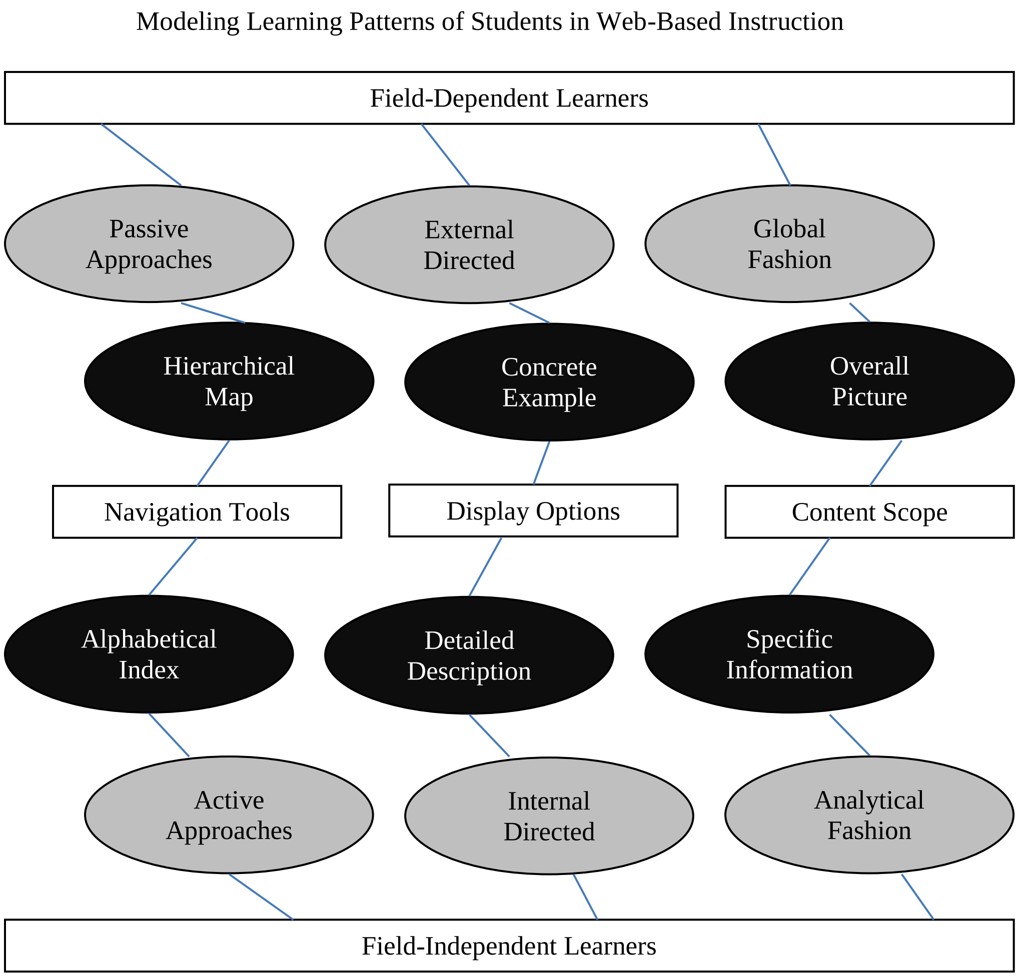


Figure 2-1: A model for the design of WBI programs (Chen & Liu, 2008)

2.5. Preferences of Individual Differences in WBI Programs and our WBI Program

Chen (2010) described how different cognitive style learners use a web-based learning program, keeping track of learners' browsing data in a log file to see how their cognitive styles and learning behaviours were related. The end goal was to develop an adapted hypermedia system and propose a design model tailored to the preferences linked with each cognitive style. The study consisted of 105 accounting information system users from a technology university in central Taiwan. The data showed that learners with different cognitive styles adopt different navigation tools to process learning. Also, learners with different cognitive styles had similar, but linear, learning approaches.

The model of Chen (2010) presented the necessary features of a web-based learning program, which should support the requirements of different learners, such as how the content is presented and how navigation tools are designed. For example, the presentation style of the content should allow learners to follow a guided learning pathway by, for example, inserting additional link buttons that help users navigate from item to item. The designer should also provide two different navigation tool features to accommodate learners from each cognitive style. Thus, web-based instructional programs should be designed to provide field-independent learners with flexible guidance tools to reach information effectively, such as an alphabetical index. A field-dependent learner might benefit from a complete picture of the content as well as their current position; one example is a hierarchical map.

There are many studies suggesting that learners with low levels of prior knowledge, in contrast to learners with higher levels of prior knowledge, have more difficulty in navigating hypermedia learning systems (McDonald & Stevenson, 1998; Mills, et al., 2002). Therefore, prior knowledge has been recognised as an important attribute because it can influence how learners select information to place in memory and link new information to that already stored in memory. Recent reviews show that the hypothesised advantages of a high level of learner control are valid for learners with high prior knowledge only (Chen, et al., 2006; Scheiter & Gerjets, 2007; Schnotz & Heib, 2009). Therefore, learners with high prior knowledge experience fewer difficulties and do not need additional support in navigating hypermedia systems. Moreover, Fidel, et al., (1999), Hill and Hannafin (1997) and Lazonder, et al., (2000) suggested that users with more system experience have more efficient navigation strategies than users with less experience.

On the other hand, Torkzadeh and Lee (2003) discuss how to understand users' prior knowledge, which can influence the system success directly and indirectly. The main conclusions were: (1) users with lower domain knowledge gain more benefits from the hypermedia tutorial than those with higher prior knowledge; (2) examples are useful vehicles for the users with low levels of domain knowledge; and (3) users who enjoy web and web-based learning are more able to cope with the non-linear interaction.

Farrell and Moore (2001) investigated whether the use of different navigation facilities (linear, main menu and search engine) influenced users' attitude and achievement. In their study, 146 eighth-grade students were placed according to their knowledge levels (low, middle, and high) into three groups, where results indicated that high-knowledge users tended to use search engines to locate specific topics and low-knowledge users seemed to benefit from hierarchical maps.

We have relied in our design on three major elements of the findings of Chen, et al., (2006) which are additional support, content scope and navigation tools. Their findings suggested that these features were important to hypermedia learning systems in order to be effective.

- ***Additional Support***

Additional support can be provided to help novices in hypermedia learning systems. Thus, graphical overviews and structural cues are powerful and beneficial in providing navigation guidance to novices to ease potential disorientation problems (Torkzadeh & Lee, 2003). Moreover, field-dependent users look at examples, while field-independent users frequently examine detailed descriptions (Chen & Liu, 2008).

- ***Content Scope***

As for the content scope, findings in Chen, et al., (2006) indicate that experts focused on locating specific information while novices tended to get an overall picture. A field-independent user performs well in terms of analytical thought, whereas field-dependent users have global perceptions (Goodenough, 1976). For field-dependent students, a global picture of the subject can be assisted with popup windows (Chen & Liu, 2008).

- ***Navigation Tools***

As for navigation tools, Chen, et al., (2006) showed that index tools were helpful for experts. On the other hand, map and menu tools were beneficial for novice learners in hypermedia learning systems. Field-independent users often prefer an alphabetical index, whereas field-dependent users often use a hierarchical map (Chen & Liu, 2008; Chen & Macredie, 2010; Farrell & Moore, 2001). In Table 2-6, we provide the summary of models provided by Chen, et al., (2006) and Chen and Liu (2008).

System Features / Human Factors	Navigation tool		Display options		Content scope	
	Alphabetical Index	Hierarchical Map	Detailed Description	Concrete Example	Specific information	Overall Picture
Field-independent Experts	✓		✓		✓	
Field-dependent Novices		✓		✓		✓

Table 2-6: Mechanism of our WBI program resulting from Chen, et al., (2006) and Chen and Liu (2008)

Gaps in understanding learners' preferences

Many studies have been engaged in understanding learners' preferences using web-based programs. Some studies have shown that user prior knowledge plays a significant role in the use of navigation tools in hypermedia learning systems (Chen, et al., 2006; Lee, et al., 2009; Minetou, et al., 2008). Many studies have shown that index tools are helpful for experts. On the other hand, map and menu tools have been shown to be beneficial for novice learners (Chen, et al., 2006; Chen, 2010; Minetou, et al., 2008). However, others have argued that there is no significant difference between experts and novices in the use of a hierarchical map (Calisir & Gurel, 2003), where experts and novices opened equal number of nodes in a hierarchical document. The lack of significant differences is inconsistent with the findings of McDonald and Stevenson (1998) where it was found that experts opened more nodes than novices in a hierarchical environment. In this thesis, we explore those contradictions from the perspective of existing studies. Thus, we will investigate the impact of prior knowledge on learners' preferences using our WBI program.

Previous findings have shown that a learner's cognitive style has an impact on learning preferences. Field-independent users often prefer an alphabetical index, whereas field-dependent users often use a hierarchical map (Chen, 2010; Chen & Liu, 2008; Farrell & Moore, 2001; Ford & Chen, 2000). While those studies have investigated the cognitive style alone, it is not clear how the cognitive style of learners would be influenced by gender and prior knowledge. Thus, in this thesis, we investigate the preferences of learners identified by using a single individual difference and by identifying learners according to the intersection of three individual differences (prior knowledge, cognitive style and gender) as combined individual differences of each learner. Combined individual differences will henceforward be known as multiple individual differences (Multi-ID).

2.6. Studies on Learners' Perception and Performance in WBI Programs

Earlier research studies have indicated that various factors influenced the learning performance of the users. Additionally, the enjoyment of using web instructions improves their perception. Related to learner enjoyment using hypermedia systems, many studies have indicated that learners who enjoy using the web probably have positive perceptions of interaction in hypermedia systems. The study by Mitchell, et al., (2005b) examined the influence of web enjoyment of users with a high level of system experience using non-linear navigation on their learning performance and perception. Results indicated that there were positive relationships between the levels of web enjoyment and learning performance and perceptions.

With regard to performance, a traditional, non-multimedia learning environment, matching a user's cognitive style with content presentation has been shown to enhance performance and improve perception (Ford & Chen, 2001). Moreover, Ford and Chen (2001) examined how prior knowledge influences users' learning performance in, and perceptions of, a hypermedia system. Results indicated that the learning performance of participants with lower domain knowledge had greater improvement than those with higher domain knowledge. "*The use of navigation tools* *may affect the learner performance*", suggested de Jong and van der Hulst (2002), who state that visual cues provide learners with a systematic route through the domain and may thus lead to a better acquisition of the structure of the domain. Learners in the study by Minetou, et al., (2008) do not take advantage of such visual cues provided by navigation tools, so the acquisition of their knowledge is influenced. This may explain the results of the lack of the appropriate use of navigation tools that may hinder learners' performance. The conclusion in Minetou, et al., (2008) showed that the users' prior knowledge played a significant role in their use of navigation tools. Additionally, the use of navigation tools has a great impact on a user's learning performance.

A number of studies have suggested that experts and novices differ in their performance depending on content structure in hypermedia learning systems, with findings suggesting that a hierarchical structure is most appropriate for novices. Calisir and Gurel (2003), Pazzani (1991), and Shin, et al., (1994) examined the effects of hierarchical structure and network structure on hypermedia learning, and their results indicated that novices gained more benefit from a hierarchical structure than from the network structure. On the other hand, experts were able to function equally well in both. Gauss and Urbas (2003) evaluated the usability of a prototype for learning modules in the subject matter of process systems engineering, and no significant findings were discovered on the relationship between prior domain knowledge and learning outcomes. Chen, et al., (2006) developed a framework to integrate prior knowledge into the design of hypermedia learning systems. Research results have shown that experts perform better than novices in hypermedia learning systems, mostly because of their background knowledge of the subject domain which helped to guide their exploration. On the other hand, their empirical findings have shown that novices suffer in hypermedia learning. Their suggestion was to give support to the novice learners by presenting an effective user interface to avoid disorientation, and to provide appropriate navigation support which should be useful for them to develop conceptual structure and integrate knowledge. The framework can be applied to guide designers in integrating a learner's prior knowledge into the development of hypermedia systems. However, the study did not consider other individual differences elements, such as gender and cognitive styles, in the development of hypermedia systems. Therefore, based on the implications of Chen and Liu (2008), a WBI program to support the unique needs of each cognitive style group. Thus, WBI programs should be flexible enough to provide multiple options tailored to the distinctive cognitive styles. Figure 2-1 shows the results of this study accommodating the preferences of both field-independent and field-dependent learners.

Derived from the previous discussions, we will combine the the two models (Chen, et al., 2006; Chen & Liu, 2008) in designing our web-based program. Also, we explore the area suggested in Chen and Liu (2008): "*it would be valuable to see whether such WBI programs and the web-based applications can promote learners' performance and increase their satisfaction*".

From the aforementioned studies, we demonstrate that many studies were engaged in studying the preferences of learners with different individual differences, and how this could affect their learning performance. The performance of learners was measured using different measurement attributes in the use of hypermedia systems.

Attributes of Measuring Performance

Previous studies have used different attributes in measuring learner performance after interacting with hypermedia learning systems; measured attributes are time, number of visited pages and gained score (Chen, et al., 2006; Chen & Liu, 2008; Kim, 2001; Large, et al., 2002; McDonald & Stevenson, 1998; Mitchell, et al., 2005a; Mitchell, et al., 2005b; Roy, et al., 2003).

A study by Ford and Chen (2000) looked at the effect of individual differences on users' navigation behaviours and learning performance when using hypermedia systems. They found users with higher system experience could browse more pages and could reach more detailed levels of the display options than those with lower levels of system experience.

McDonald & Stevenson (1998) investigated the effect of prior knowledge and three types of content structure – hierarchical, non-linear and mixed (hierarchical structure with cross-referential links) – on navigation performance in hypermedia learning. Thirty university students participated, half of whom were knowledgeable about the subject matter of the system. Navigation performance was measured in terms of speed and accuracy in answering questions and locating particular nodes. One of the results showed that the performance of knowledgeable participants was better than that of non-knowledgeable participants.

Conversely, Mitchell et al., (2005a) examined the influence of prior knowledge on students' learning performance and perception of a hypermedia tutorial. Performance was measured by a *gain score*, calculated as the post-test score minus the pre-test score (g-score). They found that those who performed poorly on the pre-test made a greater improvement on the post-test than those who performed better on the pre-test. This could be explained by the fact that the tutorial is less useful to the knowledgeable student because they might be seeking to learn additional new material that was not given in the tutorial. The study of Kim (2001) investigated how differences in cognitive style and online search experience influenced the search. They also used the time spent and the number of nodes visited for retrieving information as indicators of search performance.

For number of visited pages as a performance-measuring factor in the WBI programs, studies have found that male, field-dependent experts browse more pages than female, field-independent novices (Chen & Liu, 2008; Ford & Chen, 2000; Large, et al., 2002; Roy, et al., 2003). As for time spent in browsing the WBI programs, some studies have found that male, field-independent users spend less time than female, field-dependent users (Chen & Liu, 2008; Lee, et al., 2009; Roy, et al., 2003). As for the gain score, studies have found that novices achieved a higher g-score than experts (McDonald & Stevenson, 1998; Mitchell, et al., 2005a). However, in using these attributes to measure learner performance, there are still gaps in understanding the learner performance using more than one attribute at a time to measure its level.

2.7. Data Analysis

Organisations can automatically collect large volumes of data generated by web servers and then collected in server access logs. Data collected from the log file of web-based learning applications often contain valuable information for in-depth understanding of users' needs and behaviours (Zhao & Luan, 2006). This has become a critical and essential aspect for researchers to extract valuable information from large amounts of data. Web-based learning applications are able to record learning behaviours of each user and then provide a huge amount of learning records to be analysed using traditional statistics or data mining techniques. Traditional statistics and data mining are analytical approaches of data analysis to uncovering the knowledge existing in data.

Traditional Statistics

Traditional statistics require assumptions to be made beforehand. They are often used to verify prior hypotheses or existing knowledge to prove a known relationship (Moss & Atre, 2003). Traditional statistics are used to determine if there are statistically significant differences among the tested data.

Data Mining

Data mining, also known as knowledge discovery (Fayyad & Uthurusamy, 1996), is the process of discovering interesting, unexpected or valuable information from large datasets (Hand, 2007) and comprises techniques from a number of fields, including information technology, statistical analyses and mathematical sciences (Bohen, et al., 2003). It uses data to find unexpected relationships and patterns (Wang, et al., 2002). By doing so, hidden relationships and inter-dependencies can be discovered and predictive rules generated (Gargano & Raggad, 1999; Hedberg, 1995). This can help institutions make critical decisions faster or with a greater degree of confidence (Gargano & Raggad, 1999; Urtubia, et al., 2007) without the need to predefine underlying relationships between dependent and independent variables as some of the statistical methods require (Chang & Chen, 2005).

Data mining can be broadly divided into supervised discovery and unsupervised discovery. Classification and clustering rules (Witten, et al., 2011) can be examples of supervised and unsupervised divisions. Classification is a process of supervised discovery which discovers predictive patterns where a predicted attribute can be nominal or categorical. The predicted attribute is called the ‘class’. Subsequently, a data item is assigned to one of a predefined set of classes by examining its attributes (Changchien & Lu, 2001). In other words, the objective of classification is not to explore the data to discover interesting segments, but is used both to understand existing data and to predict how new cases will behave (Chen & Liu, 2008).

Clustering is unsupervised discovery of a hidden data concept (Hand, 1999). It is part of the Exploratory Data Analysis (EDA) (Hartwig & Dearing, 1979; Tukey, 1977), used in those situations where a training set of pre-classified records is unavailable. It is a division of data into groups of similar objects (Nolan, 2002). Each group, called a 'cluster', consists of objects that are similar among themselves and dissimilar from objects of other groups (Roussinov & Zhao, 2003). This technique has the advantage of uncovering unexpected trends or patterns, without making assumptions about the structure of the data.

Clustering methods may be grouped into the following two categories: *hierarchical* and *non-hierarchical* clustering (Jain & Dubes, 1999; Kaufman & Rousseeuw, 1990). A hierarchical clustering procedure involves the construction of a hierarchy or tree-like structure, a nested sequence of partitions (Fraley & Raftery, 1998), while non-hierarchical or partitioned procedures end with a particular number of clusters at a single step.

2.8. Summary

This chapter presented a review of the previous literature investigating the effect of individual differences on users' preferences and performance in the use of web-based applications. Three individual differences were identified, namely cognitive style, prior knowledge and gender differences. Also, the design features of WBI applications and their impact on the learners' interaction were highlighted. Moreover, the review demonstrates that there is a need to conduct further research into the key factors that significantly affect users' preferences and performance for web-based applications. More specifically, individual differences and system features were reviewed and a number of significant links were identified to understand their influence on the learners' performance level of learning behaviour. Additionally, suitable data mining tools were identified for analysis.

CHAPTER THREE

METHODOLOGY DESIGN

3.1. Introduction

In Chapter 2, literature related to hypermedia systems and how they have gained attraction for the purposes of teaching and learning was identified. These systems provide users with freedom of navigation, allowing them to develop learning pathways. Empirical evidence indicates that not all learners can benefit from hypermedia learning systems. In order to develop a learning environment, individual differences need to be taken into account to ensure they impact on learners' achievements. Thus, many research studies have attempted to find ways of building systems to be robust and which can also accommodate preferences of individual differences. In this chapter, we propose a web-based instruction (WBI) program which accommodates the needs of some individual differences such as learner's prior knowledge and cognitive styles. These considerations were reflected in the three key design elements – navigation tools, display options and content scope – in the structure of our proposed program.

Our WBI program logs data that can be used to identify the learners' cognitive style; more specifically it can identify field-dependent and field-independent learners by observing participants' preference of navigating to the topics pages (map vs. index). More supporting data was collected using a pre-test and post-test of the participants, where prior knowledge and gain score (g-score) were measured.

The structure of this chapter is as follows. Section 3.2 identifies an appropriate research methodology approach, followed by the experimental design and research instruments in Section 3.3. Participants and experiment procedures are presented in Sections 3.4 and 3.5 respectively. Section 3.6 describes collected data, followed by a description of the pilot study and modifications of the experiment in Section 3.7. Section 3.8 determines the data analysis techniques used with respect to the experimental studies, followed by our proposed framework in Section 3.9. Finally, Section 3.10 provides a summary of this chapter.

3.2. Methodology Approach

It is important to understand the nature of our investigated problem in order to choose the most appropriate methodology. There are different methodologies that may be suited for different scenarios. Qualitative studies (for example, case studies and phenomenological studies) are generally more appropriate when the problem under investigation is not very specific (Leedy, 1997). Quantitative methodologies (for example, experimental methods and questionnaires) are appropriate when the problem is clearly defined, with subsequent clearly defined investigation aims (Leedy, 1997). Such methods allow for investigation of variables to be discovered.

Since the problem in this investigation is clearly defined, with clearly defined research aims, a quantitative, experimental method and questionnaire were, deemed appropriate. The problem under investigation is based on a large set of collected data from the methods used. In this thesis, we used experimental methods and questionnaires to collect our data. An experimental method is used “to determine if a specific treatment influences an outcome” (Creswell, 2009). A questionnaire provides a quantitative or numeric description of trends, or opinions of participants (Creswell, 2009).

3.3. Experimental Design and Research Instruments

Chapter 2 shows that there are many studies engaged in studying learner’s behaviour using hypermedia systems, trying to accommodate their preferences in the design of such systems. Using existing designs (Chen, et al., 2006; Chen & Liu, 2008) helped us to build an agile WBI program; this should be flexible enough to offer multiple options tailored to the distinctive cognitive style such as field-dependent and field-independent learners, in addition to expert and novice learners. Our proposed WBI program will focus on the structure of three key design elements: navigation tools, display options and content scope.

Many studies have investigated the preferences and performance of learners using different measurement factors after using hypermedia systems; those measurement factors include time, number of visited pages and gained score (Chen, et al., 2006; Chen & Liu, 2008; Kim, 2001; Large, et al., 2002; McDonald & Stevenson, 1998; Mitchell, et al., 2005a; Roy, et al., 2003). The following section provides our research instruments and how we used them in collecting our data. Those instruments are our WBI program, tasks sheet, pre-test, post-test and questionnaire.

3.3.1. WBI Program

Our WBI program presents instructions on how to complete several tasks using Microsoft PowerPoint. We chose Microsoft PowerPoint as the subject for the experiment because it is one subject that is taught to all of the different majors in the Higher Institute of Telecommunication and Navigation (HITN) in Kuwait, where they use it for their projects and to present their work.

We programmed our WBI instruction using Hypertext Mark-up Language (HTML) and Personal Home Page (PHP). The content of a document includes text, images and other support media through hypertext links which connect one document to another (Musciano & Kennedy, 2002). PHP is known as a server-side scripting language designed specifically for the web. PHP code can be embedded within an HTML page and executed each time the page is visited. The PHP code is interpreted at the web server and produces HTML that the user will see (Welling & Thomson, 2008). The simplicity in having less code is what makes PHP successful (Lerdorf, et al., 2006). As for the server-side scripting, PHP was designed to create dynamic web content. Moreover, as a command-line script tool, PHP can run scripts from the command line for system administration tasks such as backup and log parsing (Lerdorf, et al., 2006).

Navigation Tools

Our WBI program provides users with hyperlinks within the text-based instructions, navigation tools, including a hierarchical map and alphabetical index. In Chen and Liu (2008), results showed that field-independent users often prefer the alphabetical index, whereas field-dependent users often use the hierarchical map. Therefore, one of the solutions provided by Chen and Liu (2008) is to accommodate their different preferences by allowing the learners to see both navigation tools at the same time by using frames.

The main navigational page of the WBI program was divided into two frames as illustrated in Figure 3-1. An alphabetical Index was placed inside the left frame, while the Hierarchical Map Index was placed inside the right frame. Users were able to see the index on the left and map on the right.

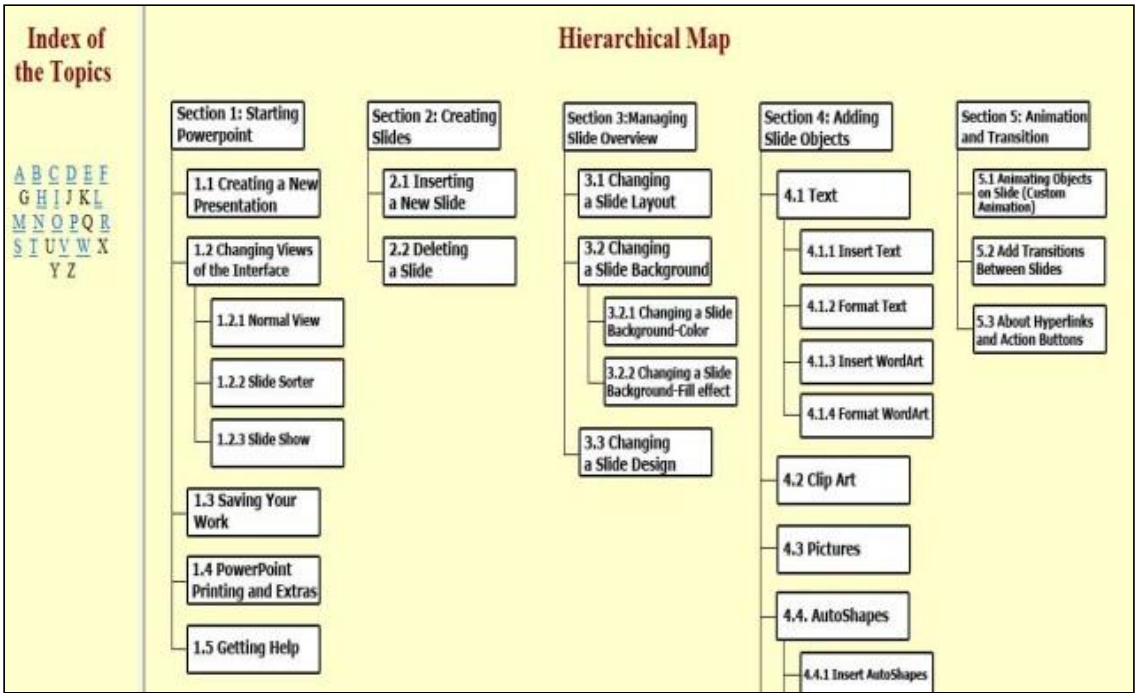


Figure 3-1: The main page of the WBI.

The following are the descriptions of the window and its two frames:

1) Hierarchical Map (the right frame):

   In this frame, a user has a hierarchical structure which includes 31 topics displayed in five main sections. Each of the topics is a hyperlink; when a user clicks on it, two actions occur. The first is that the current window (including the left and the right frame) is changed to another view; the chosen topic will be highlighted on the hierarchical map frame. At the same time, the topic title will be displayed under the letters shown in the index frame on the left of the window (Figure 3-2). The other action is that a popup window will be introduced to show the instructions of the chosen topic (Figure 3-3).

   As an example, in the right frame, when a user chooses a topic such as "*3.2.2 Changing a Slide Background-Fill Effect"* by clicking on the icon in the hierarchical structure, this topic will be highlighted in pink (Figure 3-2). At the same time, in the left frame, the letter "B" for the key word "*Background"* will be bold and the chosen topic title will be shown in that frame.

2) Index of the Topics (the left frame):

When a user clicks on a letter trying to search for a specific topic, the frame is changed to show keywords of some topics, giving the user the ability to choose a specific topic (Figure 3-4). However, the right frame will not be changed until a specific topic is chosen from the links under the index letter (Figure 3-4). After the user has chosen their topic from the listed topics shown on the left frame, two actions occur; the first is that the topic is listed on the left frame, and at the same time that topic is highlighted on the right frame (Figure 3-2). The other action is that a popup window is introduced to show the instructions of the chosen topic (Figure 3-3).

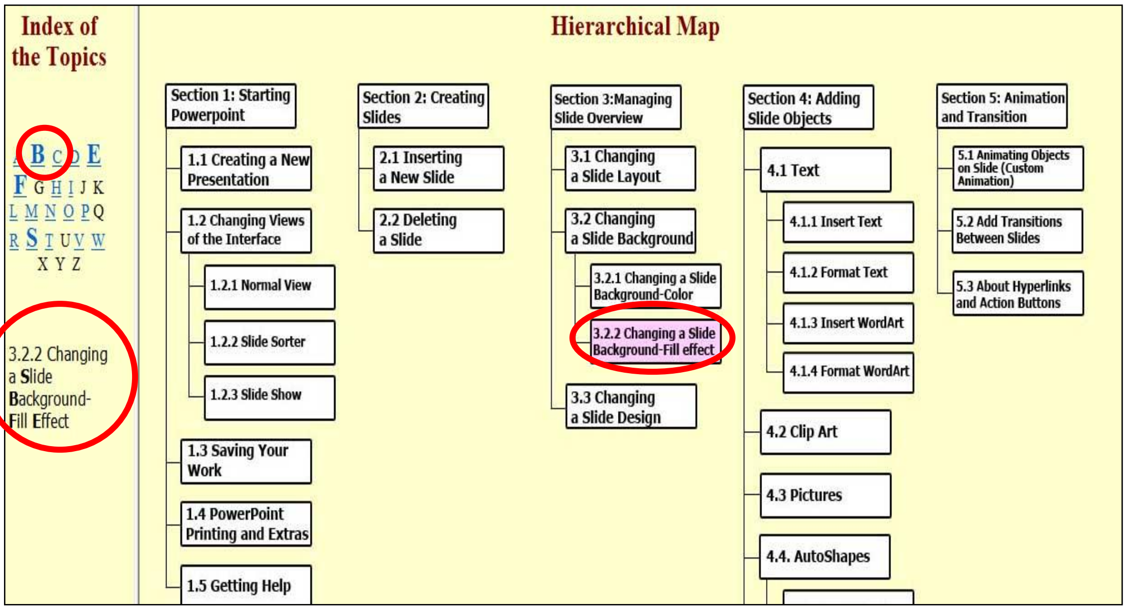


Figure 3-2: The chosen topic from the Hierarchical Map frame.

Display Options

As stated in Chen and Liu (2008): "field-dependent students rely more heavily on external cues, thus, they prefer to get concrete guidance from examples". In their study, they provided a way to address learners' different needs by showing the display options, detailed description and concrete examples, within one table. This table should provide relevant information about a particular topic instruction. This table should consist of two columns. One column can be used to present the detailed descriptions of a particular topic, while the other column provides the illustration with examples for such topic.

Figure 3-3 shows the design of a topic page presenting the same structure (description and examples). All topics, either reached from the index or the map, conform to the same design (Figure 3-3) so that we do not influence participants' choices between the two different navigational tools.

Content Scope

According to Chen and Liu (2008), field-dependent learners browse more pages to build an overall picture. One of the potential solutions that Chen and Liu (2008) provided is to deal with their different requirements by using a popup window. This secondary window for providing additional information about a selected topic should be popped up by clicking a hypertext link provided.

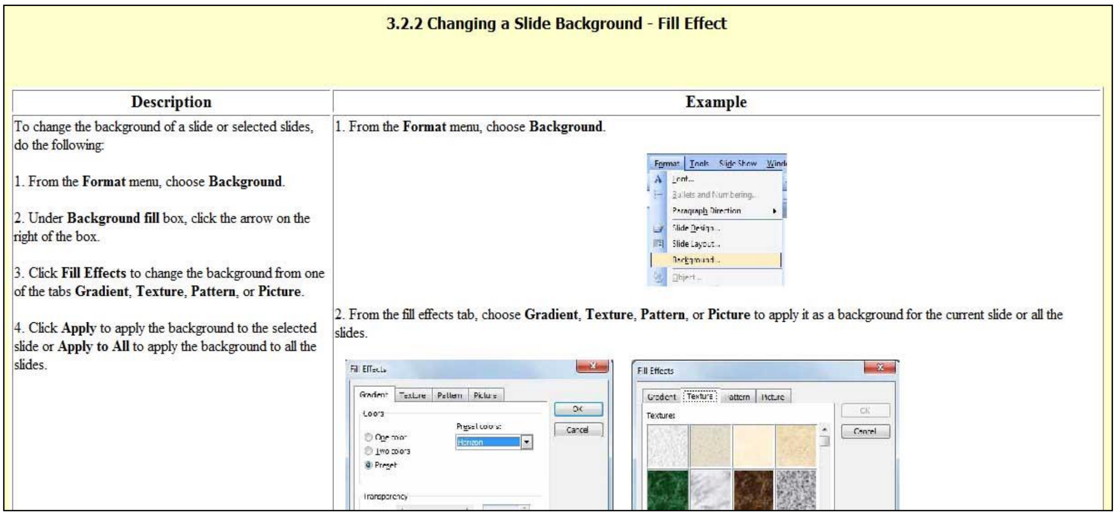


Figure 3-3: The webpage design of the popup window to display the topic contents.

The WBI program provides users with an additional hyperlinked popup window named "Further Details", which displays more in-depth instructions about the topic they are currently viewing (Figure 3-5). A link for a Further Details popup window can be found in the Topic window (Figure 3-3). The user can then close any currently opened popup windows (either that shown in Figure 3-3 or in Figure 3-5) and return to the frame's page (shown in Figure 3-2).

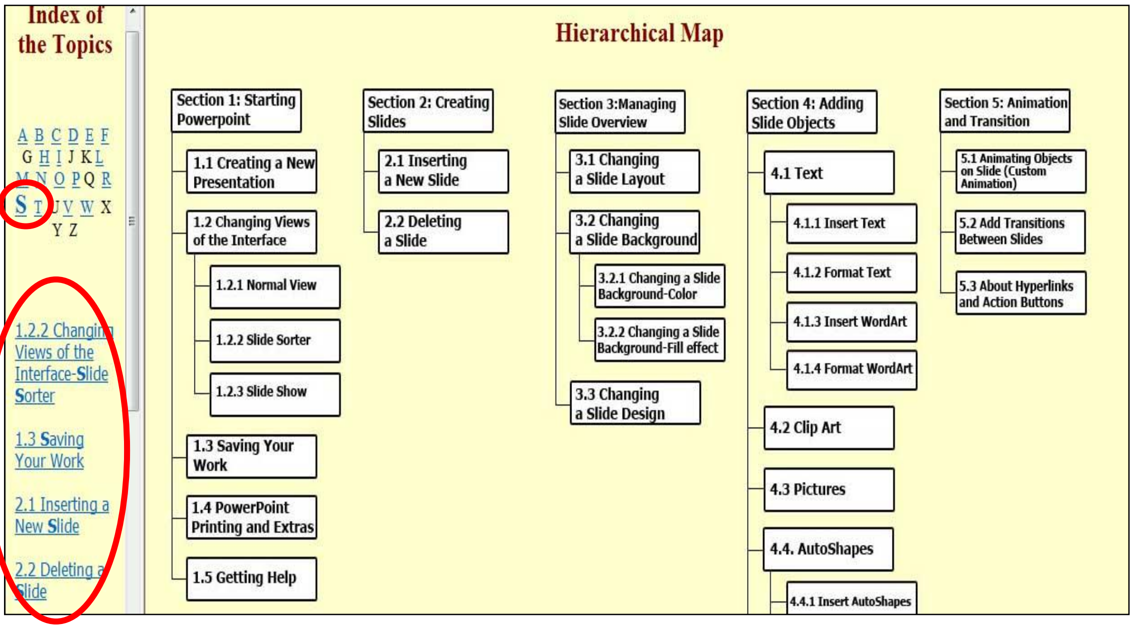


Figure 3-4: Topics displayed after choosing a letter from the index.

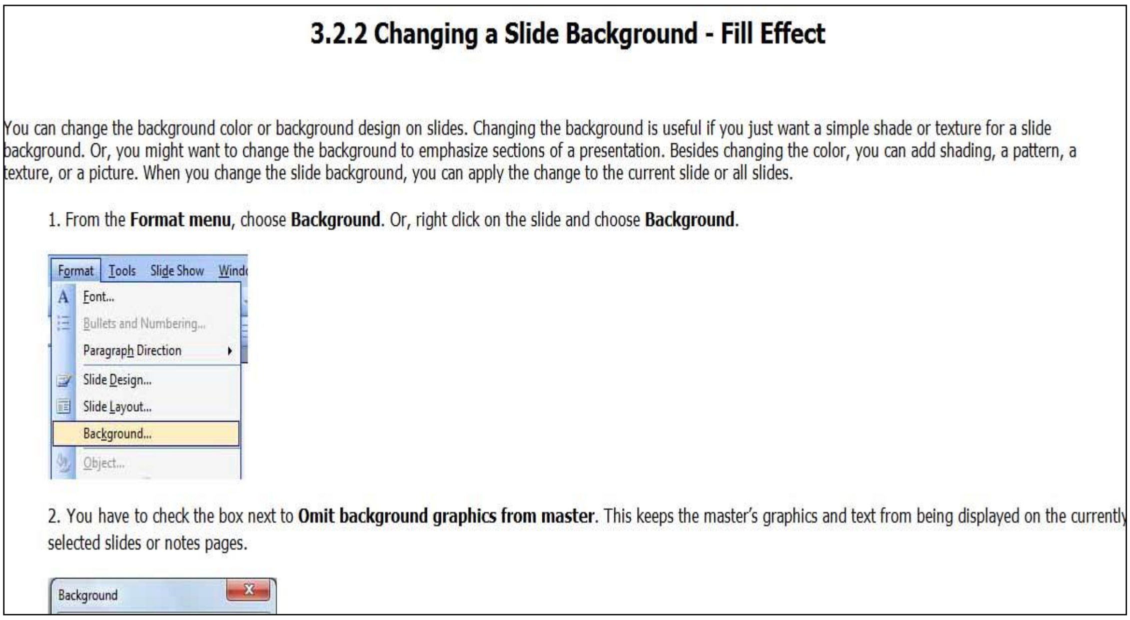


Figure 3-5: The secondary popup window to display further details of the chosen topic.

Our WBI Program consists of a log file which logs every click the participant makes, the log file is explained below:

Log file:

We logged the display of each page when a participant clicked on any link in the WBI program; the chosen hyperlink was either from an index or from a map frame. Table 3-1 shows a sample of the data saved in the log file. Column A shows the participant's name (each participant typed in their name once they entered the WBI program). The name was removed from the table for confidentiality. Column B shows the date of conducting the experiment. Column C shows the time of hitting the page on the browser. The last column (column E) shows the page displayed currently on the browser and by the time shown in column C. Column D shows the page visited by the participant just before the current page (current page is the page shown in column E).

In cell E1, the participant is using an index frame to find a topic. This is shown in cell D1, where the participant chose the letter 'B' from the index shown on the last displayed window (as shown in Figure 3-2). Cell E2 shows that the participant is now displaying a topic page clicked from the index frame which contains the letter 'B' and more specifically, the topic *"3.2.2 Changing a Slide Background-Fill Effect"*. D2 shows that the currently displayed topic popped up after a participant had clicked on the letter "B".

When the participant clicks on the page from D1, four pages will be displayed on the browser: E1, E2, E3, and E4. E1 is the frames page (Figure 3-2), E3 and E4 are the left and right frames respectively resulting from E1 (the left frame is the index page and the right frame is the map page). Additionally, E2 is a popup window which displays the page containing the topic contents (Figure 3-3). Thus, the number of displayed pages is known for each click.

	A	B	C	D	E
1	Participant-01	2/5/2012	08:20:04	Index of letter B.php	3.2.2 Changing a Slide Background-fill effect frames.php
2	Participant-01	2/5/2012	08:20:04	Index of letter B.php	3.2.2 Changing a Slide Background-Fill Effect-topic.php
3	Participant-01	2/5/2012	08:20:05	3.2.2 Changing a Slide Background-fill effect frames.php	3.2.2 Changing a Slide Background-fill effect letter.php
4	Participant-01	2/5/2012	08:20:05	3.2.2 Changing a Slide Background-fill effect frames.php	3.2.2 Changing a Slide Background-fill effect map.php

Table 3-1: A sample of the log file

After observing the log file of each participant (91 records), we removed records of all redundant popup pages shown in the log file (Table 3-2). Those redundant pages were removed easily since when we designed the WBI program, we knew in advance the number of popup pages made visible on each click. Thus, any additional number of pages was removed manually from each participant's record to avoid any discrepancy in our analysis. Redundant records were probably caused by a lag from our remote website's server or a lag from the local network in the classroom. It should be noted that the logged time of the records with a fraction of a second in time difference were considered redundant. The difference (fraction of a second) in recorded time did not affect the participant's total time spent on topic pages. The mean time spent on topic pages by participants was 2015.36 seconds.

Time of hitting the page	Popup page
1:50:01	5.1 Animating Objects On Slide frames.php
1:50:01	5.1 Animating Objects On Slide-topic.php
1:50:01	**5.1 Animating Objects On Slide frames.php**
1:50:02	**5.1 Animating Objects On Slide-topic.php**
1:50:02	5.1 Animating Objects On Slide letter.php
1:50:02	**5.1 Animating Objects On Slide-topic.php**
1:50:03	5.1 Animating Objects On Slide map.php
1:50:03	**5.1 Animating Objects On Slide-topic.php**

Table 3-2: A sample of the log file showing the redundant pages (bold and shaded).

From this log file and in each participant's record, we calculated the number of topic pages visited, number of map and index frames visited and the time that the participant hit a page.

3.3.2. Participants

A total of 91 participants volunteered with an age range of 18 to 25 years. Males (M) and females (F) were treated as two independent groups during the experiment.

To recruits participants, we visited seven scheduled lectures at HITN PC laboratories representing seven different classes: these comprised four groups of females and three groups of males. The visits were done at the beginning of the semester on seven different days within a two week period. We explained the purpose of the experiment and the experimental procedures involved (these procedures are explained in Section 3.4). We asked all students if they were interested in volunteering. Two slots of laboratory sessions (four hours in total) were reserved for the experiment. Prior to the experiment, we notified students that they were free to leave the laboratory at any time and their records would be deleted in such a case. Each participant was handed a sheet of instructions (Appendix A) and asked to read and sign for their agreement; this agreement could be revoked at any time. All students completed the tasks (although for several logistical reasons, four students were removed from consideration in the data analysis; three for non-completion of pre-and post-test and one due to a corrupted log file).

Participants had different computing and internet skills. We chose Microsoft PowerPoint as the subject for the experiment because it is one subject that is taught to all of the different majors in HITN. We chose all the classes who were going to use PowerPoint for their projects and thus needed it to present their work in that semester.

Participants were classified in terms of cognitive style and prior knowledge based on the experiment. In keeping with findings from previous studies, field-independent learners favoured using the index navigational tool. Conversely, field-dependent learners preferred to use the map navigational tool (Ford & Chen, 2000; Chen & Liu, 2008; Chen & Macredie, 2002). We used these findings to identify field-dependent and field-independent learners using our WBI program. This was deduced using a subjective classification when analysing the log file of each participant; we calculated the number of map and index pages that each user had navigated to. If the number of map navigated pages was more than 50% of the total navigated pages, the participant was identified as field-dependent. On the other hand, if the number of index navigated pages was greater than 50% of the total navigated pages, the participant was identified as field-independent. The 50% scale is the midpoint between the two navigational methods and therefore was considered as the cutting point between the two cognitive styles.

As for the prior knowledge level of our participants, novice (N) or expert (E), we calculated the median of the pre-test scores of all participants. The calculated median was 9 (mean was 8.48) out of a possible 20. If the participant’s score in the pre-test was less than 9, the participant was identified as novice (N), whereas if the participant’s pre-test score was greater than or equal to 9, then the participant was identified as expert (E). Table 3-3 shows the number of participants after identifying them in their individual differences classes (FI/FD, N/E, and M/F).

Individual differences classes	Cognitive style		Gender		Prior knowledge	
	FD	FI	M	F	E	N
Number of participants	51	40	45	46	48	43

Table 3-3: Number of participants in each class

To check the validity of our experiment from any threats or biases, the participants chosen in the experiment had an age range from 18 to 25 years, and they had finished their high school level. Thus, they have similar intellectual backgrounds. Finally, to minimise errors in the collected data, we eliminated the data from four participants. Three did not complete the pre-test and post-test of the experiment. The last did not have a log for the interactivity with the WBI program as he/she did not utilise the WBI program to complete the requested tasks.

3.3.3. Tasks Sheet

The participants were handed out a set of tasks to complete on PowerPoint while utilising the WBI. The tasks sheets contained 17 different main tasks which were used to cover the questions provided in the pre-test and post-test. Figure 3-6 shows an example of a task in the tasks sheet. The maximum allowed time to complete the tasks was two hours. Our WBI program presented instructions on how to complete several tasks. The tasks sheet contained 17 tasks to be completed using the PowerPoint application while interacting with the WBI Program to find a suitable way to solve a task. The full tasks sheet is shown in Appendix B.

4. In Slide 1, do the following:

   a. Change the slide Background to any Texture Fill Effect to this slide only.
   b. Use any of the existing Placeholders to write the following: "Enjoy the slide Content"

Figure 3-6: An example of a task in the tasks sheet

3.3.4. Pre-test and Post-test

Pre-test and post-test were gauged at the beginning and at the end of the experiment. We used these tests to measure the g-score of each participant. Participants completed a pre-test and a post-test without a time limit for the completion of these tests. Participants were informed that there was no time limit for answering the tests in order to give them comfort in defining their answers. The pre-test was used to identify the participant's prior knowledge of using PowerPoint, to decide whether they were novices or experts. The post-test was used to calculate the g-score for each participant and was calculated as the post-test score minus the pre-test score.

Both pre-test and post-test consisted of 20 multiple-choice questions. Each question had five different answers with an "I don't know" choice being the last. Participants were instructed to choose only one response. The questions were matched on the pre-test and post-test so that each question on the pre-test had a similar (but not the same) question on the post-test. Creating similar questions on the post-test was achieved by re-phrasing the question. Figure 3-7 shows a question and Figure 3-8 shows the same question after rephrasing. Participants were awarded one point for each correct answer. Pre-test and post-test are shown in Appendix C and Appendix D, respectively.

The following can be known as a slide layout:

a) Title Only
b) Title and Text
c) Blank
d) All of the above
e) I don't know

Figure 3-7: Example of a question in pre-test.

Slide Layouts contains:

a) Placeholders
b) Clip art
c) Table
d) All of the above
e) I don't know

Figure 3-8: Example of a question in post-test

3.3.5. Questionnaire

Learning perception was determined by the participants' responses to the various closed and open statements about the experiment from a questionnaire. A questionnaire was used to capture the users' subjective feelings and perceptions regarding the hypermedia learning environment. This was chosen for several reasons. Firstly, a questionnaire allows several participants to answer statements concurrently. Secondly, it ensures that all participants are asked the same statements in the same way. Finally, a questionnaire allows for easy recording of data, since answers are written by the participants themselves.

The closed statements in our questionnaire were adapted from different studies (Ajzen & Fishbein, 1975; Frias-Martinez, et al., 2007; Frias-Martinez, et al., 2008; Lewis, 1995; Mampadi, et al., 2011; Mitchell, et al., 2005a; Mitchell, et al., 2005b). These statements have been modified for the purpose of this research. The questionnaire was designed to obtain user perceptions and attitudes towards the hypermedia system used. The questionnaire had 20 closed statements divided into three sections: “display options”, “functionality and usability” and “general perceptions” (Ajzen & Fishbein, 1975; Mitchell, et al., 2005a; Mitchell, et al., 2005b; Lewis, 1995). The questionnaire responses were made up of 5-point Likert scales.

For example, the statement, “I like the fact that I can see both the hierarchal map frame and the index frame”, had the following possible responses: “strongly agree”, “agree”, “neutral”, “disagree”, and “strongly disagree”. At the end of our questionnaire, two open statements were added, asking the participant to write down what they liked and disliked most about the WBI system. The full questionnaire can be found in Appendix E. Moreover, statements were both positive and negative regarding the system. For example, “I did not get lost when browsing the links in the WBI system” represents a positive statement, whilst, “I felt frustrated when having to follow the suggested route through the WBI” represents a negative statement.

3.4. Procedures

The experiment was performed over a number of participants (91 volunteers) at the Higher Institute of Telecommunication and Navigation (HITN) in Kuwait. Each participant worked individually on a PC. The experiment consisted of five phases to be completed in four hours as follows:

Phase 1, Participants’ Prior Knowledge:

Participants were asked to refresh their prior knowledge by practising 30 minutes on PowerPoint.

Phase 2, Pre-test:

A pre-test, (paper-based) prior to performing the experiment via WBI program, was conducted on the participants to measure their prior knowledge (novice or expert).

Phase 3, WBI Utilisation:

All participants were given an introduction to the use of the WBI program highlighting the map and index navigational tools. Participants were given the freedom to choose between those tools. The subjects were then handed out a set of tasks to complete on PowerPoint while utilising the WBI. All of their interactions with the WBI were logged by the system. The maximum allowed time to complete the tasks was two hours.

Phase 4, Post-test:

The subjects were given another paper test (post-test) to measure their knowledge gain from utilising the WBI program. Gain score (g-score) was calculated by subtracting the pre-test score from the post-test score.

Phase 5, Questionnaire:

A questionnaire was given to the participants as a final stage to collect the participants' perception of using our WBI program and about the whole experience of the experiment.

3.5. Description of the Collected Data

The following is an explanation of the data presented after conducting our experiment. The data is divided into 11 columns (Table 3-4). The first two columns were calculated using two different paper tests (pre-test and post-test). The first step of the experiment was to complete the pre-test to measure prior knowledge. Following the pre-test, subjects were guided to complete the practical tasks. Once the practical tasks were completed, subjects were asked to complete the post-test. Scores of the pre-test and post-test are presented in the first two columns, respectively. The third column, gain score (g-score) was calculated by subtracting the score of the pre-test from the score of the post-test.

The fourth and fifth columns were calculated from the log file of the WBI in each participant's record. "Number of pages visited using map" and "Number of pages visited using index", respectively. Map pages were used to identify field-dependent (FD) and index pages used to identify field-independent (FI) learners (as described in Section 3.4).

The sixth column is "Total number of topics pages visited". It is calculated based on every topic visited, taking into account repeated visits. For example; if the subject had visited a single topic three times, the number in this column will reflect all three visits (assuming the participant did not comprehend the topic thoroughly on the first visit and had to come back to the same topic for more understanding).

The seventh column is number of "Further Details" pages that the learner clicked on. This page is the secondary page which displays additional information about a selected topic (as shown in Figure 3-5).

	1	2	3	4	5	6	7	8	9	10	11
Collected Data / Participants	Pre-test	Post-test	Gain score (G-score = Post-test–Pre-test)	Number of pages visited using map	Number of pages visited using index	Total number of topics visited (index pages + map pages)	"Further Details" pages	Total time (in seconds) spent on topic pages	Gender (F / M)	Prior knowledge (E / N)	Cognitive Style (FD / FI)
Participant-01	12	13	1	3	15	17	1	1567	F	FI	E

Table 3-4: An example of the collected data

The eighth column is the "Total time spent (in seconds) visiting topic pages" on WBI; this includes the time spent on multiple visits for a single topic. Gender is the ninth column, as the experiment was conducted on groups of males (M) and females (F).

The tenth column is prior knowledge, calculated using the median (value =9) of the pre-test scores of all the subjects (91 participants). If the subject's score in the pre-test was less than 9, the participant was identified as a novice (N), whereas if the score of the pre-test was greater than or equal to 9 the participant was identified as an expert (E).

Finally, cognitive style of the participants was calculated in the last column. The method for identifying FI or FD was based on subjective classifications of the participants' choice when navigating the WBI. If the number of pages navigated using the map was greater than 50% of the total pages they had visited, the participant was identified as field-dependent (FD). On the other hand, if the number of pages navigated using the index was greater than 50% of the total pages they had visited, the participant was identified as field-independent (FI).

The provided data can be used to study the learners' performance in terms of g-score, time spent reading topics and the frequency of visiting topic pages. Furthermore, behavioural preferences for individual differences can be measured using visited pages from map and visited pages from index navigational tools on WBI (The full set of data for the 91 participants can be found in Appendix F).

3.6. Pilot Study

A pilot study was carried out to determine whether the experiment was appropriate on a number of measures. These tested that:

1. The hypermedia program did not contain any faults and that navigation records were correctly logged on the web server.
2. The amount of time given for each phase of the experiment was appropriate.
3. The questions given in the tests were of a suitable level of difficulty.
4. The statements given in the questionnaire were understandable and not subject to misinterpretation.

Pilot studies were conducted in exactly the same environment as the planned experiments and involved ten participants. These were conducted approximately three weeks prior to the start of the full experiment, to allow time to make any necessary changes. These participants were F/M, FI/FD, and E/N learners. Therefore, these individual differences give more confidence in identifying both classes in each individual difference in our experiment. However, these participants did not take part in our final study to check the validity of the tools used in our experiment. As a result, the pre-test and post-test were modified by adding a fifth choice, “I don’t know” (Figure 3-7 and Figure 3-8); this choice was scored with a zero mark. This was done to avoid any biases in answering the questions; where participants could choose any of the other four options randomly that could result in a correct answer without really knowing it and affecting the test score.

3.7. Statistical Analysis and Data Mining

A number of statistical tests were conducted and were appropriate for the different measures investigated. These were based on the types of data being analysed in each study. Each study is discussed in Chapters 4, 5 and 6, respectively. The independent variables in this investigation involved different types of data. We used individual differences (N/E, FI/FD, and F/M) as independent data where all are nominal variables. On the other hand, the dependent data are time spent on topic pages, number of the visited topic pages, gained score, number of visited map pages and number of visited index pages, which are identified as scale variables. The uses of these variables in each study are discussed in Chapters 4, 5 and 6.

The statistical tests used therefore represented the particular variables being analysed. Tests included t-test, ANOVA, K-means, Two-Step and hierarchical clustering tests. In all cases, a significance level of 0.05 was adopted. Statistical analysis was used to provide an objective assessment of any differences observed between variables. Studies using these tests are discussed in the next three chapters.

3.8. Proposed Framework

Many previous studies have demonstrated the importance of individual differences in the design of web-based instruction. Such individual differences have significant effects on user learning in web-based instruction, which may affect the way they learn from, and interact with, hypermedia systems. Many studies have shown that the learners' individual differences and different system features are core concerns that should be taken into account for the effective design of hypermedia learning systems (Chen, et al., 2006; Chen & Liu, 2008; Dillon & Zhu, 1997).

The novelty of our designed WBI system is to integrate the mechanism provided in Chen and Liu (2008) and the framework of Chen et al., (2006). Furthermore, we introduced gender into our analysis to identify behavioural preferences. Additionally, the originality of our design was to build the whole system from the ground up to accommodate the testing environment. This has helped us to reflect on our participants' cognitive styles. Figure 3-9 shows our proposed framework used in this thesis. To develop a learning environment in this framework, individual differences need to be taken into account to ensure they impact on learners' achievements. Thus, our WBI program, which accommodates the needs of some individual differences and their interaction and intersection (Multi-ID), reflects key design elements of navigation tools, display options and content scope in its structure.

3.9. Summary

This chapter outlined the methodology used in this investigation. It has demonstrated that the experimental methodology chosen was appropriate for a number of reasons. Firstly, since the aim of this investigation was to examine individual differences in hypermedia systems, it was necessary to create the required hypermedia program from scratch. Secondly, an experimental methodology allowed for the control of variables to be closely analysed. This chapter has also described the nature of the experiment conducted, detailing the design, the materials used and the sample used. Additionally, it described the pilot study conducted, the data analysis used, and our proposed framework. The following three chapters provide our studies, analysis and discussion of results and findings.

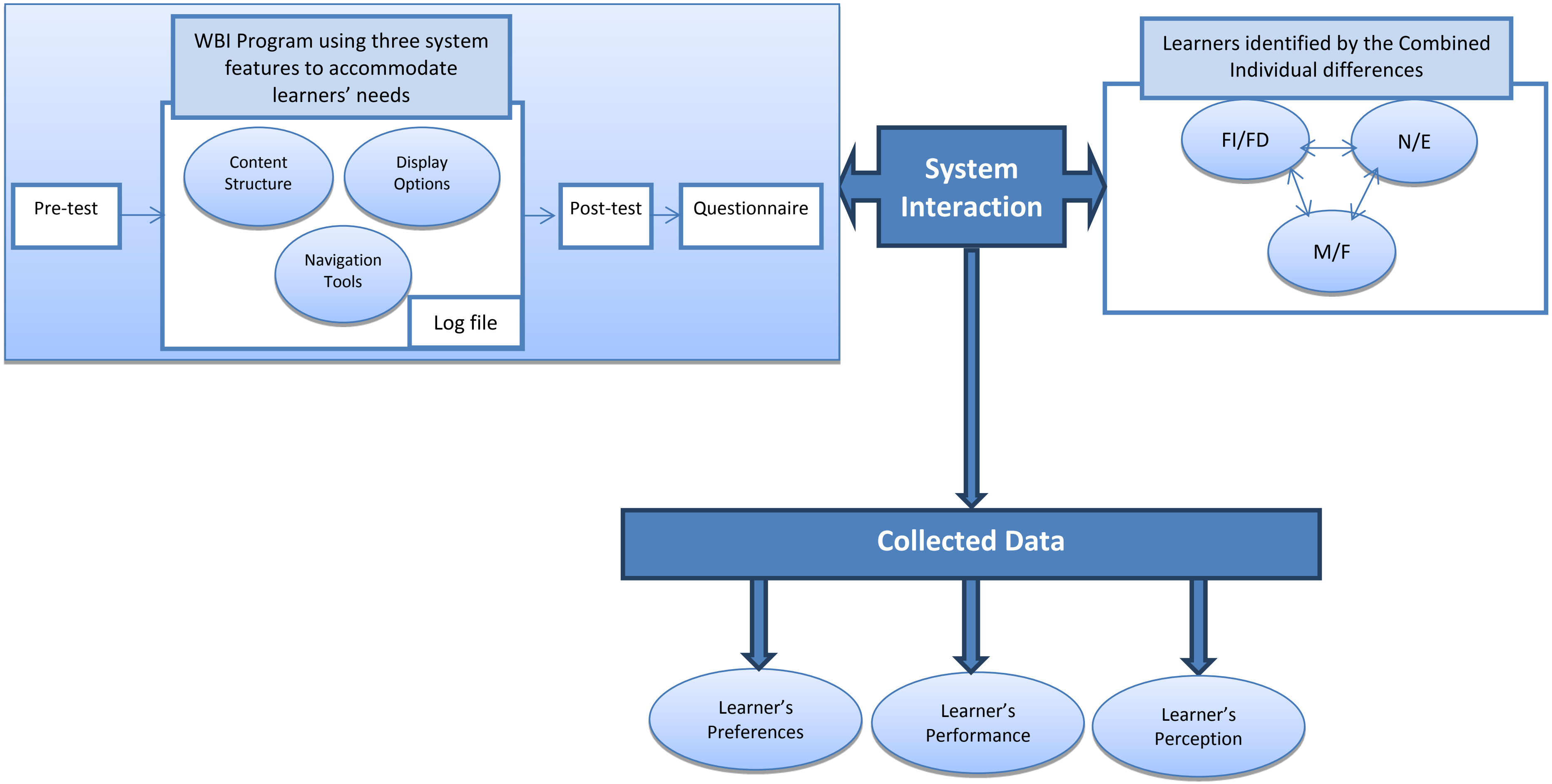


Figure 3-9: Thesis Approach

CHAPTER FOUR

THE EFFECT OF INDIVIDUAL DIFFERENCES ON LEARNING PERFORMANCE USING WEB-BASED INSTRUCTION

4.1. Introduction

Hypermedia systems provide users with freedom of navigation that allows them to develop learning pathways. Many studies have attempted to find ways of building robust hypermedia systems which can accommodate preferences of individual differences through the modelling of individual differences such as learner's prior knowledge and cognitive styles (Calcaterra, et al., 2005; Mitchell, et al., 2005a; Samah, et al., 2011). Our objective in this chapter is two-fold. Firstly, models resulting from Chen and Liu (2008), and Chen, et al., (2006) will be adapted to design a hypermedia system where cognitive style and prior knowledge will be analysed and gender will be incorporated. The WBI program will focus on the structure of using three key design elements (navigation tools, display options and content scope) as well as their interactions in the resulting learning performance. Secondly, we combine three attributes to measure performance (gain score, number of visited pages and time spent on these pages) of the three interacting individual differences. These advances and their associated findings constitute useful contributions to knowledge in the area of hypermedia systems.

In particular, we attempt to answer the following research questions: Firstly (RQ1), does the design of our developed WBI program affect learners' behaviour? Secondly (RQ2), how is a learner's performance affected by relating individual differences? To achieve this, two studies are presented where we compare results from our program with previous studies, thus evaluating its design in one, while a data mining approach is used to investigate the effect of individual differences and how that could influence learner performance in the other.

This chapter is organized as follows. Firstly, the chapter starts by defining the related work to understand learners' behaviour using WBI systems, discussing the factors needed to measure the learners' performance (Section 4.2). This is followed by the presentation of the statistical techniques that have been used on the two studies and the corresponding findings (Section 4.3). At the end of the chapter, a summary is produced (Section 4.4).

4.2. Attributes of Measuring Learners' Performance

Many studies have focused on understanding the performance of learners using web-based systems. Some studies have found that males process information at a more superficial level than females (Large, et al., 2002; Riding & Rayner, 1998; Roy, et al., 2003). Other findings have revealed that there is no relationship between gender differences and search frequency (Hupfer & Detlor, 2006). McDonald and Stevenson (1998) measured navigation performance in terms of speed and accuracy in answering questions and locating particular nodes. Results showed that the performance of experts was better than that of novices. Conversely, Mitchell, et al., (2005a) measured the performance by gain score, calculated as scores of post-test minus pre-test. They found that novices made a greater improvement on the post-test. Moreover, Ford and Chen (2000) found that experts could browse more pages than novices. Kim (2001) investigated how differences in cognitive style and online search experience influenced the search. The findings show that online search experience affected navigational style, whereas cognitive style influenced search time. Experienced searchers tended to initiate jumps more frequently than novices. Additionally, field-dependent learners spent longer in search time than field-independent ones.

Thus, for number of visited pages, studies have found that male, field-dependent and experts browse more pages than female, field-independent and novices (Chen & Liu, 2008; Ford & Chen, 2000; Large, et al., 2002; Roy, et al., 2003). As for time spent in browsing WBI programs, some studies have found that male and field-independent users spent less time than female field-dependent (Chen & Liu, 2008; Lee, et al., 2009; Roy, et al., 2003). Other studies have found that novices achieved a higher g-score than experts (McDonald & Stevenson, 1998; Mitchell, et al., 2005a). However, there is a lack of studies demonstrating the influence of related individual differences on learners' performance using such measurements together after interacting with a WBI system.

Thus, in this study, we investigate and understand the impact of the related individual differences on learners' performance. This will be done after evaluating our proposed system by comparing its results with related studies.

4.3. Results and Findings

In this section, we discuss two studies, as well as statistics and the data mining used in these studies. In the first study, validation of the system will be illustrated, whereas in the second study, the influence of relating individual differences on learning performance will be investigated.

4.3.1. Validation of the System

In an attempt to answer RQ1 (the first study in this section), we evaluated our WBI program by examining the impact of gender, prior knowledge and cognitive style as individual differences on learning behaviour while using our hypermedia systems as described in Chapter 3. This was done using a t-test to compare means of total number of topics pages visited (t-pages), total time spent in the topics pages (t-time) and the gain score (g-score) of each of the individual differences, in order to understand learners' behaviour, and then comparing our results with related studies. In the t-test, individual differences were used as independent variables. The variables t-pages, t-time, and g-score were used as dependent variables.

We started by calculating the mean value of each of the independent variables in addition to the mean of pre-test and the post-test scores for the three individual differences (Table 4-1). The values for the pre-test and post-test are given to provide a global view about how each of the individual differences performed before and after using the WBI program. The mean values were calculated to compare between mean values of experts vs. novices, female vs. male and field-independent vs. field-dependent. For each of the individual differences, we compared the mean of their g-score (mean of pre-test scores subtracted from mean of post-test scores). From the log file, we also collected the total number of topics pages visited, which displayed the topic content (t-pages) and the total time spent in the topics pages in seconds (t-time).

Table 4-1 shows the mean values resulting from each of the individual differences, mean of each of t-pages, t-time, g-score, pre-test scores and post-test scores. After observing the histogram of each factor (dependent vs. independent variables), each variable was found to be approximately normally distributed.

		t-pages	t-time	g-score	Pre-test	Post-test
Prior Knowledge	E	14.23	1,891.19	1.67	11.19	12.85
	N	16.60	2,153.98	4.00	5.56	9.56
	Sig.	>0.05	>0.05	<0.05	<0.05	<0.05
Gender	F	13.50	2,211.43	2.39	8.93	11.33
	M	17.24	1,814.93	3.16	8.11	11.27
	Sig.	<0.05	>0.05	>0.05	>0.05	>0.05
Cognitive Style	FI	15.83	1,765.33	3.65	8.40	12.05
	FD	14.98	2,211.47	2.08	8.63	10.71
	Sig.	>0.05	<0.05	<0.05	<0.05	<0.05

Table 4-1: Compared means of each individual differences

To study learner behaviour, we compared means using a matrix comparison. We compared the means horizontally (by rows) and vertically (by columns) using Table 4-1. The horizontal comparison requires comparison of the mean value for each of the individual differences. In terms of prior knowledge, novices achieved a higher g-score (4.00) than experts (1.67). However, experts visited fewer t-pages (14.23) and spent less t-time (1,891.19). In terms of gender, males achieved a higher g-score (3.16) than females (2.39). Moreover, females visited fewer t-pages (13.50) and spent more t-time (2,211.43). In terms of cognitive style, field-independent learners achieved a higher g-score (3.65) than field-dependent learners (2.08). Moreover, field-independent subjects visited more t-pages (15.83) and spent less t-time (1,765.33).

Secondly, the vertical comparison is when we compare the mean value for each independent variable. In terms of number of pages visited, we found that novices (16.60), males (17.24) and field-independent (15.83) learners visited more t-pages than experts (14.23), females (13.50) and field-dependent (14.98) learners. In terms of time spent on reading topics pages, we found that experts (1,891.19), males (1,814.93) and field-independent (1,765.33) learners spent less time on t-pages than novices (2,153.98), females (2,211.43) and field-dependent (2,211.47) learners. In terms of g-score, we found that novices (4.00), male (3.16) and field-independent learners (3.65) had higher g-scores than experts (1.67), females (2.39) and field-dependent (2.08) learners.

In our attempt to answer RQ1, we evaluate our findings in Table 4-2, which shows the conformity (or otherwise) between our study and previous studies. From the previous discussions, our comparison shows that we have succeeded in implementing a hypermedia system that accommodates preferences of each of the individual differences impacting a learner's performance. Thus, we found that our WBI program did indeed affect learners' behaviour, and have matched the majority of the existing studies' findings in how individual differences affected learners' behaviour interacting with hypermedia systems. Therefore, our findings demonstrate that such individual differences have an impact on learners' behaviour.

<table>
<tr><th colspan="2">Findings of Previous Studies</th><th>Supported Findings</th><th>Further Findings</th></tr>
<tr><td colspan="4">Number of Topic Pages Visited</td></tr>
<tr><td>M visited more pages per minutes than F</td><td>(Large, et al., 2002; Riding & Rayner, 1998; Roy, et al., 2003)</td><td>Supported</td><td rowspan="4">FI browse more pages than FD

N browse more pages than E</td></tr>
<tr><td>FI browse fewer pages than FD</td><td>(Chen & Liu, 2008)</td><td>Not supported</td></tr>
<tr><td>E browse pages more than N</td><td>(Ford & Chen, 2000)</td><td>Not supported</td></tr>
<tr><td>N visited more nodes than E</td><td>(Kim, 2001; Lazonder, et al., 2000)</td><td>Supported</td></tr>
<tr><td colspan="4">Time Spent in Topic Pages</td></tr>
<tr><td>M spent less time on pages than F</td><td>(Large, et al., 2002; Roy, et al., 2003)</td><td>Supported</td><td rowspan="3"></td></tr>
<tr><td>FI spent less time navigating. FD spent more time navigating.</td><td>(Kim, 2001; Lee, et al., 2009)</td><td>Supported</td></tr>
<tr><td>N spent more time than E</td><td>(Kim, 2001; Lazonder, et al., 2000; McDonald & Stevenson, 1998)</td><td>Supported</td></tr>
<tr><td colspan="4">g-score</td></tr>
<tr><td>N achieved higher g-score than E</td><td>(McDonald & Stevenson, 1998; Mitchell, et al., 2005a; Mitchell, et al., 2005b)</td><td>Supported</td><td>M achieved higher g-score than F

FI achieved higher g-score than FD</td></tr>
</table>

Table 4-2: Evaluation of findings compared with previous studies

4.3.2. Influence of Individual Differences on Learning Performance

In this section, we explore whether performance can be affected by the behaviour of the individual differences individually. Moreover, we explore the relationship between individual differences impacts on learner performance. The performance was measured by using three factors: t-pages, t-time and g-score. We used a data mining technique, which is the process of discovering interesting, unexpected or valuable information from large amounts of data (Hand, 2007). Data mining can be divided into *clustering, classification* and *association rules* (Witten, et al., 2011). Clustering methods may be grouped into hierarchical and non-hierarchical (Jain & Dubes, 1999). A hierarchical clustering procedure involves the construction of a hierarchy or tree-like structure, which is a nested sequence of partitions (Fraley & Raftery, 1998); a non-hierarchical or partitioned procedure concludes with a particular number of clusters at a single step.

In our attempt to answer RQ2, we have relied on applying data mining to group users into clusters; a Two-Step Cluster method was used because of its ability to automatically find the optimal number of clusters. This technique can handle both categorical and continuous variable/attributes. It has two steps; firstly, pre-clustering the cases into many small sub-clusters, and then secondly, clustering the sub-clusters resulting from the first step as input and then grouping them into the desired number of clusters. It can also automatically select the number of clusters.

To calculate the distance between clusters, a log-likelihood or Euclidean measure can be used. The log-likelihood distance measure can handle both categorical and continuous variables and is a probability-based distance. It is also assumed that the variables are independent of each other and so are the cases. The distance between two clusters is related to the decrease in log-likelihood as they are combined into one cluster. In calculating log-likelihood, multinomial distributions for categorical variables are assumed, as are normal distributions for continuous variables. On the other hand, the Euclidean distance measure can only be applied if all variables are continuous. The distance between two points, cluster centres, is clearly defined. A cluster centre is defined as the vector of cluster means of each variable. From these two calculations, log-likelihood is used because we have categorical and continuous variables to be clustered such as t-time, t-pages and g-score for each of the individual differences (Chiu, et al., 2001; Zhang, et al., 1996).

The Two-Step Cluster method is an exploratory data mining technique used to reveal clusters in a dataset which are not necessarily obvious using ‘traditional’ statistics. As a result of the clustering method, learners were grouped into five clusters.

Table 4-3 shows the number of participants in each cluster and the number of individual differences allocated into each cluster. For example, the total number of participants allocated in cluster 1 is 21. As for the gender group, all the 21 participants are females (there are no males in this cluster). For prior knowledge, 21 novices are allocated while no expert participants were shown in this cluster. For the field-dependent groups, in this cluster, 3 field-independent and 18 field-dependent participants are allocated.

Table 4-4 shows the comparison of mean values for each cluster with the global mean value of all participants: Cluster 4 has the highest number of participants, whereas the lowest number was allocated to cluster 5 (Table 4-3). In Table 4-4, results show that the highest g-score was in cluster 5 and the lowest in cluster 3. Additionally, we find that highest t-time was in cluster 1 and the lowest in cluster 5. Moreover, the highest number of t-pages was in cluster 5 and the lowest in cluster 3.

Cluster	**Participants**	**F**	**M**	**E**	**N**	**FI**	**FD**
1	21	21	0	0	21	3	18
2	16	0	16	9	7	0	16
3	17	17	0	17	0	0	17
4	22	8	14	22	0	22	0
5	15	0	15	0	15	15	0
Combined	**91**	**46**	**45**	**48**	**43**	**40**	**51**

Table 4-3: Cluster Distribution Frequencies

Cluster	g-score			t-time			t-pages		
	Cluster Mean	Mean Level	Standard Deviation	Cluster Mean	Mean Level	Standard Deviation	Cluster Mean	Mean Level	Standard Deviation
1	3.67	High	2.517	2,442.19	High	1,369.052	15.05	Low	9.677
2	1.81	Low	2.428	1,948.81	Low	964.253	16.50	High	6.782
3	0.76	Low	2.195	2,233.24	High	1,357.356	13.24	Low	6.340
4	2.64	Low	2.150	1,775.23	Low	920.305	13.95	Low	6.779
5	5.00	High	3.094	1,594.07	Low	440.043	19.00	High	4.158
Global mean values	**2.77**		**2.785**	**2,015.36**		**1,105.759**	**15.35**		**7.268**

Table 4-4: Clusters profiles and compared level with global mean values

Figure 4-1 shows a summary of the shared characteristics of individual differences allocated into each cluster. An explanation of each cluster after comparing each value by the global mean values shown in Table 4-4 is as follows:

- Cluster 1: this cluster has 21 learners who had high g-score, spent the highest t-time and visited a low number of t-pages. It contains only females (there are no males in this cluster) who are all novices, with more field-dependent than field-independent learners.
- Cluster 2: this cluster had 16 learners who had low g-score, spent low t-time and visited a high number of t-pages. In this cluster, they are all males and field-dependent learners, with close numbers of experts and novices learners.
- Cluster 3: this cluster had 17 learners who had the lowest g-score, spent high t-time and visited the lowest number of t-pages. It contains only females, experts and field-dependent learners.
- Cluster 4: this cluster had 22 learners who had low g-score, spent low t-time and visited a low number of t-pages. Those learners are all experts, field-independent learners and there are almost twice as many males as females.
- Cluster 5: this cluster had 15 learners who had the highest g-score, spent the lowest t-time and visited the highest number of t-pages. The learners in this cluster are all males who are novices and field-independent learners.

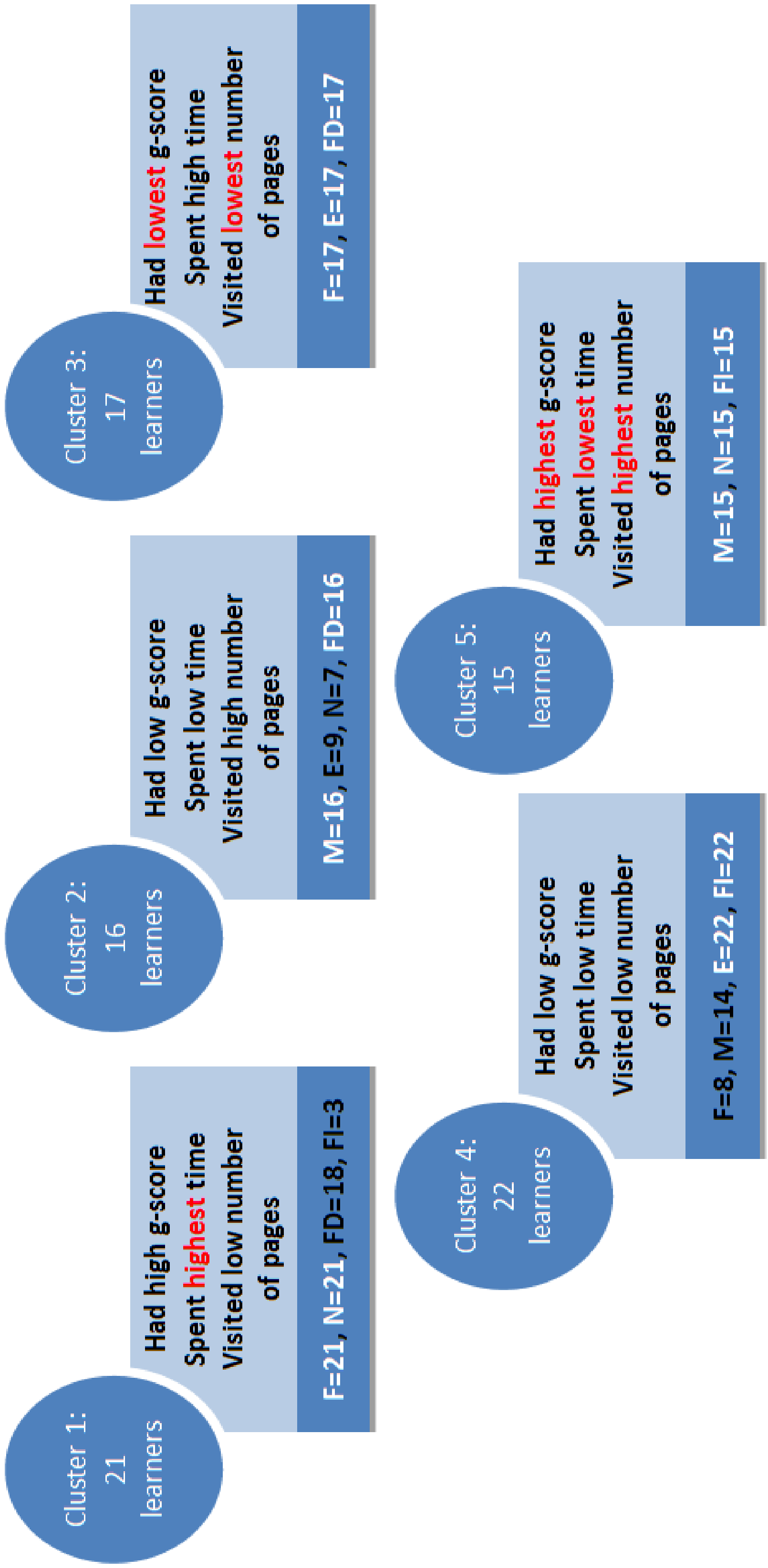


Figure 4-1: Results of related individual differences

We next compared between clusters according to continuous variables. These comparisons are shown in Figure 4-2, Figure 4-3 and Figure 4-4 and by using the number of individual differences allocated in each cluster in Figure 4-1.

In Figure 4-2, we noticed that males browsed more t-pages than females, which is consistent with the findings of Large, et al., (2002), Riding & Rayner (1998), and Roy, et al., (2003). We also found that novices browsed more t-pages than experts, which is inconsistent with the findings of Ford and Chen (2000) but consistent with the results of Kim (2001). In our study, we found that males spent less t-time than females. This finding is consistent with the findings of Large, et al., (2002) and Roy, et al., (2003) that males spend less time than females in visiting pages. We also found that field-independent learners spent less t-time than field-dependent. The finding is consistent with the findings of Kim (2001) and Lee, et al., (2009) that field-independent learners spent less t-time than field-dependent in visiting pages. From Figure 4-4, 36 novices of a total 43 are located in clusters 1 and 5, where those clusters contain learners who achieved a high g-score. This finding is consistent with both that of McDonald and Stevenson (1998), and Mitchell, et al., (2005a).

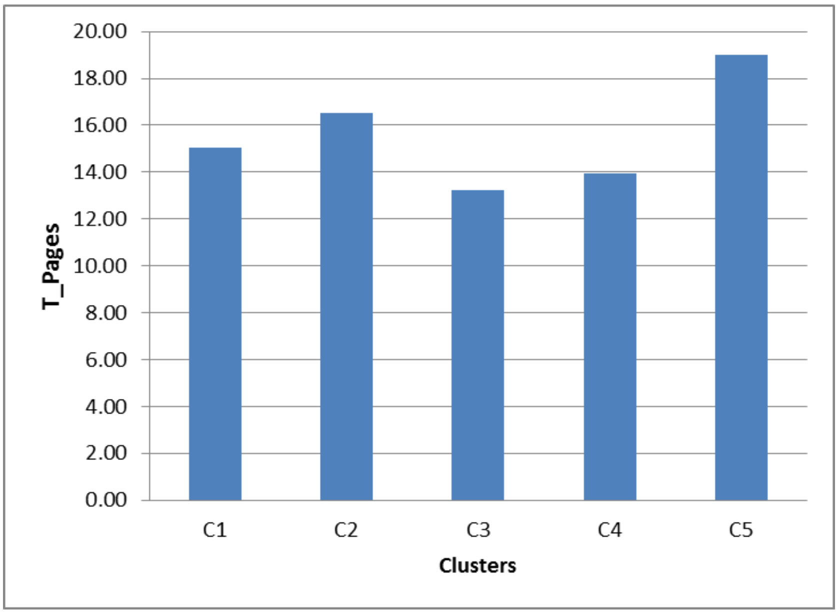


Figure 4-2: Mean values of t-pages visited in each cluster

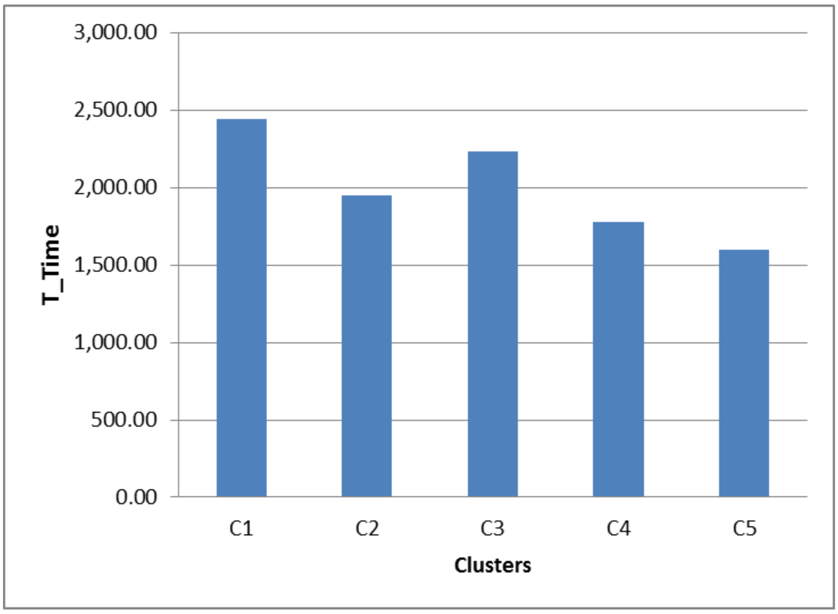


Figure 4-3: Mean values of t-time in each cluster

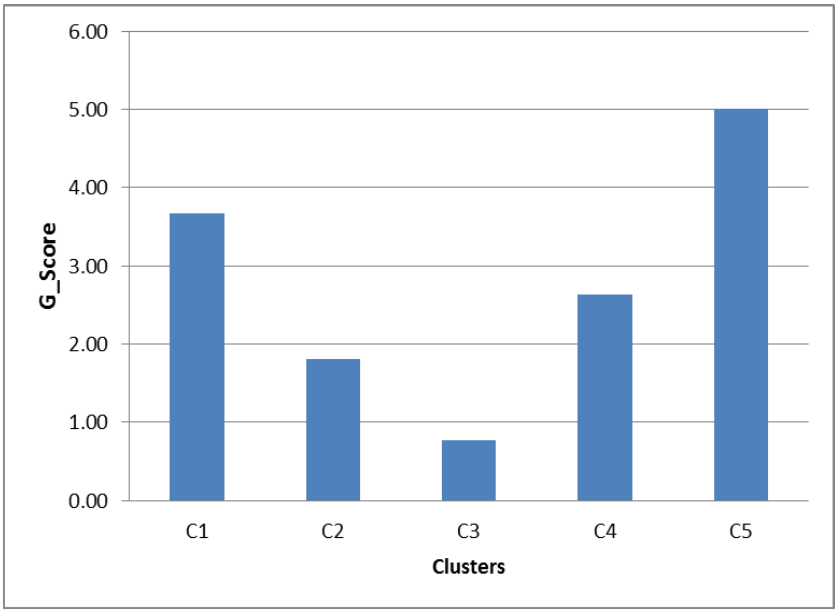


Figure 4-4: Mean values of g-scores in each cluster

To summarise the findings of study 2, we found that performance can be affected by the behaviour of the individual differences individually. Additionally, we found that the relationship between individual differences had an even higher impact on a learner’s performance.

As a result of Study 1 and in answering RQ1 (does the design of our developed WBI program affect learners' behaviour?); we found evidence to support the view that our WBI program did indeed affect learners' behaviour. Table 4-2 shows that our findings from our WBI program have matched more than majority of existing studies' findings. Therefore, the evidence can be clearly marked by observing Table 4-1, which indicates that our novices, males and field-independent participants had the highest knowledge gain from utilizing our WBI program. Results from Study 2 helped us answer RQ2 (How is a learner's performance affected by relating individual differences?). By applying data mining methods to our collected data we have related several individual differences (gender, cognitive style, and prior knowledge) into five clusters. Figure 4-5 answers RQ2 by demonstrating related individual differences and their effect on their learning behaviour. Thus, we can note the following observations which can help to do more investigations on how individual differences may affect learners' behaviour:

1. Learners who have low g-score, low t-time and high t-pages are males who are field-dependent.
2. Learners who have high g-score, low t-time and high t-pages are males who are novices and field-independent.
3. Learners who have high g-score, high t-time, and low t-pages are novices and females.
4. Learners who have low g-score, low t-time, and low t-pages are experts who are also field-independent.
5. Learners who have low g-score, high t-time and low t-pages are females, experts and field-dependent.

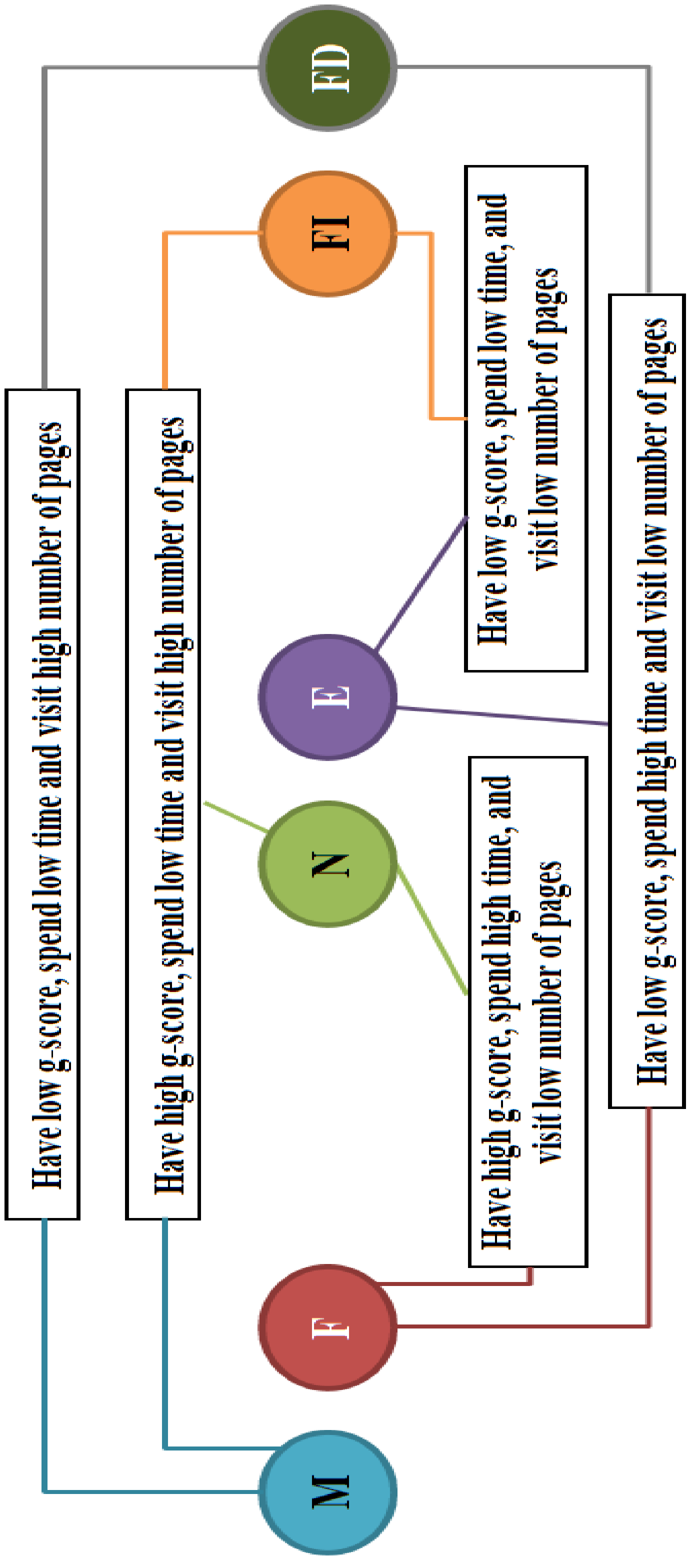


Figure 4-5: Conclusion of related individual differences (M: male, F: female N: novice, E: expert, FI: field-independent and FD: field-dependent)

4.4. Summary

The aim of this chapter was to examine the gender, prior knowledge and cognitive style as individual differences in learning behaviour while using hypermedia systems. We built a WBI program to be used for data collection from the participants in the experimental study. Our findings demonstrate that such individual differences have an impact on learners' behaviour. Additionally, we have found that the relationship between individual differences had an even higher impact on learners' performance. Few previous studies have been carried out to investigate system features (navigation tools, display options and content scope) to see how they can help users acquire information to meet their individual needs. In this chapter, we extended previous work (Chen, et al., 2006; Chen & Liu, 2008) by incorporating one of the important individual differences, gender, as well as studying their interactions in learning performances. Additionally, it was shown that it is essential to take into account a learner's identification using more than one of the individual differences to understand behaviour in using web-based systems. Thus, in the next chapter we will investigate how the intersection of individual differences (Multi-ID) may affect learners' behaviours resulting in its impact on their preferences and perception.

Therefore, the preferences that have been accommodated using system features presented by Chen et al., (2006) and Chen and Liu (2008) have been recognised to play an influential role in student learning patterns within the WBI program. More investigations on how learners with different individual differences interacted with our proposed WBI program will be handled in Chapter 5. More specifically, we will focus on learners' performances and perception in using our WBI program, which was designed using the three system features.

CHAPTER FIVE

THE INFLUENCE OF MULTIPLE INDIVIDUAL DIFFERENCES ON LEARNER PREFERENCES

5.1. Introduction

There has been an increasing focus on web-based instruction (WBI) systems which accommodate individual differences in educational environments. Much of those studies have focused on understanding learners’ preferences and behaviours using WBI systems. In this chapter, we investigate the influence of multiple individual differences on learners’ preferences using a specially-designed WBI program which accommodates learning needs using navigation tools. As our WBI program logs all the navigational activities of each user, we use the log file data to conduct our analysis. In this chapter, we study three individual differences (cognitive style, prior knowledge, and gender) to evaluate their effect on user preferences while acquiring knowledge. Moreover, we analyze each of the individual differences individually and compare our findings with previous studies. Henceforward, we analyze several combinations of individual differences to investigate how each combination influences the learning preferences based on our individual tests. We found that some individual differences and their combination have an impact on learners' preferences when choosing navigation tools. The related individual differences therefore altered a learner’s preferences. Therefore, designers of WBI applications need to consider the combination of individual differences rather than considering them individually.

This chapter is structured as follows. In Sections 5.2 to Section 5.4, we investigate learners’ preferences and perception using the three system features (navigation tools, content scope and display option). In Section 5.2, we investigate the behaviour of learners using the navigation tools. In Section 5.3, we investigate the behaviour of learners using the second system features, the content scope, using their log file. Additionally, we try to understand their perception which will be analyzed using their survey results. After that, in Section 5.4, understanding learners’ perception using the third system feature, the display options, is discussed. Learners’ perception and satisfaction of using our WBI system is provided in Section 5.5. At the end of the chapter, a summary is produced (Section 5.6).

5.2. Learners' Preferences Using Navigation Tools

5.2.1. Hypermedia and Program Design Elements, Findings and Gaps

Some studies have shown that prior user knowledge plays a significant role in the use of navigation tools in hypermedia learning systems (Chen, et al., 2006; Lee, et al., 2009; Minetou, et al., 2008). Many studies have shown that index tools are helpful for experts. On the other hand, map and menu tools have been shown to be beneficial for novice learners (Chen, 2010; Chen, et al., 2006; Minetou, et al., 2008). However, others have argued that there is no significant difference between experts and novices in the use of a hierarchical map (Calisir & Gurel, 2003), where experts and novices opened an equal number of nodes in a hierarchical document. The lack of significant differences is inconsistent with the findings of McDonald and Stevenson (1998) where it was found that experts opened more nodes than novices in a hierarchical environment. In this section, we explore those contradictions from the perspective of existing studies. This will be done by investigating the impact of Multi-ID on learners' behaviour and whether it has a significant impact on altering learners' preferences. Moreover, we will focus on gender since there is a general lack of studies considering their preferences in using the navigation tools. Additionally, we will investigate prior knowledge preferences using navigation tools and compare our results with existing studies. The preferences of learners with different cognitive styles, more specifically field-dependent and field-independent, in using navigation tools, were known in advance since they were identified using the log file described in Section 3.3.1.

Existing studies have investigated the behaviour of individual differences *individually* (cognitive style, prior knowledge or gender) to understand learner preferences. However, in our study we investigate the intersection of two and three individual differences using navigational tools. This will henceforward be known as multiple individual differences (Multi-ID). The Multi-ID we studied were the intersections of two and three individual differences. The two individual differences of the Multi-ID were gender vs. cognitive style, prior knowledge vs. cognitive style, and gender vs. prior knowledge. The third intersection of three individual differences is gender vs. cognitive style vs. prior knowledge.

Previous findings have shown that a learners' cognitive style has an impact on learning preferences. Field-independent users often prefer an alphabetical index, whereas field-dependent users often use a hierarchical map (Chen, 2010; Chen & Liu, 2008; Farrell & Moore, 2001; Ford & Chen, 2000). While those studies have investigated the cognitive style alone, it is not clear how the cognitive style of learners is influenced by gender and prior knowledge. We also examined the intersection of gender and prior knowledge without cognitive style to understand preferences in using navigation tools. From previous discussions, we attempt to answer the following research questions using our analysis;

RQ3: "Does Multi-ID have an influence on learners' preferences using the navigational tools of our WBI program?" and

RQ4: "How do the factors of Multi-ID affect learners' preferences in using navigation tools of our WBI program?"

5.2.2. Using Statistical Analysis and Data Mining

In this chapter, we use two statistical tests, an independent-sample t-test and analysis of variance (ANOVA). The independent-sample t-test is used to determine whether there is a statistically significant difference between means in two unrelated groups. ANOVA is useful in comparing three or more groups or variables (by comparing the means) for statistical significance. A post hoc analysis of mean differences using a Tukey's Honestly Significant Difference Test (Tukey's HSD) was used to investigate significant differences. Thus, we expanded the ANOVA test with Tukey's HSD to identify which groups were significantly different from each other.

Using an independent-sample t-test, we firstly studied the preferences of our participants based on individual differences individually. Secondly, we use the ANOVA test because it allows the testing of differences for three or more independent groups (Multi-ID). More specifically, the frequencies of using (preferring) the hierarchical map and the index between groups were analyzed. For both tests, we considered the independent variables to be participants' cognitive style, prior knowledge and gender. The dependent variable used for both tests was the number of pages visited from the index and map navigational tools. We chose the t-test because it compares the means of two groups, in our case, field-dependent vs. field-independent, novice vs. expert, and males vs. females. We use the ANOVA test to investigate the learning preferences of Multi-ID. For our study, we grouped our independent variables into four and eight groups. Four groups were the result of intersecting two independent variables, while the eight groups were the result of intersecting all three of the independent variables. The novelty of our study is to investigate the learning preferences of those pre-identified groups. A significance level of $p < 0.05$ was adopted for the studies. In the next section, we highlight our findings of learners' preferences in using navigation tools for those who were pre-identified using the individual differences individually or by using multiple individual differences (Multi-ID).

5.2.3. Results and Findings Discussions

5.2.3.1. Using t-test

In this study, we discuss the preferences of each individual difference in using the navigation tools of our WBI program. An independent-samples t-test was used to study participants' preferences. This was done by investigating the mean values of visited map and index pages for each individual difference collected from the recorded log file.

Cognitive style:

Previous studies have shown that field-dependent subjects often use a hierarchical map, whereas field-independent subjects often access the alphabetical index (Chen & Liu, 2008; Chen, 2010; Farrell & Moore, 2001; Ford & Chen, 2000). Using a t-test, we identified field-dependent participants (51) by those who preferred visiting map pages (mean = 12.63 and SD = 7.60) more than index pages (mean = 2.35 and SD = 2.93). We identified field-independent participants (40) by those who preferred visiting index pages (mean = 12.35 and SD = 5.88) more than map pages (mean = 3.50 and SD = 2.76).

Gender:

Our participants comprised 46 females and 45 males. After they interacted with the WBI program, we found that using index pages had a significant impact based on gender (p of map is > 0.05 and p of index < 0.05). Results show that females preferred to use map pages (mean = 10.04 and SD = 7.95) more than index pages (mean = 3.46 and SD = 4.27). On the other hand, we found that males preferred to use index pages (mean = 10.11 and SD = 7.06) compared to map pages (mean = 7.16 and SD = 6.76).

Prior knowledge:

Our participants were distributed as 48 experts and 43 novices (Table 5-1). We found that (p of map is > 0.05 and p of index < 0.05). The calculated means of Table 5-1 show that novices and experts both preferred using the map more than index pages. Thus, in using map pages, our findings were supported by previous studies that map pages were preferred by novices over index pages (Chen, et al., 2006; Chen, 2010; Minetou, et al., 2008). Our findings are also consistent with previous studies in which experts preferred using map pages compared to index pages (Calisir & Gurel, 2003; McDonald & Stevenson, 1998). These findings are inconsistent with previous studies in using index tools, where Chen, et al., (2006) found that index tools were helpful for experts more than map tools.

	E: Expert, N: Novice	Number of participants	Mean	Std. Deviation
Topics pages from map	E	48	8.02	6.30
	N	43	9.28	8.65
Topics pages from index	E	48	6.23	6.02
	N	43	7.33	7.380

Table 5-1: Identifying participants according to prior knowledge

5.2.3.2. Using ANOVA Test

This test requires the intersection of two or more independent variables, in our case the individual differences. The Multi-ID was divided into the following groups: a) *gender vs. cognitive style*, b) *cognitive style vs. prior knowledge*, c) *gender vs. prior knowledge*, and d) *gender vs. cognitive style vs. prior knowledge.* The Tukey test was used to identify which groups were significantly different from each other.

a) Gender vs. cognitive style (G-CS) groups:

In this part of the study, Multi-ID groups were identified as follows:

1. FFI (11 participants): Female Field-independent.
2. MFI (29 participants): Male Field-independent.
3. FFD (35 participants): Female Field-dependent.
4. MFD (16 participants): Male Field-dependent.

The ANOVA test shows significant results in a participants' preference of navigation tools. It is evident in the results of map pages (F = 17.419, df = 3 and p< 0.001) and index pages (F = 52.127, df = 3 and p< 0.001).

Using Tukey's (HSD) we found that MFD and FFD preferred using map pages (Table 5-2, Table 5-3) over index pages. On the other hand, MFI and FFI preferred the use of index pages more than map pages (Table 5-2, Table 5-3). Although MFI and FFI used index pages more than map pages, the Tukey test revealed that males showed a significant difference in preferring index pages more than females. More specifically, MFI visited more index pages than FFI, consistent with our t-test result that females preferred using map pages more than index pages. However, we were expecting to find FFD to have the highest preference on using map pages based on our t-test results, where F preferred map pages more than M, but we found that MFD had the highest preference of map pages. This means that gender did influence the learning preferences of FD participants in using map pages.

	Subset for alpha = .05	
G_CS	1	2
FFI	3.36	
MFI	3.55	
FFD		12.14
MFD		13.69
Sig.	1.000	.863

Table 5-2: Results of Tukey test for G-CS groups using map pages

	Subset for alpha = .05		
G_CS	1	2	3
FFD	2.14		
MFD	2.81		
FFI		7.64	
MFI			14.14
Sig.	.959	1.000	1.000

Table 5-3: Results of Tukey test for G-CS groups using index pages

b) Prior knowledge vs. Cognitive style (PK-CS) groups:

In this part of the study, Multi-ID groups were identified as follows:

1.EFI (22 participants): Expert Field-independent.

2.NFI (18 participants): Novice Field-independent.

3.EFD (26 participants): Expert Field-dependent.

4.NFD (25 participants): Novice Field-dependent.

The ANOVA test shows significant results in participants' preference of navigation tools. It is evident in the results of map pages (F = 17.360, df = 3 and $p< 0.001$) and index pages (F = 41.981, df = 3 and $p< 0.001$). We found that NFD and EFD preferred using map pages (Table 5-4, Table 5-5) over index pages. More specifically, we found that NFD visited more map pages than EFD, consistent with our t-test results that novices preferred using map pages more than experts. On the other hand, we found that NFI and EFI preferred using index pages (Table 5-4, Table 5-5) more than map pages. Although NFI and EFI used index pages more than map pages, the Tukey test revealed that prior knowledge significantly influenced the cognitive style of the participants. More specifically, NFI visited more index pages than EFI, which is consistent with our t-test results but inconsistent with previous studies, which found that novice learners preferred using map pages to index pages (Chen, 2010; Chen, et al., 2006; Minetou, et al., 2008).

	Subset for alpha = .05	
PK_CS	1	2
EFI	3.32	
NFI	3.72	
EFD		12.00
NFD		13.28
Sig.	.996	.893

Table 5-4: Results of Tukey test for PK-CS groups using map pages

	Subset for alpha = .05		
PK_CS	1	2	3
NFD	2.24		
EFD	2.46		
EFI		10.68	
NFI			14.39
Sig.	.998	1.000	1.000

Table 5-5: Results of Tukey test for PK-CS groups using index pages

c) Gender vs. prior knowledge (G-PK) groups:

In this part of the study, Multi-ID groups were identified as follows:

1. MN (22 participants): Male novice.
2. ME (23 participants): Male expert.
3. FE (25 participants): Female expert.
4. FN (21 participants): Female novice.

The ANOVA test shows significant results in participants' preference for navigation tools. It is evident in the results of index pages ($F = 10.655$, $df = 3$ and $p < 0.001$). On the other hand, there was no significant result in using map pages ($F = 2.084$, $df = 3$ and $p > 0.05$). Although there were no significant differences between G-PK learners in using map pages (Table 5-6), we found that females were more inclined to use map pages than males, consistent with our t-test results. Additionally, the Tukey test clearly revealed that males were more inclined to use index pages (Table 5-7), also consistent with our t-test results.

	Subset for alpha = .05
G_PK	1
MN	6.73
ME	7.57
FE	8.44
FN	11.95
Sig.	.086

Table 5-6: Results of Tukey test for G-PK groups using map pages

	Subset for alpha = .05	
G_PK	1	2
FN	3.10	
FE	3.76	
ME		8.91
MN		11.36
Sig.	.980	.491

Table 5-7: Results of Tukey test for G-PK groups using index pages

From Table 5-7, we can observe that both males and novices had the highest preference for index pages, which confirms the results previously discussed in parts (a) and (b) as well as the t-test results. This is inconsistent with previous studies, which indicate that novices prefer map pages to index pages when being investigated individually (Chen, 2010; Chen, et al., 2006; Minetou, et al., 2008). This inconsistency clearly indicates the influence of gender over prior knowledge. It is evident that when gender was combined with prior knowledge, we noticed a change in the preferences of novices for index over map.

d) ***Gender vs. cognitive style vs. prior knowledge (G-CS-PK) groups:***

In this part of the study, Multi-ID groups were identified as follows:

1.FFIE (8 participants): Female field-independent expert.

2.MFIN (15 participants): Male field-independent novice.

3.MFIE (14 participants): Male field-independent expert.

4.FFIN (3 participants): Female field-independent novice.

5.FFDE (17 participants): Female field-dependent expert.

6.FFDN (18 participants): Female field-dependent novice.

7.MFDE (9 participants): Male field-dependent expert.

8.MFDN (7 participants): Male field-dependent novice.

Using the ANOVA test, we found that there were significant results when participants used navigation tools. The ANOVA results were observed for map pages (F = 7.403, df = 7 and $p < 0.001$) and for index pages (F = 22.841, df = 7 and $p < 0.001$).

From Table 5-8, we observe that FFDN, MFDN, and MFDE have significant differences in their preference of using map pages from FFIE, MFIN, and MFIE. This means that the intersection of gender and prior knowledge did not have any impact on cognitive style preferences. However; the Tukey test indicates that FFIN and FFDE had some common ground when using map pages; Table 5-9 shows that they are different in their preference for using index pages. Furthermore, the Tukey test results in Table 5-9 revealed that FFDN, FFDE, and MFDN had significantly different preferences when using index pages to those in FFIN, MFIE and MFIN. Additionally, the Tukey test indicates that MFDE and FFIE had close preferences when using index pages; however, from Table 5-8, they do not share any preferences when using map pages.

Based on our findings from (a), (b) and (c) we might have expected to find that novices exceeded experts in their preferences; however, we found that experts had a higher preference when using map pages. More specifically, MFDE used map pages more than MFDN. This is inconsistent with part (c) and the results of our t-test, as well as previous studies (Chen, 2010; Chen, et al., 2006; Minetou, et al., 2008). Additionally, we were expecting to find the use of map pages were preferred by females more than males according to our findings in part (c) and the t-test results. However, we found that males had a higher preference for using map pages than females. More specifically, MFDE and MFDN had the highest preference among map users, followed by FFDN and FFDE.

	Subset for alpha = .05	
Human groups	1	2
FFIE	2.88	
MFIN	3.53	
MFIE	3.57	
FFIN	4.67	4.67
FFDE	11.06	11.06
FFDN		13.17
MFDN		13.57
MFDE		13.78
Sig.	.130	.061

Table 5-8: Results of Tukey test for G-CS-PK groups using map pages

	Subset for alpha = .05			
Human groups	1	2	3	4
FFDN	2.11			
FFDE	2.18			
MFDN	2.57			
MFDE	3.00	3.00		
FFIE	7.13	7.13	7.13	
FFIN		9.00	9.00	
MFIE			12.71	12.71
MFIN				15.47
Sig.	.206	.066	.110	.865

Table 5-9: Results of Tukey test for G-CS-PK groups using index pages

We investigated the influence of the intersection of two and three individual differences on the learning preferences of participants using navigation tools. We tested the preferences of the individual differences such as gender and prior knowledge individually, and we then combined gender, prior knowledge and cognitive style to investigate if navigational preferences would be affected by the intersection(s).

When investigating a combination of individual differences, our conclusion indicates that learning preferences are influenced in a different way when those individual differences were investigated individually. We found that the combination of those factors had a marked impact on learners' preferences and played a significant role in changing the preferences using their navigational pace. Designers of WBI applications need to consider the combination of individual differences, rather than considering them individually. Moreover, designers of hypermedia systems do not need to consider prior knowledge individually as a part of the design process - our results show that prior knowledge does not influence the navigational preferences of participants. As we have shown, it is clear that learning preferences are influenced by gender when combined with prior knowledge. Moreover, few previous studies have investigated how navigation tools can help users with gender differences acquire information to meet their individual needs; we have extended previous work (Chen & Liu, 2008; Chen, et al., 2006) into our study of one of the important individual differences. Designers should take the intersection between individual differences into consideration when identifying a learner, since this can have a great impact on the alteration of a learner's preferences. These advances and their associated findings constitute the key contributions to knowledge in the area of hypermedia systems.

5.2.4. Learners' Perception of Using Navigation Tools

In this section, we illustrate the findings of our questionnaire about learners' perceptions in using navigation tools. The closed statements in our questionnaire were adapted from different studies using standardized questionnaires (Ajzen & Fishbein, 1975; Frias-Martinez, et al., 2007; Frias-Martinez, et al., 2008; Lewis, 1995; Mampadi, et al., 2011; Mitchell, et al., 2005a; Mitchell, et al., 2005b). Our questionnaire was used to capture the user's subjective feelings and perceptions regarding the hypermedia learning environment of our experiment. More details about the questionnaire are explained in Section 3.3.4. We used the data collected from the questionnaire, more specifically data collected from the following statements:

Q6: I like the fact that the WBI allows me to learn topics in specified frames.

Q7: I like the fact that I have the ability to control the pace of instruction using a hierarchical map.

Q8: I like the fact that I have the ability to control the pace of instruction using the index.

Q11: I like the fact that I can see both the hierarchical map frame and the index frame.

After analyzing the results of those statements, we found that most of the learners were satisfied and had a positive perception of the WBI program; the results were skewed to the options "Agree" and "Strongly Agree" (Figure 5-1). The questionnaire data for each statement is provided in Appendix F.

To look at the data from the individual differences view, we note the following from Figure 5-2:

- For Q6, MFDE learners had the least mean value in the agreement of this statement. However, referring to Q6 in Figure 5-1, we found that most of the learners chose the "Agree" option (6 of 9 MFDE learners).
- For Q7, we found that MFIN learners had the lowest mean value in the agreement of this statement. However, referring to Q7 in Figure 5-1, we found that a number of participants chose the "Neutral" option, 6 of 15 participants, with 8 equally distributed between the choices "Agree" and "Strongly Agree". One explanation for this is that the participants were field-independent learners who mostly preferred using index frames.

- For Q8, we found that FFDN learners had the lowest mean value in the agreement for this statement. From Q8 in Figure 5-1, we found that the option “Strongly Disagree” appeared here, which probably affected their results. One explanation is that participants were field-dependent learners who mostly prefer using map frames.
- For Q11, all the mean values appeared for the participants to be “Agree” and “Strongly Agree”. Learners liked the design of the system of seeing both map and index frames at the same time in one window.

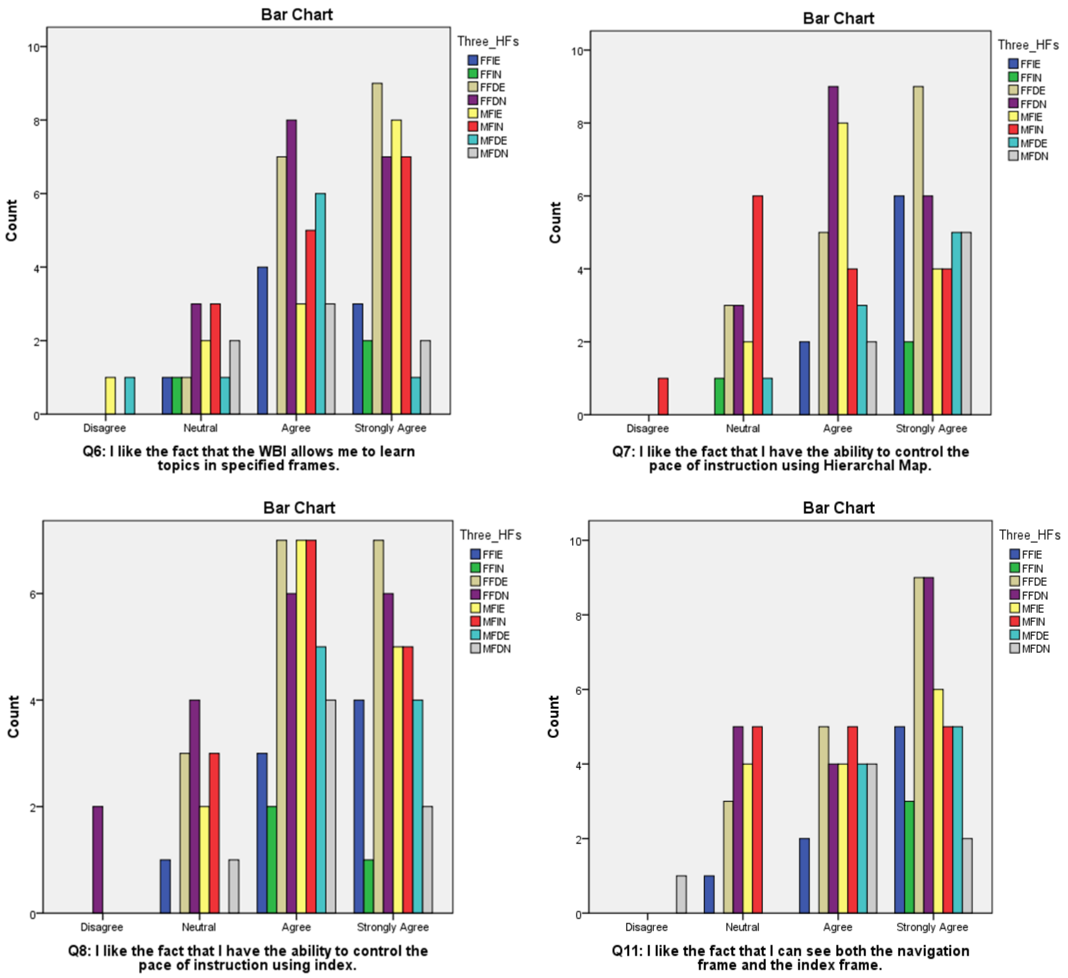


Figure 5-1: Questionnaire results for Q6, Q7, Q8, and Q11

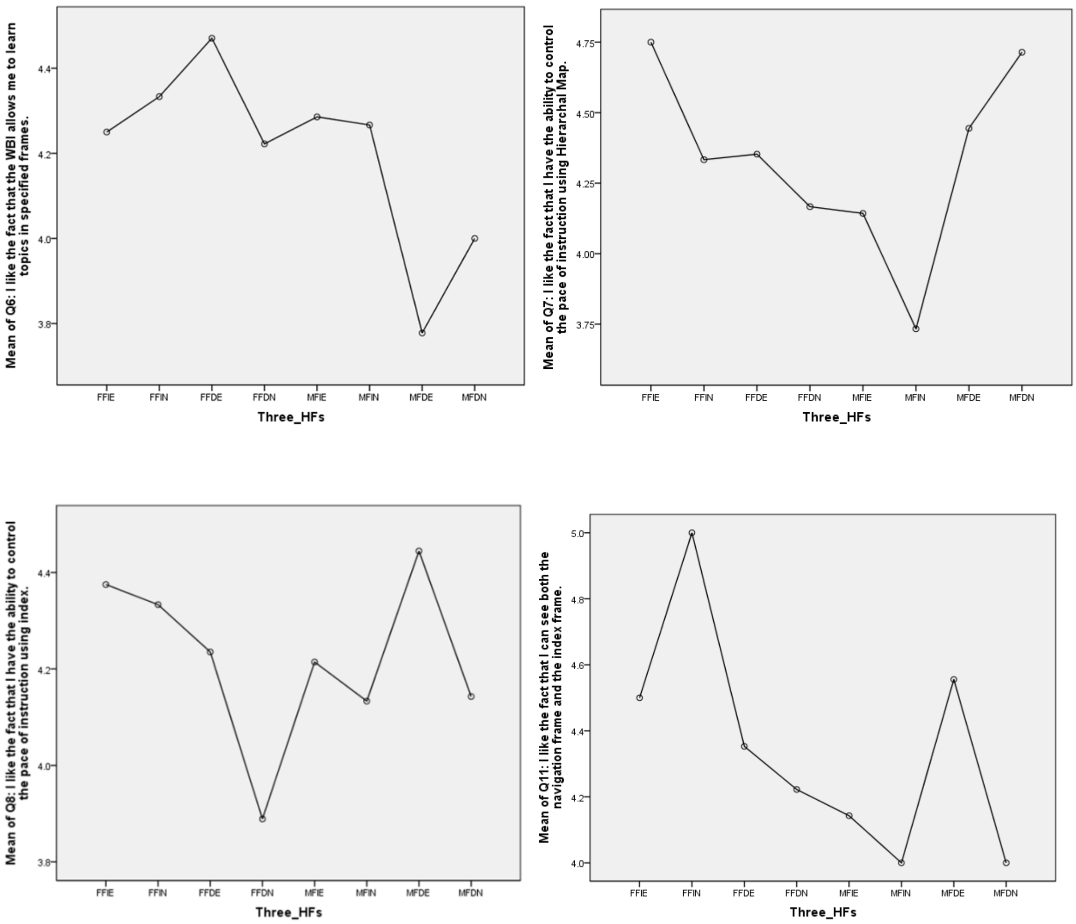


Figure 5-2: Means plot diagrams for Q6, Q7, Q8, and Q11 for each Multi-ID

5.3. Learners' Preferences Using Content Scope

The WBI program provides users with an additional hyperlinked pop-up window named "Further Details" which displays more in-depth instructions about the topic they are viewing. That was one of the possible solutions to deal with the learners' different requirements as suggested in the design of Chen and Liu (2008); this is a secondary window to provide additional information about a selected topic. A K-means clustering test was used to analyze learners' behaviour in using the Further Details pages. We used three *K* values to place learners into three different clusters. This was done to gain a deep understanding and more evidence as to the nature of the resulting data.

5.3.1. The Use of Further Details Pages

After calculating the number of Further Details pages that each learner had visited, we found that most of the learners did not visit those pages. However, some learners had, but this number was very low. From Table 5-10 we notice that the maximum number of pages visited was 5, which were visited by one participant of the total number of participants (91 participants). Also, one participant visited 4 pages. Additionally, 2 and 3 pages were visited by 4 and 3 participants, respectively. Moreover, we found that 74.70% of learners did not visit these pages and 15.40% of learners had visited such pages only for one visit. On the other hand, the other 9.90% of learners had visited such pages more than one time.

Figure 5-3 illustrates clearly that the majority of learners are those who did not visit the pages or those who visited them just once. Data mining was applied using a k-means cluster test. This test was done using 2, 3 and 4 values of *k* to have more evidence on the nature of our data.

Number of pages visited		Number of participants visiting these pages	Percentage for number of participant
Valid	0	68	74.7
	1	14	15.4
	2	4	4.4
	3	3	3.3
	4	1	1.1
	5	1	1.1
	Total	91	100.0

Table 5-10: Frequencies of using Further Details pages

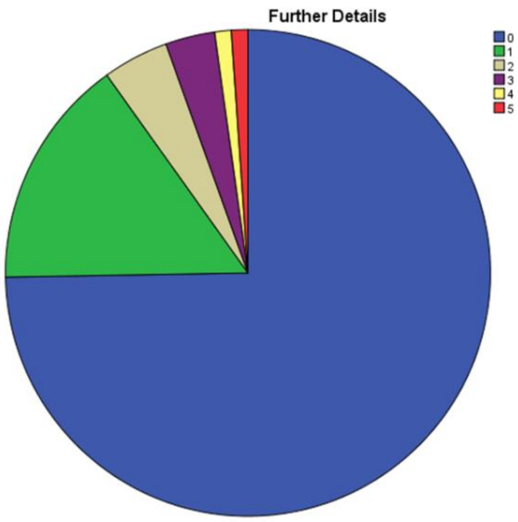


Figure 5-3: The distribution of number of learners using Further Details pages

- ***2 Clusters***

When we applied *K*=2 we found from Table 5-11 that participants who visited the Further Details pages once or did not visit such pages were located in cluster 2, whereas all others were located in cluster 1 (sig <0.01). Figure 5-4 illustrated the number of participants who visited the pages (0 to 5 pages) and their division in these two clusters.

		Number of Further Details pages						Number of participants in each cluster
		0	1	2	3	4	5	
Cluster Number	1	0	0	4	3	1	1	9
	2	68	14	0	0	0	0	82
Total		68	14	4	3	1	1	91

Table 5-11: Two clusters, number of Further Details pages and number of participants

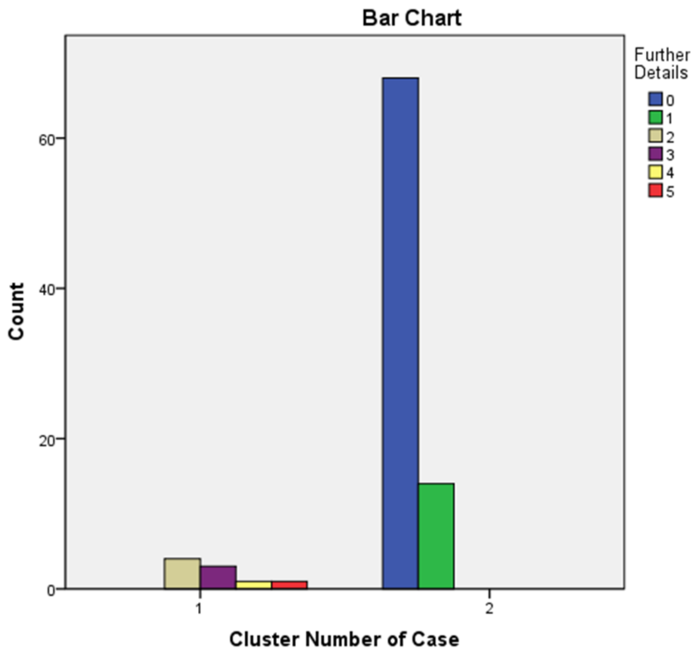


Figure 5-4: Further Details pages in two clusters

- ***3 Clusters***

When we applied *K*=3 we found from Table 5-12 that participants who either visited 4 or 5 Further Details pages were located in cluster 1. On the other hand, those who visited the pages once or did not visit such pages remain in one cluster (cluster 2). Others who visited 2 or 3 pages are located in cluster 3 (sig <0.01). Figure 5-5 illustrates the number of participants who visited the pages (0 to 5 pages) and their division in these three clusters.

		Number of Further Details pages						Number of participants in each cluster
		0	1	2	3	4	5	
Cluster Number	1	0	0	0	0	1	1	2
	2	68	14	0	0	0	0	82
	3	0	0	4	3	0	0	7
Total		68	14	4	3	1	1	91

Table 5-12: Three clusters, number of Further Details pages and number of participants

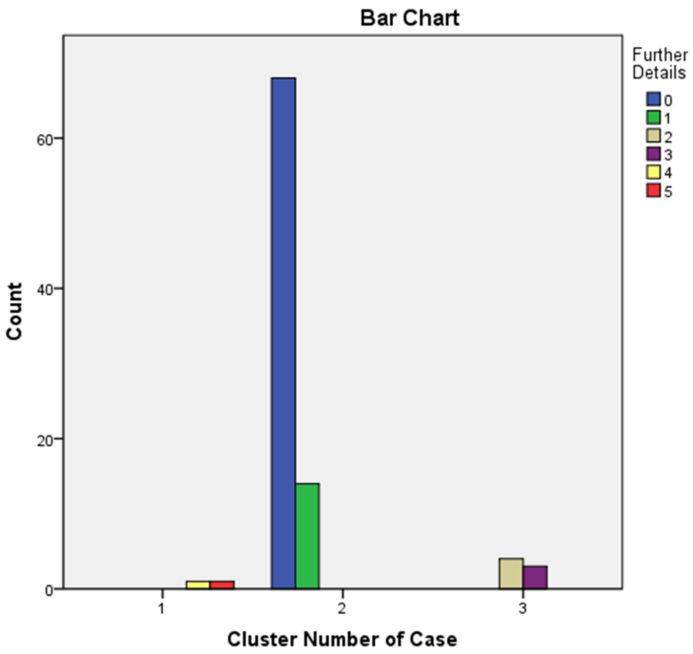


Figure 5-5: Further Details pages in three clusters

- ***4 Clusters***

When we applied *K*=4 we found from Table 5-13 that participants who either visited 4 or 5 Further Details pages remain in one cluster (cluster 1). Additionally, those who visited the pages once or did not visit such pages remain in one cluster (cluster 2). On the other hand, others who were visited 2 or 3 pages are located separately in cluster 4 and cluster 3, respectively (sig <0.01). Figure 5-6 illustrates the number of participants who visited 0 to 5 pages and their division into these four clusters.

		Number of Further Details pages						Number of participants in each cluster
		0	1	2	3	4	5	
Cluster Number	1	0	0	0	0	1	1	2
	2	68	14	0	0	0	0	82
	3	0	0	0	3	0	0	3
	4	0	0	4	0	0	0	4
Total		68	14	4	3	1	1	91

Table 5-13: Four clusters, number of Further Details pages and number of participants

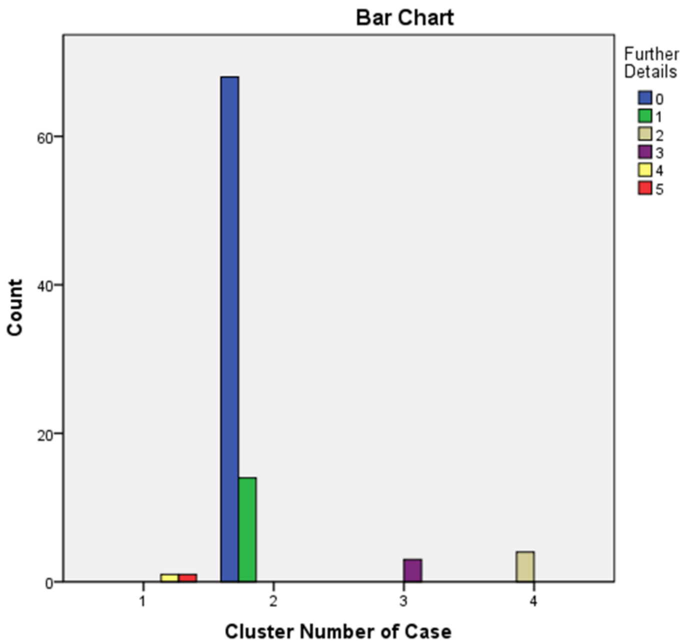


Figure 5-6: Further Details pages in four clusters

From the previous discussion, those learners who did not visit the Further Details pages or visited only one by some participants were always located in one cluster since they share similar characteristics. Thus, we can say that visiting Further Details pages was not preferred by participants. Learners had enough information from the Topic pages (the first popup page). Thus the topic contents provided by these pages seem to be enough for learners to obtain the contents they need, either by the description details or illustrated examples.

5.3.2. Learners' Perception Using Content Scope

We used the data collected from the questionnaire to answer the following questions:

- Q12: I prefer every topic link I click to generate a popup window of that topic.
- Q14: I like the fact that more details on a topic can be provided in another popup window.

After analyzing the results of those statements, Figure 5-7 and Figure 5-8 show that most of the learners were satisfied and had a positive perception on using the WBI program; the results were skewed to the options "Agree" and "Strongly Agree". The questionnaire data for each statement are provided in Appendix F.

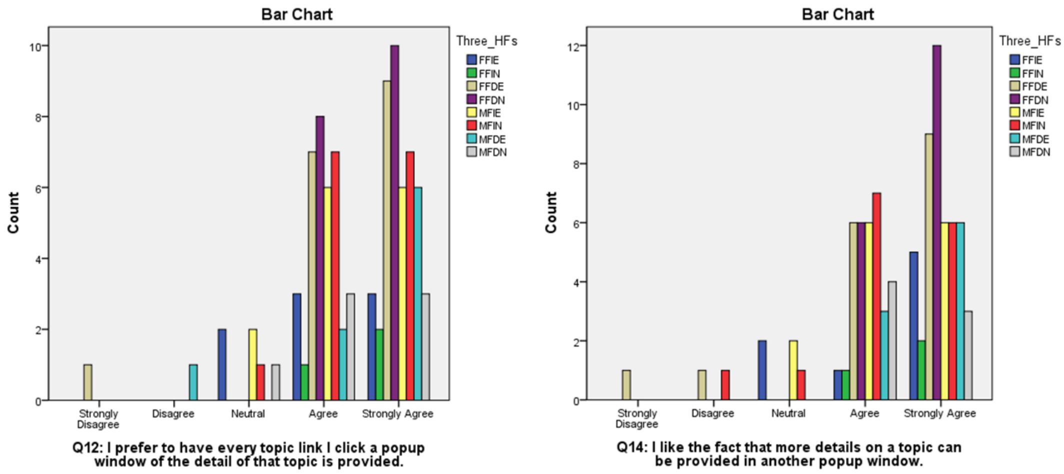


Figure 5-7: Questionnaire results for Q12 and Q14

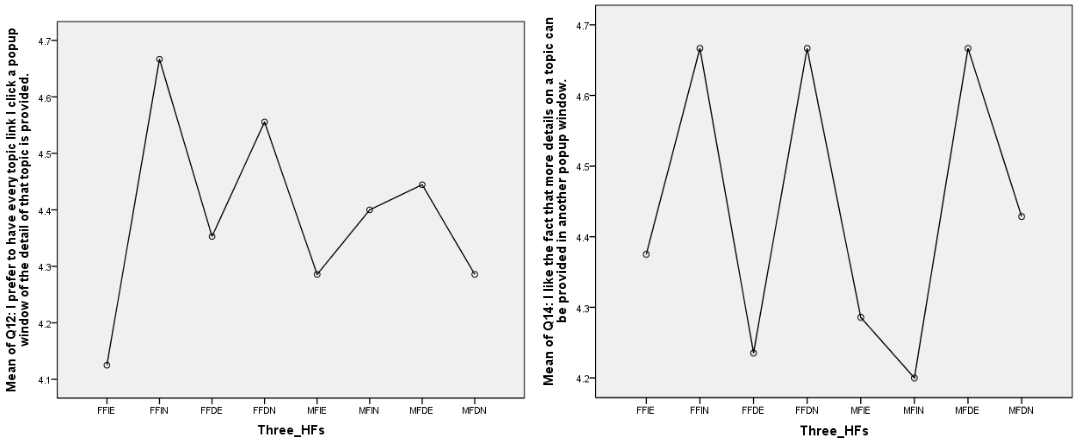


Figure 5-8: Means plot diagrams for Q12, and Q14 for each Multi-ID

5.4. Learners' Preferences Using Display Options

Display options are one of the three system features that are used in designing our WBI program. Integrating the display options in the design of our WBI program was done in the topic pages of the program. We provided the topic instructions using a table with two columns. The left column presents the detailed descriptions of a particular topic, while the other column provides the illustration with examples for that topic (Figure 3-1). A learner can read the topic content either from the left column (the detailed descriptions) or from the right column (illustration with examples). Thus, the learner's choice of reading the topic will not be registered in the log file. Therefore, learner's behaviour will not be recognized in terms of whether they chose the left or the right column. That was one of the limitations of our study. However, this can be analyzed by using the questionnaire statement Q13, which is "I like the fact that I can see the detailed descriptions and the illustration with examples shown within one table". Figure 5-9 shows that MFIN learners had the smallest mean; this could be explained from the bar chart where one learner chose "Strongly Disagree" and another chose "Disagree". The majority of learners (12 of 15 MFIN learners) opted for choices "Agree" (8 learners) and "Strongly Agree" (4 learners). The questionnaire data for each statement are provided in Appendix F.

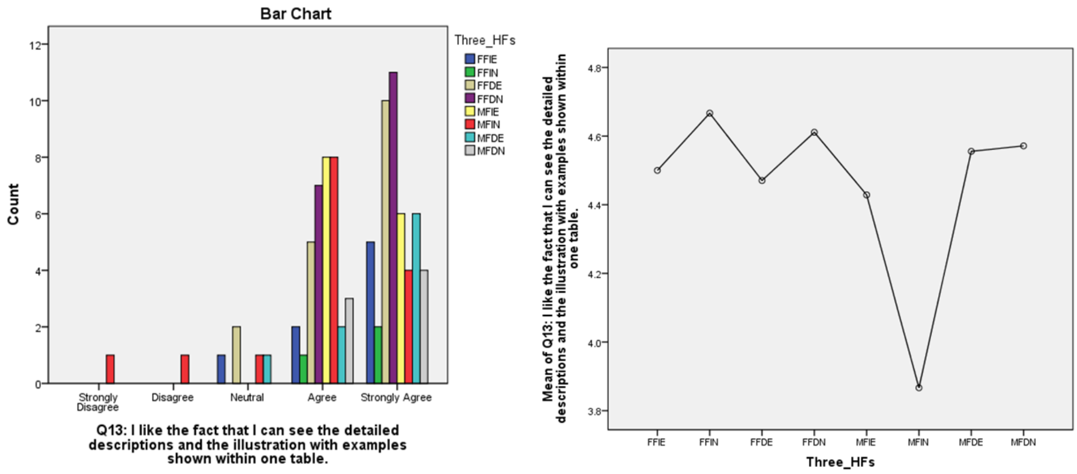


Figure 5-9: Questionnaire results for Q13 and the means plot diagram for each Multi-ID

5.5. Learners' Perceptions of Using WBI System

5.5.1. Disorientation Problem

In this section, we study whether our WBI program succeeded in reducing the disorientation problems of learners using our system. Thus, in Q9 and Q10 we asked participants directly whether they felt dissatisfied using our system. These two statements are:

- Q9: I felt frustrated when having to follow the suggested route through the WBI.
- Q10: I did not get lost when browsing the links in the WBI system.

We should highlight that Q9 was revised to Q9-R: I did not feel frustrated when having to follow the suggested route through the WBI.

From the results of these two statements, shown in Figure 5-10 and Figure 5-11, we found that participants did not suffer from a disorientation problem and were able to navigate easily, remember where they had been, and decide how to get to where they wanted to go.

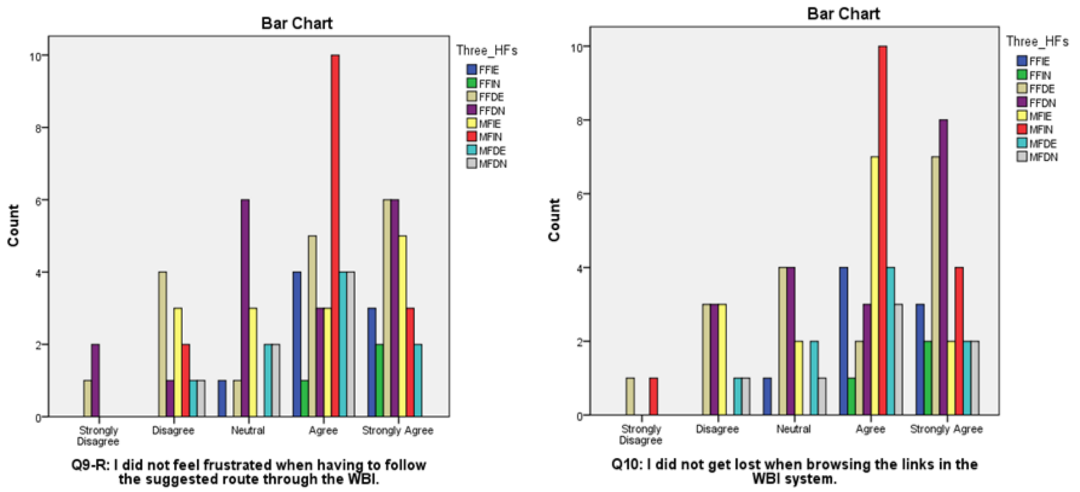


Figure 5-10: Questionnaire results for Q9 and Q10

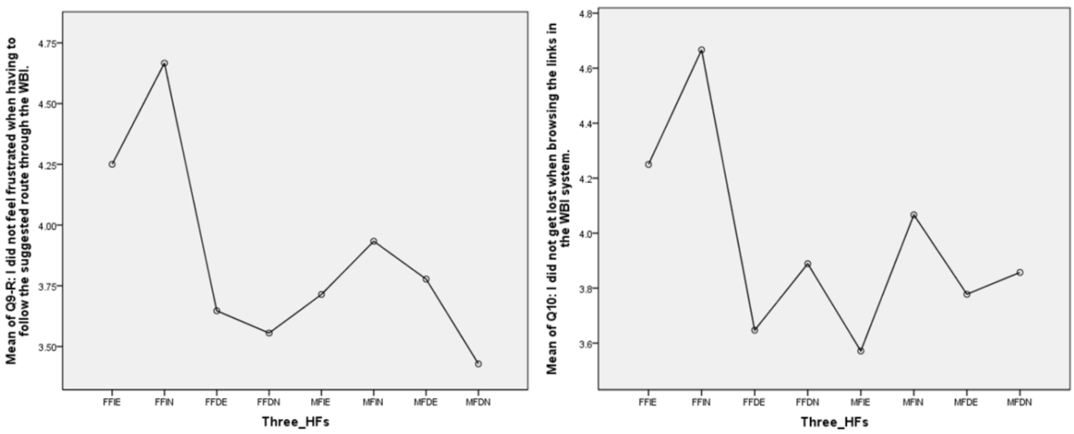


Figure 5-11: Means plot diagrams for Q9 and Q10 for each Multi-ID

5.5.2. Satisfaction to the Display Options of the System

To understand learners' satisfaction of using our system regarding the display options, five statements were provided:

- Q1: This WBI is only useful for learners who have basic knowledge about PowerPoint.
- Q2: This WBI is more helpful for novice learners.
- Q3: It is easy to learn PowerPoint using the WBI without additional help.
- Q4: After using the WBI I found it easy to use my knowledge to answer the multiple-choice post-test.
- Q5: I find it is difficult to design a presentation using PowerPoint although I have taken the tutorial of WBI.

We should highlight that Q5 was revised to Q5-R: I find it is not difficult to design a presentation using PowerPoint although I have taken the tutorial of WBI. Analyzing the results illustrated from Figure 5-12 and Figure 5-13 we found the following:

In the results of Q1, we found that FFDN and FFDE had the lowest mean values. Their results were affected by some of the participants who disagreed with the WBI program being only useful for those who had a basic knowledge about PowerPoint (domain experience). However, most of the users found that it was useful for those who have basic knowledge about the subject.

In Q2, most learners found that this system was helpful for novices. Moreover, in Q3, they found that it was easy to learn instructions using the WBI without additional help. In Q4, FFIN learners had the lowest mean. This can be explained by the fact that they were only 3 participants and more evidence is needed using larger samples. Thus, 2 of these 3 participants chose the "Agree" and "Strongly Agree" options, whereas only one participant disagreed. However, the majority indicate that, after using the WBI program, participants were confident enough in using their knowledge to answer the post-test.

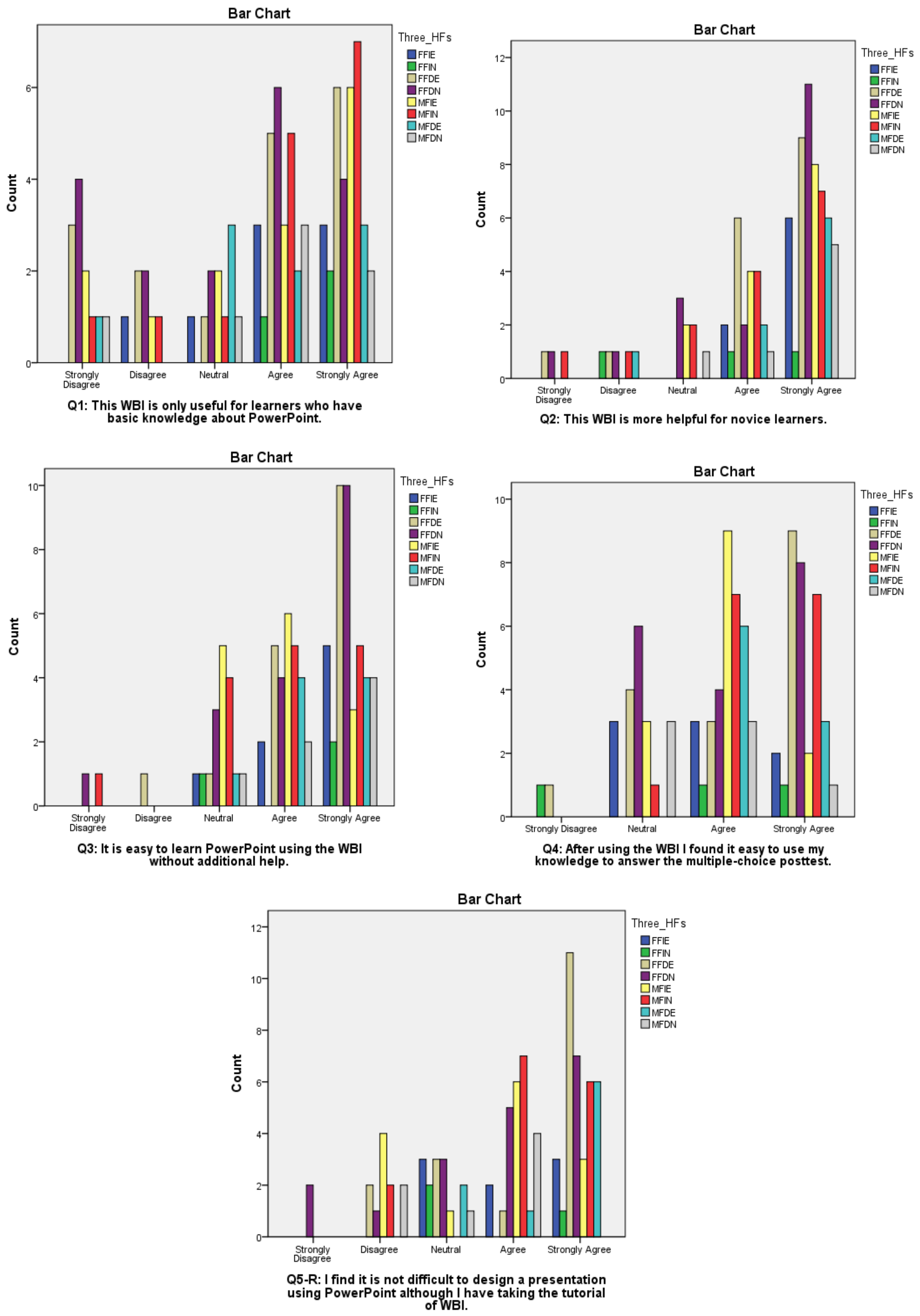


Figure 5-12: Questionnaire results for Q1 to Q5

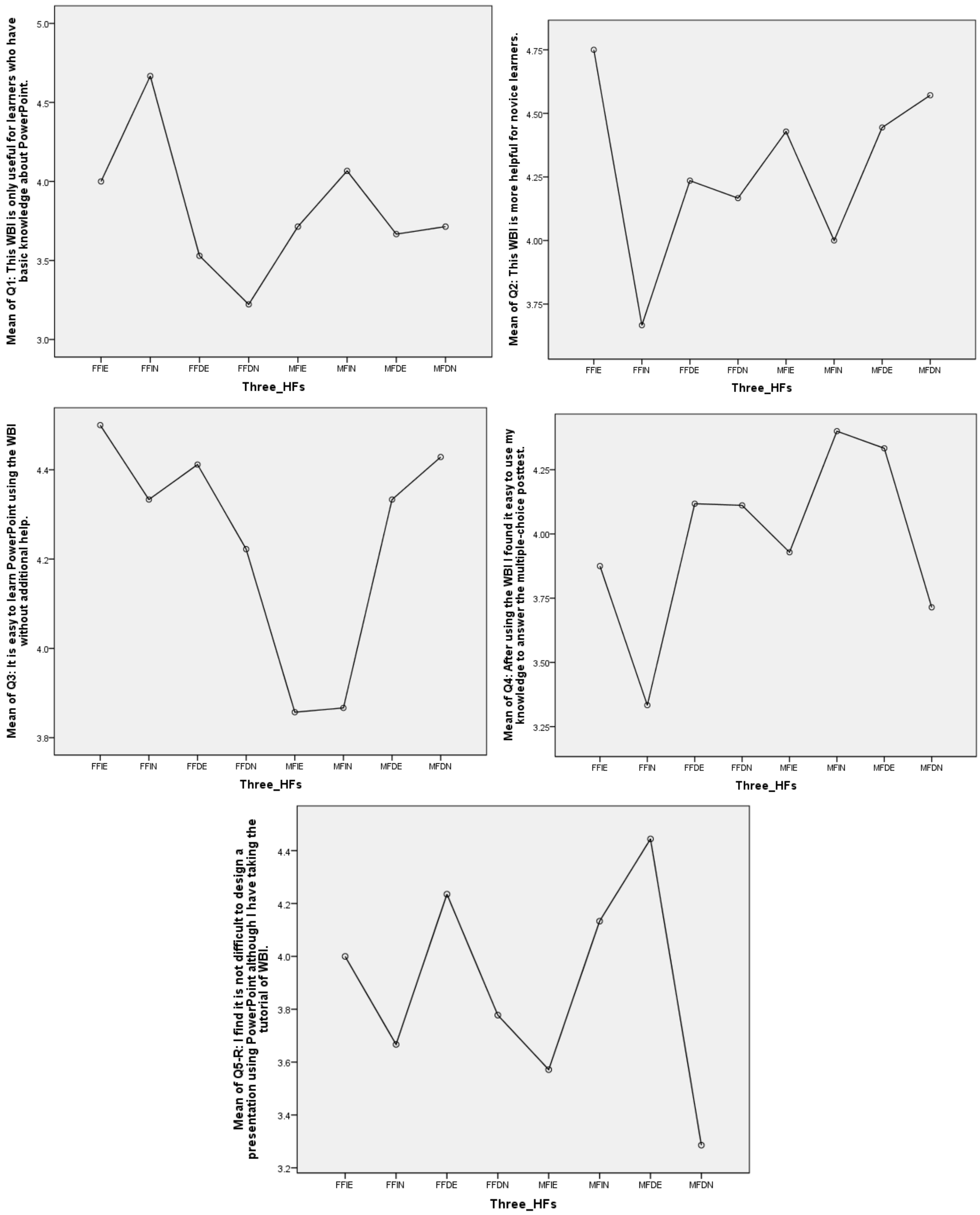


Figure 5-13: Means plot diagrams for Q1 to Q5 for each Multi-ID

In Q5, most learners agreed with this statement. On the other hand, MFDN learners had different feelings. Four of them agreed, one preferred to give a "Neutral" answer, and two of them found it difficult to design a presentation using PowerPoint although they had taken the WBI tutorial. However, they were confident in Q3 and Q4. Thus, more samples might be needed of this group to provide more evidence.

5.5.3. Overall Satisfaction and General Perceptions

To understand the overall satisfaction of the learners after interacting with our system, six statements were provided, which are:

- Q15: I like using the interface of this system.
- Q16: It was simple to use this system.
- Q17: I feel comfortable using this system.
- Q18: Overall, I was very satisfied with the presentation of instructional material.
- Q19: Overall, I was very satisfied with the system.
- Q20: Overall, I had a very positive learning experience.

From Figure 5-14 we see that the majority results of participants were above neutral. The means illustrated in Figure 5-15 show that they were satisfied using the system, since the results were above 3 (neutral) of the scale of 5 (from strongly disagree to strongly agree). However, in Q15, FFIE learners have the lowest mean value in Figure 5-15, because four participants chose “Neutral”, two participants chose “Agree” and another two participants chose “Strongly Agree”. To find out the explanation for this, we found from the open statements of the questionnaire that those four participants who chose “Neutral” had the following perception about the WBI program’s interface in the questionnaire’s open questions:

- “The interface was very simple.”
- “Not much in design and color scheme.”
- “Needs search instead of index.”

However, these results have no effect in changing the design of our WBI, which was based on the three system features.

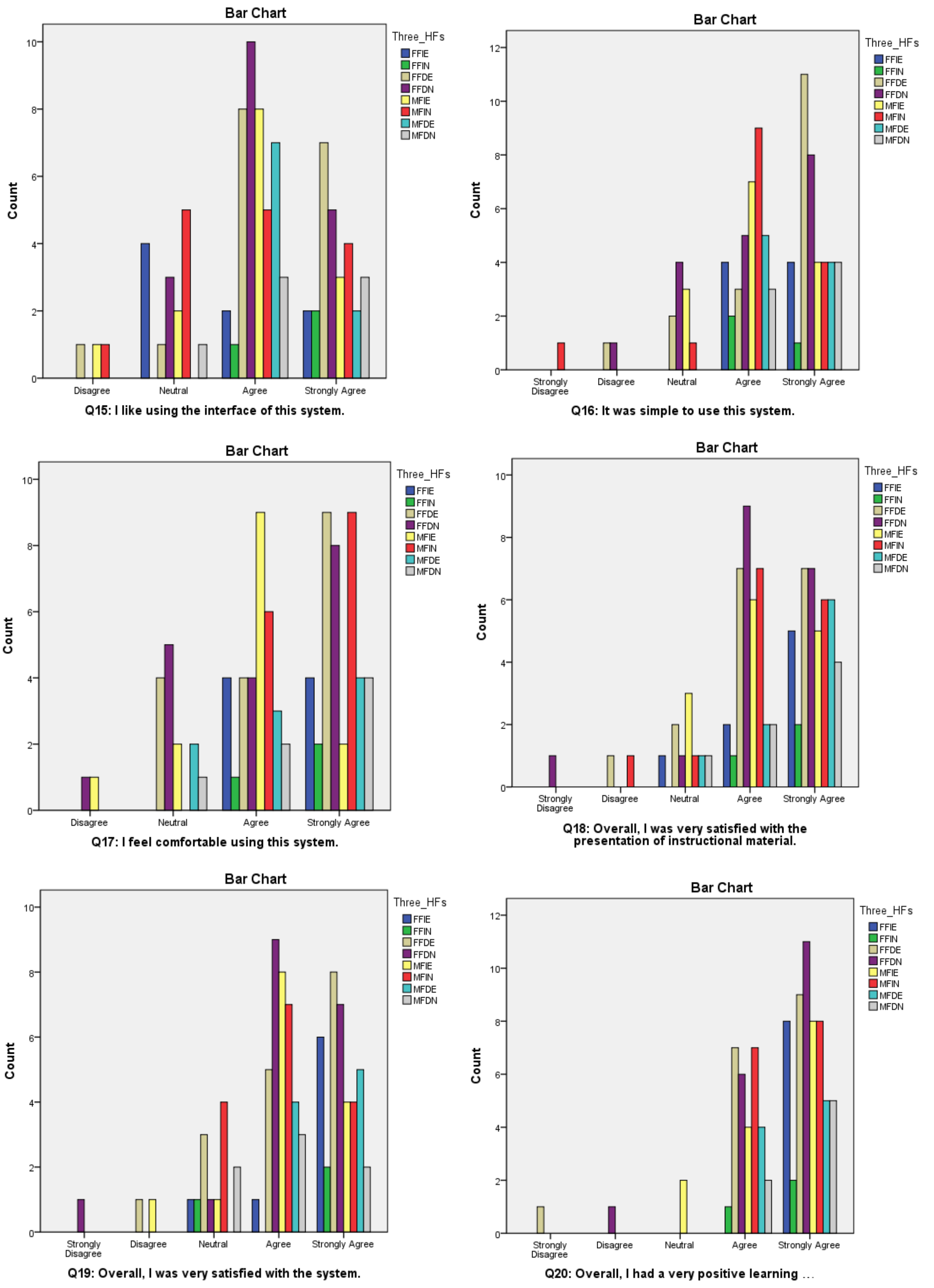


Figure 5-14: Questionnaire results for Q15 to Q20

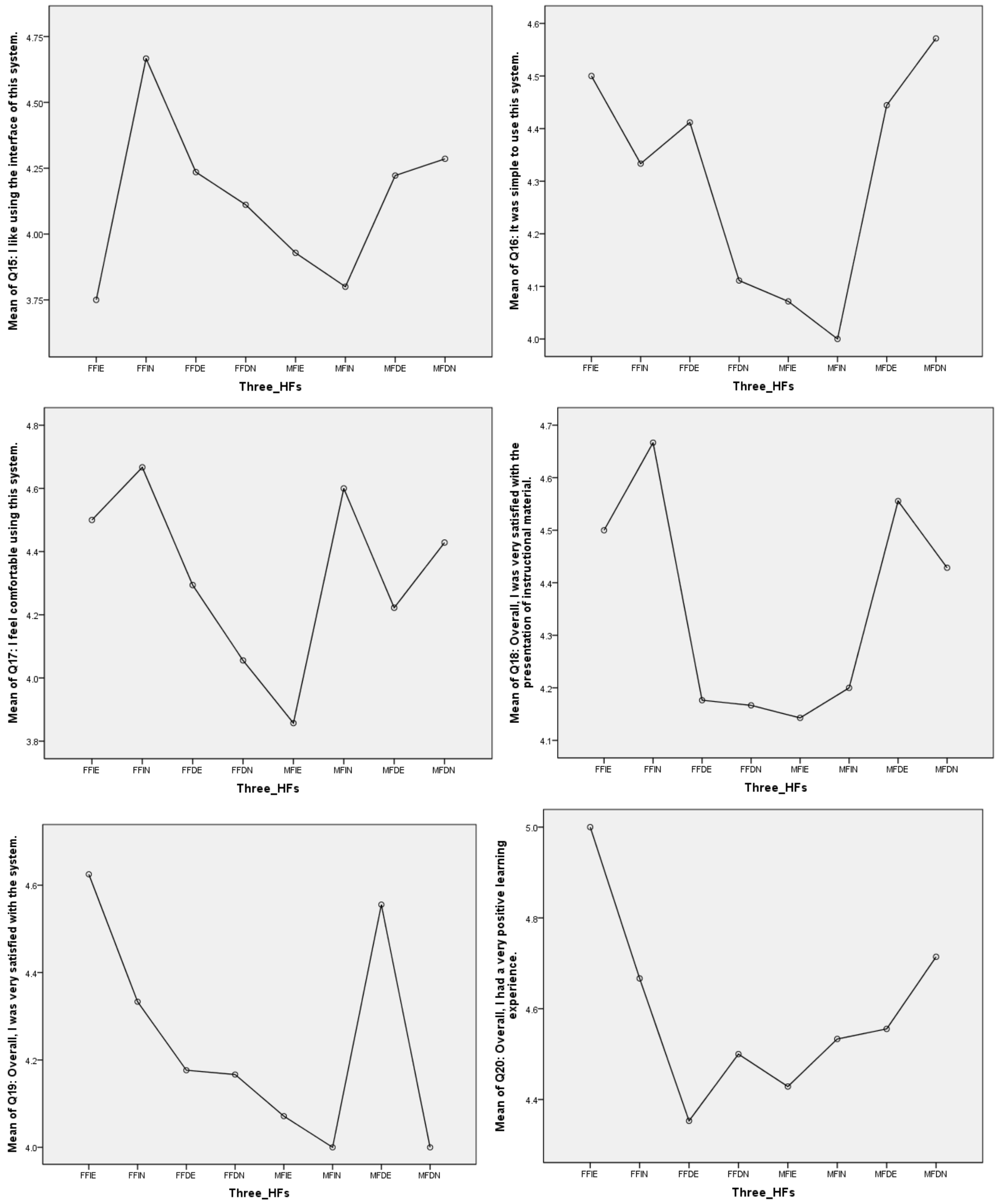


Figure 5-15: Means plot diagrams for Q15 to Q20 for each Multi-ID

It is clear that successful web applications rely upon the capability of the application to meet the needs and preferences of each learner. Thus, if a learner's preferences are successfully met, they will have a more beneficial interaction with the WBI program and complete their tasks in a more efficient and effective way, and be satisfied in using such well-designed systems.

5.6. Summary

In this chapter, we investigated learners' preferences and perception using our WBI program designed to accommodate their needs using three system features: navigation tools, content scope and display options.

Firstly, we analyzed the preferences of each one of the individual differences using navigation tools and compared our findings with previous studies. We then analyzed several combinations of intersected individual differences to investigate how each combination influenced the learning preferences based on our individual tests. We noted that some individual differences and their intersection had an impact on learners' preferences when choosing navigation tools. We found that the related individual differences therefore altered a learner's preferences, and that the designers of WBI applications need to consider the combination of individual differences rather than considering them individually. Furthermore, it was clear that learning preferences are influenced by gender when combined with prior knowledge. It may not be necessary, though, for the designers of hypermedia systems to consider prior knowledge as a part of the design process, since our results appear to show that prior knowledge did not influence the navigational preferences of participants individually. However, the combination of individual differences needs to be considered. Moreover, our findings demonstrate that such multiple individual differences (Multi-ID) have an impact on learners' preferences and perception of using WBI systems. Finally, it is nice to note that they were satisfied using our WBI program.

CHAPTER SIX

INVESTIGATING ATTRIBUTES AFFECTING THE PERFORMANCE OF WBI USERS

6.1. Introduction

Numerous research studies have explored the effect of hypermedia on learners' performance using web-based instruction (WBI). In this chapter, we investigate how differences between individuals influenced learners' performance using a hypermedia system to accommodate an individual's preferences.

The literature on the effects of hypermedia systems on user performance (as discussed in Chapter Two) focuses extensively on measurement attributes such as time spent using the system by a user, gain score (g-score) and number of pages visited in the system. In this chapter, we use a data mining approach to analyze the results by comparing between two clustering algorithms (K-means and hierarchical) using two different numbers of clusters in each comparison. As shown previously in Chapter Four, individual differences had a significant impact on learner behaviour in our WBI program. Additionally, we found that the attributes that measure performance played an influential role in exploring a learner's performance. In this chapter, the relationship between such measuring attributes induced rules in measuring levels of learners' performance. Additionally, in Chapter Five, we analyzed several combinations of individual differences (cognitive style, prior knowledge, and gender) to investigate how each combination influences the learning preferences. We found that the related individual differences therefore altered a learner's preferences. Therefore, WBI applications need to consider the combination of individual differences rather than considering them individually. Thus, in this chapter, we consider the combination of individual differences (Multi-ID) when exploring level of learners' performance instead of considering their performance individually. In particular, we attempt to answer the following research questions:

RQ5: "What are the relationships between attribute values in measuring the performance level of the individual differences?"

RQ6: "How does the behaviour of individual differences influence a learner's performance using three performance measurement attributes?"

In an attempt to answer RQ5, we understand the relationships between measurement attributes (gain scores, number of pages visited in a WBI program and time spent on such pages) to explore the performance level.

In an attempt to answer RQ6, we investigate the influence of individual differences on learning performance level by exploring relationships between measurement attributes that affect performance level.

The chapter is structured as follows. In Section 6.2, we present related work about attributes used in measuring the learners' performance and techniques applied to the analysis of the corresponding data. Findings of our analyses when comparing the results of two clustering algorithms, k-means and hierarchical clustering algorithms using two different numbers of clusters (4 and 5 clusters) are discussed in Section 6.3. Section 6.4 presents the discussions and conclusion of our study. Additionally, this section suggests rules of the performance levels and provides the best and the worst performance levels of learners with Multi-ID. At the end of this chapter, a summary is presented in Section 6.5.

6.2. Measuring Learners' Performance and Performance Level

Previous studies have indicated that various factors influenced learners' performance. The literature focuses on the effects of individual differences and system design elements on user performance and attributes, such as time spent using the hypermedia system by a user, gain score and number of pages visited in the system (Chen, et al., 2006; Chen & Liu, 2008; Kim, 2001; Large, et al., 2002; McDonald & Stevenson, 1998; Mitchell, et al., 2005a; Mitchell, et al., 2005b Roy, et al., 2003;). However, there is a dearth of studies which explore the relationship between such attributes in measuring performance level. There is also a lack of studies demonstrating the influence of the behaviour of the combined individual differences (Multi-ID) on their performance after interacting with a WBI system.

Learners who have different backgrounds, especially in terms of their knowledge skills and needs, may show various levels of engagement with course content (Wang, 2007). However, a learner whose browsing behaviour was consistent with their own favoured styles was found to obtain the best performance results (Calcaterra, et al., 2005; Mitchell, et al., 2005a).

As previously provided in Section 2.6, McDonald and Stevenson (1998) measured navigation performance in terms of speed and accuracy in answering questions and locating particular nodes. Results showed that the performance of knowledgeable participants was better than that of non-knowledgeable participants. Additionally, in Mitchell, et al., (2005a), performance was measured by a *gain score*, calculated as post-test score minus pre-test score. Those subjects that performed poorly on the pre-test made a greater improvement in the post-test.

The study of Kim (2001) investigated how differences in cognitive style and online search experience influenced the search. They used time spent in retrieving information and the number of nodes visited for retrieving information as two different indicators for measuring search performance. As for the gain score, results indicated that novices showed a greater improvement in learning performance than experts. More specifically, those who performed poorly on the pre-test made a greater improvement on the post-test. As for number of visited pages in the WBI programs, studies have found that male, field-dependent experts browse more pages than female, field-independent novices (Chen & Liu, 2008; Ford & Chen, 2000; Large, et al., 2002; Roy, et al., 2003). As for time spent in browsing WBI programs, some studies have found that male, field-independent users spend less time than female field-dependent ones (Chen & Liu, 2008; Lee, et al., 2009; Roy, et al., 2003).

In this chapter, our study will focus on the following three key aspects. Firstly, learners were pre-identified using three individual differences (Multi-ID) by combining gender, cognitive style and prior knowledge when identifying a learner. Secondly, we investigated the impact of the behaviour of the Multi-ID on learners performance. Thirdly, we explored the attributes used to measure a learner's performance. Thus, in the study presented, we used data mining to group WBI users into clusters based on their characteristics, using the three attributes of measuring the performance. The attributes are gain score, defined as post-test minus pre-test (g-score), total number of topics pages visited by participants (t-pages) and total time, in seconds, that each participant spent visiting the topic pages in the WBI program (t-time). For our investigation, we used data mining, which is the process of discovering interesting, unexpected or valuable information from large datasets (Hand, 2007). It uses data to find unexpected relationships and patterns (Wang, et al., 2002). By doing so, hidden relationships and interdependencies can be discovered and predictive rules generated (Gargano & Raggad, 1999; Hedberg, 1995). Clustering is selected for analyzing data in this chapter because it is able to form groups that share similar characteristics, where each group consists of objects which are similar amongst themselves and dissimilar to objects of other groups (Roussinov & Zhao, 2003).

Clustering methods may be grouped into the following two categories: hierarchical and non-hierarchical clustering (Jain & Dubes, 1999). A hierarchical clustering procedure involves the construction of a hierarchy or tree-like structure, a nested sequence of partitions (Fraley & Raftery, 1998), while non-hierarchical or partitioned procedures end with a particular number of clusters at a single step. Commonly used non-hierarchical clustering algorithms include the k-means algorithm, graph-theoretic approaches *via* the use of minimum spanning trees, evolutionary clustering algorithms, simulated annealing based methods and competitive neural networks such as self-organizing maps (Fielding, 2007). In this chapter, hierarchical and k-means clustering algorithms were used to understand a user's behaviour. We have used both hierarchical clustering and the widely-used non-hierarchical clustering method, k-means, to group users into clusters based on their characteristic in measuring their performance using three attributes ('g-score', 't-pages' and 't-time').

K-means cluster analysis is a tool designed to assign cases to a fixed number of groups (clusters) whose characteristics are not yet known but are based on a set of specified variables (Hartigan, 1975). The k-means algorithm is used because it is easy to understand and easy to implement. It attempts to identify relatively homogeneous groups of cases based on selected characteristics. The algorithm requires the specification of a number of clusters. In the k-means clustering technique the number of clusters (k) is given as an input. The algorithm then picks k items, called seeds, from the training set in a subjective way. Next, each input is allocated to the most similar seed. Then, the seed of each cluster is re-calculated to be the centroid of all items assigned to that seed. This process is repeated until the seed coordinates stabilize.

On the other hand, hierarchical cluster analysis is used to identify relatively homogeneous groups of cases (or variables) based on selected characteristics (Anderberg, 1973), using an algorithm that starts with each case in a separate cluster and combines clusters until reaching one cluster. Statistics are displayed at each stage to help in selecting the best solution.

There are two types of hierarchical clustering: *agglomerative* and *divisive* (Brian, et al., 2011). The agglomerative approach creates a bottom-up hierarchy, whereas the divisive approach is top-down. Divisive algorithms are known to be computationally less efficient because of the complexity of deciding which cluster to divide and how to do it (Savaresi, et al., 2002). Thus, in our study, we used the agglomerative approach. The hierarchical agglomerative clustering algorithm is a nested hierarchy of trees. The tree then can be cut at a desired dissimilarity level to form a partition. The algorithm is outlined below from Frias-Martinez, et al., (2007):

> *"(1) Place each pattern in a separate cluster.*
>
> *(2) Compute the proximity matrix of all the inter-pattern distances for all distinct pairs of patterns.*
>
> *(3) Find the most similar pair of clusters using the matrix. Merge these two clusters into one, decrement number of clusters by one and update the proximity matrix to reflect this merge operation.*
>
> *(4) If all patterns are in one cluster, stop. Otherwise, go to step 2."*

The main advantage of the k-means procedure is that it is much faster than the hierarchical cluster procedure. However, the hierarchical procedure allows much more flexibility in the cluster analysis. Moreover, the k-means cluster analysis command is efficient because it does not compute the distances between all pairs of cases, as does the hierarchical clustering analysis.

A challenging issue with hierarchical clustering is how to decide on the optimal partition from the hierarchy. Our approach is to select the partition which best fits the data. To do that, we compared the results from the k-means and hierarchical analysis.

In the next section, the hierarchical and k-means clustering algorithms will be used to understand a user's behaviour by investigating different numbers of clusters for each algorithm to obtain a deeper understanding and strengthen our results. Additionally, to explore a learner's performance level after they interacted with the WBI program, we compare the results of the different clusters for each algorithm.

6.3. Results and Discussion

We compared the results of two clustering algorithms, namely k-means and hierarchical clustering algorithms. These algorithms were used to study the behaviour of the combined individual differences (Multi-ID): gender, prior knowledge and cognitive style. The cases of (Multi-ID) are as follows:

1. FFIE: Female, field-independent and expert learner.
2. FFIN: Female, field-independent and novice learner.
3. FFDE: Female, field-dependent and expert learner.
4. FFDN: Female, field-dependent and novice learner.
5. MFIE: Male, field-independent and expert learner.
6. MFIN: Male, field-independent and novice learner.
7. MFDE: Male, field-dependent and expert learner.
8. MFDN: Male, field-dependent and novice learner.

Table 6-1 shows the cases of individual differences, number of participants and the percentage for each case in our study.

	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	Total
Frequencies	8	3	17	18	14	15	9	7	91
Percentage	8.79	3.30	18.68	19.78	15.38	16.48	9.89	7.69	100

Table 6-1: Intersection of individual differences' frequencies

An ANOVA test was computed to explore any significance between individual differences as an independent variable with performance measurements attributes (g-score, t-pages and t-time) as dependent variables. We found a significant difference at the 5% level for the g-score value. However, there were no significant differences with the t-pages and t-time attributes (significance was greater than 5%). Thus, g-score will be used as the first measuring attribute to compare between learners' performance levels.

For each participant interacting with the WBI program, we used three attribute values; 'g-score' (post-test minus pre-test, where mean of pre-test of the 91 participants is 8.5 and mean of post-test is 11.30), 't-pages' and 't-time'. Table 6-2 shows the overall mean values for each attribute. These overall mean values are calculated by using the attribute values of each participant.

		g-score	t-pages	t-time
N	Valid	91	91	91
	Missing	0	0	0
Std. Deviation		2.785	7.268	1105.759
Mean		2.77	15.35	2015.36

Table 6-2: Overall mean values of attribute used for clustering

Using the k-means and hierarchical algorithms we performed clustering procedures using the measuring attributes variables of g-score, t-pages and t-time. The cases were labelled using the Multi-ID learners. We then used hierarchical agglomerative clustering to identify learners that shared similar behaviour, using a Euclidean distance to construct clusters. The hierarchical tree in Figure 6-1 shows that the number of clusters was 2, 3, 4, 5 and 7, without showing 6 clusters. Thus, we ran the k-means clustering algorithm using number of clusters 2 to 5 and 7. After comparing the results of all the given clusters, for both algorithms, we found that the most meaningful and well-matched in exploring the performance level are those for the 4 and 5 clusters. Results have been cut from the hierarchical tree (Figure 6-1) to create 4 and 5 different clusters, where the number of clusters were assigned for each learner in a new column (see Appendix F, columns: KMeans_4Cs, Hierarchical_4Cs, and KMeans_5Cs, Hierarchical_5Cs). We saved information about the clusters for each learner as new variables to be used in subsequent analyses (i.e. using ANOVA and Crosstabs).

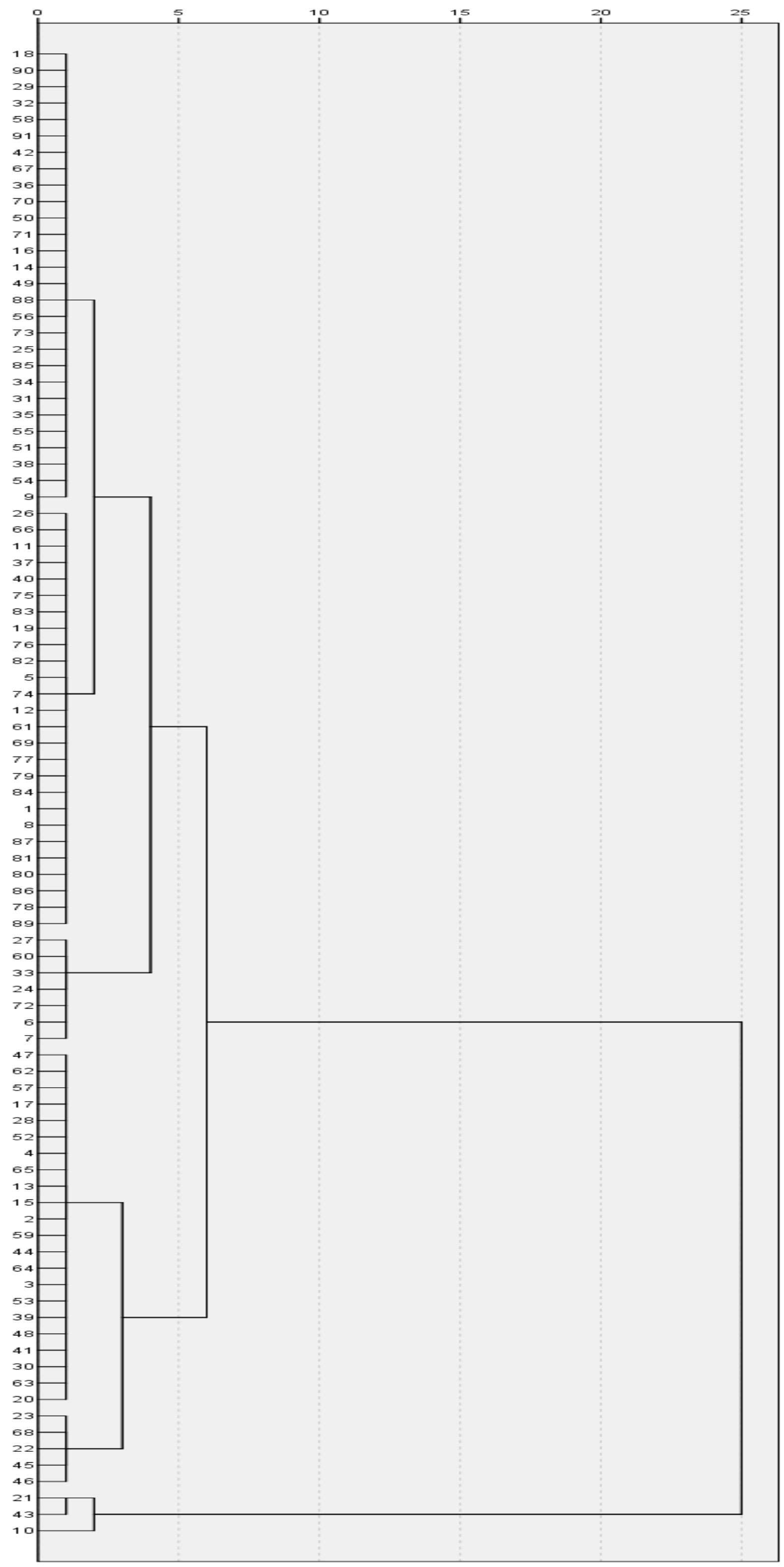


Figure 6-1: Hierarchical tree constructed using hierarchical algorithm

6.3.1. Results of Four Clusters

In this section, we study the clustering algorithms using four clusters (C1, C2, C3, C4) starting with the k-means algorithm in Analysis One and the hierarchical algorithm in Analysis Two. The mean values of g-score, t-pages and t-time of the clusters will be used to study the characteristics of each cluster by comparing these values with the overall mean values shown in Table 6-2.

6.3.1.1. Analysis One

In Analysis One, we began with the k-means algorithm using K=4; the attributes that we used in this algorithm are shown in Table 6-2. Additionally, we labelled the cases in the used algorithm of each one of the individual differences as shown in Table 6-1. Table 6-3 shows that the highest number of individual differences was located in C1 (N=37). The lowest number was located in C2 (N=4). In C1, all the individual differences were allocated into this cluster, where the highest number of individual differences is in the MFIN category. In C2, we see that FFIN, FFDE and FFDN are allocated into this cluster, where the highest number of individual differences in C2 is FFDN.

		Cases of individual differences								Total
		FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Cluster Number	C1	1	1	5	8	6	11	4	1	37
	C2	0	1	1	2	0	0	0	0	4
	C3	3	0	7	5	4	0	2	5	26
	C4	4	1	4	3	4	4	3	1	24
Total		8	3	17	18	14	15	9	7	91

Table 6-3: Cluster distribution of individual differences of k-means algorithm (4 clusters)

Table 6-4 shows the k-means clustering results. We used these attribute values to compare the mean values in each cluster (using the words High and Low) with the overall mean value of all participants; the overall mean value is given in the last row of Table 6-4 (‘Total’ row). From this comparison, we found the following:

Cluster Number		g-score		t-pages		t-time	
C1	Mean	3.05	High	15.38	Slightly	1810.30	Low
	N	37		37	High	37	
	Std. Dev	2.79		5.88		266.42	
C2	Mean	4.00	High	23.00	High	5130.75	High
	N	4		4		4	
	Std. Dev	4.97		14.85		658.40	
C3	Mean	2.08	Low	17.73	High	2954.27	High
	N	26		26		26	
	Std. Dev	2.48		5.76		409.93	
C4	Mean	2.88	High	11.46	Low	795.13	Low
	N	24		24		24	
	Std. Dev	2.71		7.44		358.28	
Total (overall values)	Mean	2.77		15.35		2015.36	
	N	91		91		91	
	Std. Dev	2.79		7.27		1105.76	

Table 6-4: Cluster centroids of k-means algorithm (4 clusters)

1. Participants allocated into clusters C1, C2 and C4 had a higher g-score than the overall mean. Those allocated into C3 had a lower g-score than the overall mean value.
2. Participants allocated into clusters C1, C2 and C3 visited more t-pages than the overall mean value; however, C1 was slightly higher. Those allocated into C4 visited fewer t-pages than the overall mean value.
3. Participants allocated into clusters C2 and C3 spent a higher t-time than the overall mean value. Those who were allocated into clusters C1 and C4 spent less t-time than the overall mean value on visiting topic pages (t-pages).

6.3.1.2. Analysis Two

In this analysis, we used a Hierarchical Clustering algorithm. We set the number of clusters equal to 4. The used attributes are shown in Table 6-2 and we labelled cases in the used algorithm of each one of the individual differences, as shown in Table 6-1.

Table 6-5 shows that the highest number of individual differences was located in C1 (N=54). On the other hand, the lowest number was located in C4 (N=3). In C1, all the individual differences were allocated into this cluster, where the highest number of individual differences is MFIN. In C4, we can see that FFIN, FFDE and FFDN are allocated into this cluster (one participant for each of the individual differences).

		Cases of individual differences								Total
		FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Cluster Number	C1	3	2	7	10	10	15	5	2	54
	C2	3	0	7	6	4	0	2	5	27
	C3	2	0	2	1	0	0	2	0	7
	C4	0	1	1	1	0	0	0	0	3
Total		8	3	17	18	14	15	9	7	91

Table 6-5: Cluster distribution of individual differences of Hierarchical algorithm (4 clusters)

From Table 6-6, we see the report of the Hierarchical clustering results. We used these attribute values to compare the mean values in each cluster (using the words High and Low) with the overall mean value of all participants; the overall mean value is given in the last row of Table 6-6 (Total row). From this comparison, we found the following:

1. Participants allocated into clusters C1 and C4 had a higher g-score than the overall mean. Those allocated into C2 and C3 had a lower g-score than the overall mean value.
2. Participants allocated into clusters C2 and C4 visited more t-pages than the overall mean value. Those allocated into C1 and C3 visited fewer t-pages than the overall mean value.

3. Participants allocated into clusters C2 and C4 spent higher t-time than the overall mean value. Those allocated into clusters C1 and C3 spent less t-time than the overall mean value.

Cluster Number		g-score		t-pages		t-time	
C1	Mean	3.11	High	14.61	Low	1551.56	Low
	N	54		54		54	
	Std. Dev	2.81		6.28		454.72	
C2	Mean	2.07	Low	17.59	High	3006.11	High
	N	27		27		27	
	Std. Dev	2.43		5.69		483.88	
C3	Mean	2.00	Low	7.86	Low	325.71	Low
	N	7		7		7	
	Std. Dev	2.00		7.84		199.76	
C4	Mean	4.67	High	26.00	High	5389.67	High
	N	3		3		3	
	Std. Dev	5.86		16.64		498.00	
Total	Mean	2.77		15.35		2015.36	
	N	91		91		91	
(overall values)	Std. Dev	2.79		7.27		1105.76	

Table 6-6: Cluster centroids of Hierarchical algorithm (4 clusters)

6.3.1.3.Discussion of Analysis One and Analysis Two

The bar charts in Figure 6-2 show the comparison between the four clusters with the three attribute values (t-pages, t-time, and g-score) using the k-means algorithm. From these charts and the results of Analysis One, we note that participants who achieved a higher g-score after they visited fewer t-pages and spent less t-time in visiting these pages demonstrate better performance, as shown from the results of C1 and C4, although the t-pages value of C1 is similar to the overall mean value.

We can also note that those participants who achieved a lower g-score after they visited more t-pages and spent higher t-time in visiting these pages did not perform well, as shown from the results of C3. We ignored cluster C2 because it has a low number of participants (4 out of 91); the majority of participants are located in C1, C3 and C4 (numbering 87).

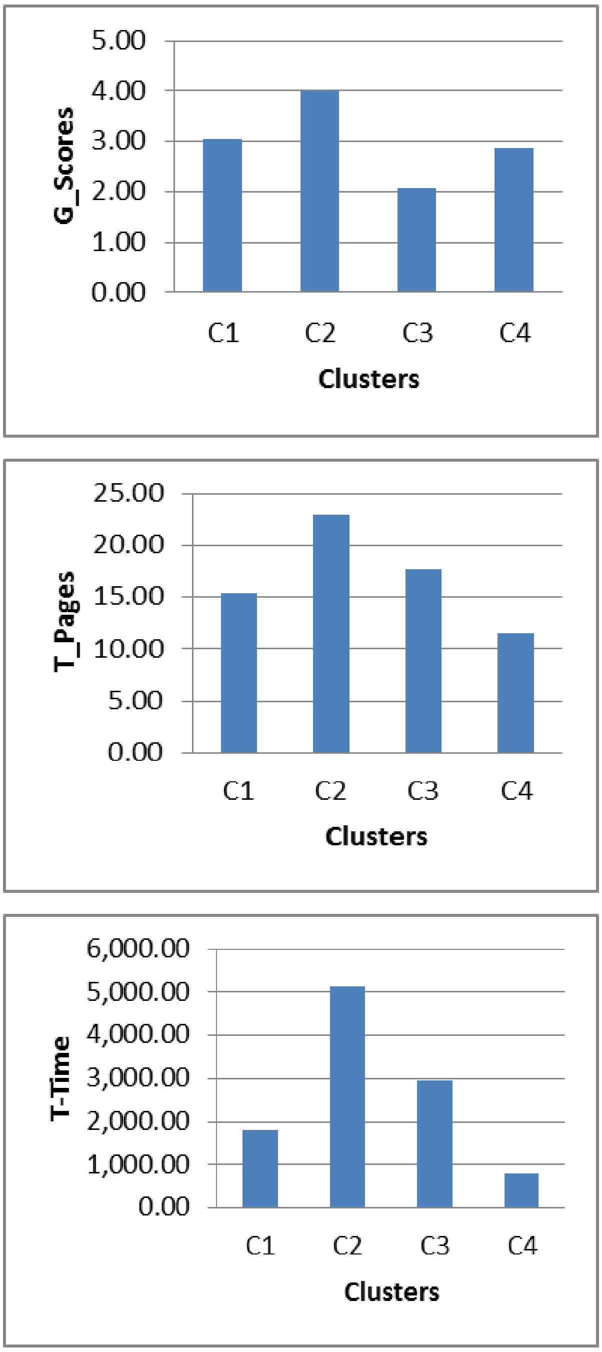


Figure 6-2: K-means algorithm for four clusters and the three attribute values

The bar charts in Figure 6-3 show the comparison between the four clusters with the three attribute values of t-pages, t-time and g-score. From these charts and the results of Analysis Two, when comparing C1 with C2, we found that participants who had achieved a higher g-score after they visited fewer t-pages and spent less t-time in visiting these pages improved their performance (C1). We can also note that those participants who had achieved lower g-score after they visited more t-pages and spent higher t-time in visiting these pages did not perform well (C2). We ignored clusters C3 and C4 because of their low number of participants (C3=7 and C4=3); the majority of participants were located in C1 and C2 (81 out of 91 participants).

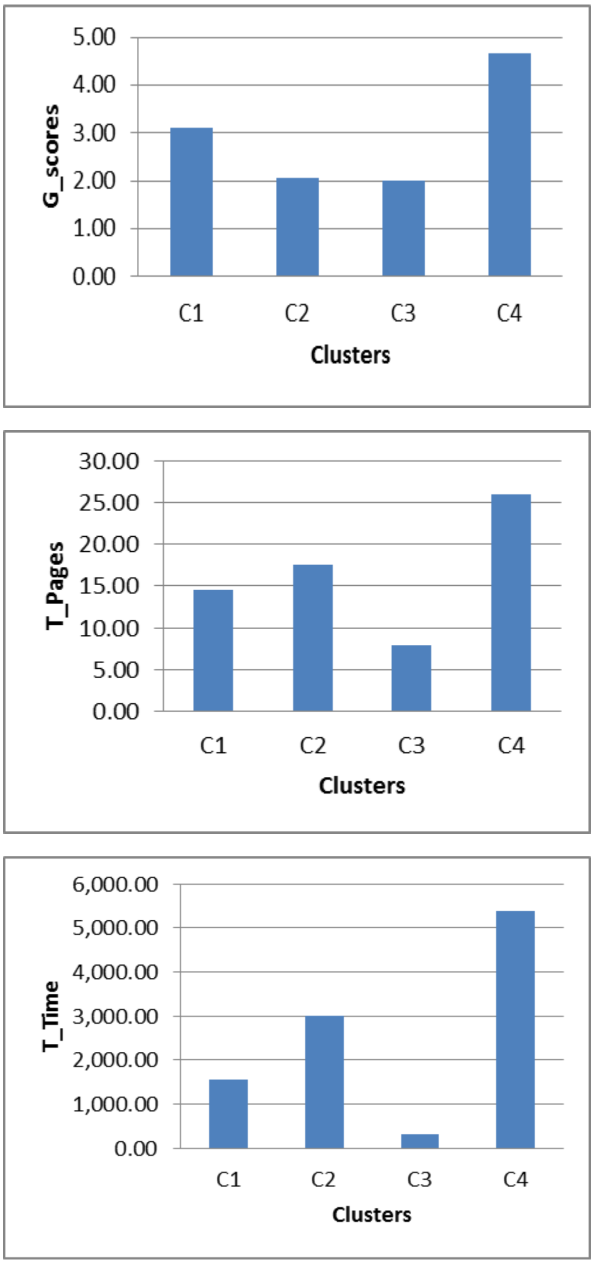


Figure 6-3: Hierarchical algorithm for four clusters and the three attribute values

6.3.2. Results of Five Clusters

In this section, we study the clustering algorithms using five clusters (C1, C2, C3, C4, C5) starting with the k-means algorithm in Analysis Three and the Hierarchical algorithm in Analysis Four. The mean values of g-score, t-pages and t-time of the clusters will be used to study the characteristics of each cluster by comparing these values with the overall mean values shown in Table 6-2.

6.3.2.1. Analysis Three

In this analysis, we started with the k-means algorithm using K=5. The attributes used in this algorithm are shown in Table 6-2. Additionally, we labelled the cases in the algorithm we used for each of the individual differences (Table 6-1).

From Table 6-7, results show that the highest number of individual differences was located in C5 (N=37). The lowest number was located in C1 (N=3). In C5, all individual differences were allocated into this cluster, where the highest number of individual differences is MFIN. In C1, we see that FFIN, FFDE and FFDN are allocated into this cluster (one participant for each of the individual differences).

		Cases of individual differences								
		FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	Total
Cluster Number	1	0	1	1	1	0	0	0	0	3
	2	4	1	4	3	4	3	3	1	23
	3	1	0	2	3	1	0	0	2	9
	4	2	0	5	3	3	1	2	3	19
	5	1	1	5	8	6	11	4	1	37
	Total	8	3	17	18	14	15	9	7	91

Table 6-7: Cluster distribution of individual differences of k-means algorithm (5 clusters)

Table 6-8 presents the k-means clustering results, we used these attribute values to compare the mean values in each cluster (using the words High and Low) with the overall mean value of all participants; the overall mean value is given in the last row of Table 6-8 (Total row). From this comparison, we conclude the following:

1. Participants allocated into clusters C1 and C5 achieved a higher g-score than the overall mean. Those allocated into C3 and C4 had a lower g-score than the overall mean value. However, C2 is slightly lower.
2. Participants allocated into clusters C1, C3, C4 and C5 had visited more t-pages than the overall mean value. Those allocated into C2 had visited fewer t-pages than the overall mean value.
3. Participants allocated into clusters C1, C3 and C4 spent a higher t-time in visiting these pages than the overall mean value. Those who were allocated into clusters C2 and C5 had less t-time in visiting pages than the overall mean value.

Cluster Number		g-score		t-pages		t-time	
C1	Mean	4.67	High	26.00	High	5389.67	High
	N	3		3		3	
	Std. Dev	5.86		16.64		498.00	
C2	Mean	2.70	Slightly	10.96	Low	773.65	Low
	N	23	Low	23		23	
	Std. Dev	2.62		7.18		350.18	
C3	Mean	2.11	Low	16.22	High	3569.33	High
	N	9		9		9	
	Std. Dev	1.76		6.96		387.36	
C4	Mean	2.26	Low	18.05	High	2702.26	High
	N	19		19		19	
	Std. Dev	2.83		4.98		207.36	
C5	Mean	3.08	High	15.62	High	1782.92	Low
	N	37		37		37	
	Std. Dev	2.82		6.01		266.53	
Total	Mean	2.77		15.35		2015.36	
(overall	N	91		91		91	
values)	Std. Dev	2.79		7.27		1105.76	

Table 6-8: Cluster centroids of k-means algorithm (5 clusters)

6.3.2.2. Analysis Four

We set the number of clusters equal to 5; the attributes used are shown in Table 6-2 and we labelled the cases in the algorithm we used of each of the individual differences as *per* Table 6-1. From Table 6-9, results show that the highest number of individual differences was located in C1 (N=54). The lowest number was located in C4 (N=3). In C1, all individual differences were allocated into this cluster, where the highest number of individual differences is for the MFIN category. In C4, we see that FFIN, FFDE and FFDN are allocated into this cluster (one participant for each of the individual differences).

		Cases of individual differences								
		FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	Total
Cluster Number	C1	3	2	7	10	10	15	5	2	54
	C2	3	0	5	4	4	0	2	4	22
	C3	2	0	2	1	0	0	2	0	7
	C4	0	1	1	1	0	0	0	0	3
	C5	0	0	2	2	0	0	0	1	5
Total		8	3	17	18	14	15	9	7	91

Table 6-9: Cluster distribution of individual differences of Hierarchical algorithm (5 clusters)

We used Table 6-10 values to compare the mean values in each cluster (again using the words High and Low) with the overall mean value of all participants; similarly, the overall mean value is given in the final row of Table 6-10 (Total row). From this comparison, we conclude the following:

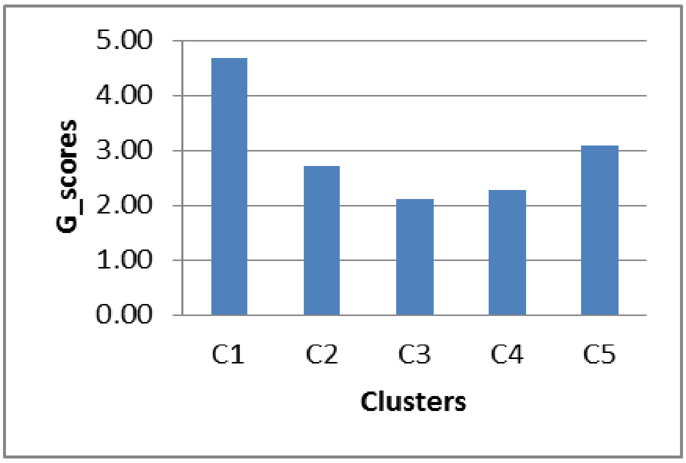
1. Participants allocated into clusters C1 and C4 achieved a higher g-score than the overall mean. Those allocated into C2, C3 and C5 had a lower g-score than the overall mean value.
2. Participants allocated into clusters C2 and C4 had more value for t-pages than the overall mean value. Those allocated into C1, C3 and C5 had fewer values of t-pages than the overall mean value.
3. Participants allocated into clusters C2, C4 and C5 had a higher t-time in visiting pages than the overall mean value. Those who were allocated into clusters C1 and C3 had less t-time in visiting pages than the overall mean value.

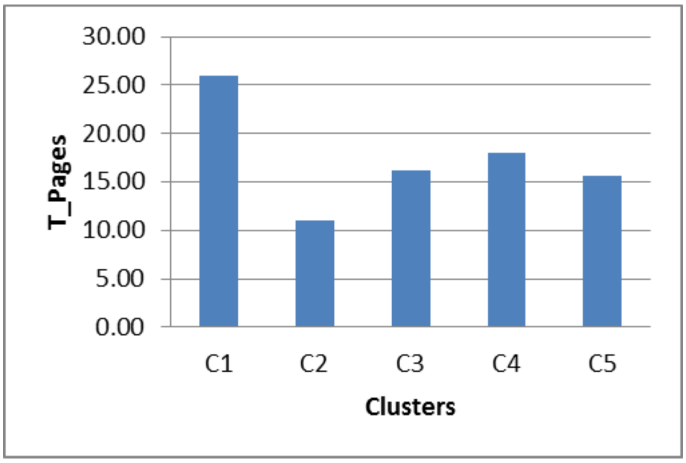
Cluster Number		g-score		t-pages		t-time	
C1	Mean	3.11	High	14.61	Low	1551.56	Low
	N	54		54		54	
	Std. Dev	2.81		6.28		454.72	
C2	Mean	2.09	Low	18.77	High	2820.73	High
	N	22		22		22	
	Std. Dev	2.58		5.58		270.21	
C3	Mean	2.00	Low	7.86	Low	325.71	Low
	N	7		7		7	
	Std. Dev	2.00		7.84		199.76	
C4	Mean	4.67	High	26.00	High	5389.67	High
	N	3		3		3	
	Std. Dev	5.86		16.64		498.00	
C5	Mean	2.00	Low	12.40	Low	3821.80	High
	N	5		5		5	
	Std. Dev	1.87		2.41		343.36	
Total (overall values)	Mean	2.77		15.35		2015.36	
	N	91		91		91	
	Std. Dev	2.79		7.27		1105.76	

Table 6-10: Cluster centroids of Hierarchical algorithm (5 clusters)

6.3.2.3. Discussion of Analysis Three and Analysis Four

The bar charts in Figure 6-4 show the comparison between the five clusters with the three attribute values, t-pages, t-time and g-score using the k-means algorithm. From these charts and the results of Analysis Three, we found that participants who had achieved higher g-score after they visited fewer t-pages and spent less t-time in visiting these pages, improved their performance. This is found from the results of C2 and C5, although the t-pages value of C5 is equal to the overall mean value. We can also note that those participants who had achieved lower g-score after they visited more t-pages and spent higher t-time in visiting these pages did not perform well, as shown from the results of C3 and C4. We ignore cluster C1 because it has a low number of participants (3 out of 91 participants); the majority of participants are located in C2, C3, C4 and C5 (88).





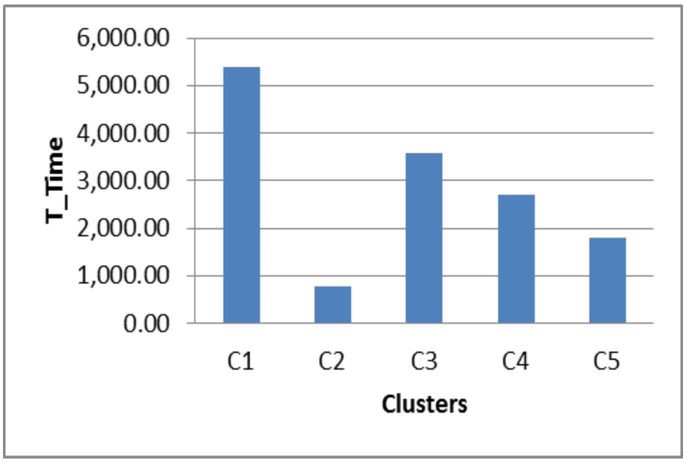


Figure 6-4: K-means algorithm for four clusters and the three attribute values

The bar charts in Figure 6-5 show a comparison between the five clusters with the three attribute values - t-pages, t-time and g-score - using the Hierarchical algorithm. From these charts and the results of Analysis Four, by comparing C1 with C2, we found that participants who had achieved higher g-score after they visited fewer t-pages and spent less t-time in visiting these pages performed better. We can also note that those participants who had achieved a lower g-score after they visited more t-pages and spent higher t-time in visiting these pages did not perform well. We ignore clusters C3, C4 and C5 because of their low number of participants (C3=7 and C4=3, C5=5); the majority of participants are located in C1 and C2 (76 out of 91 participants).

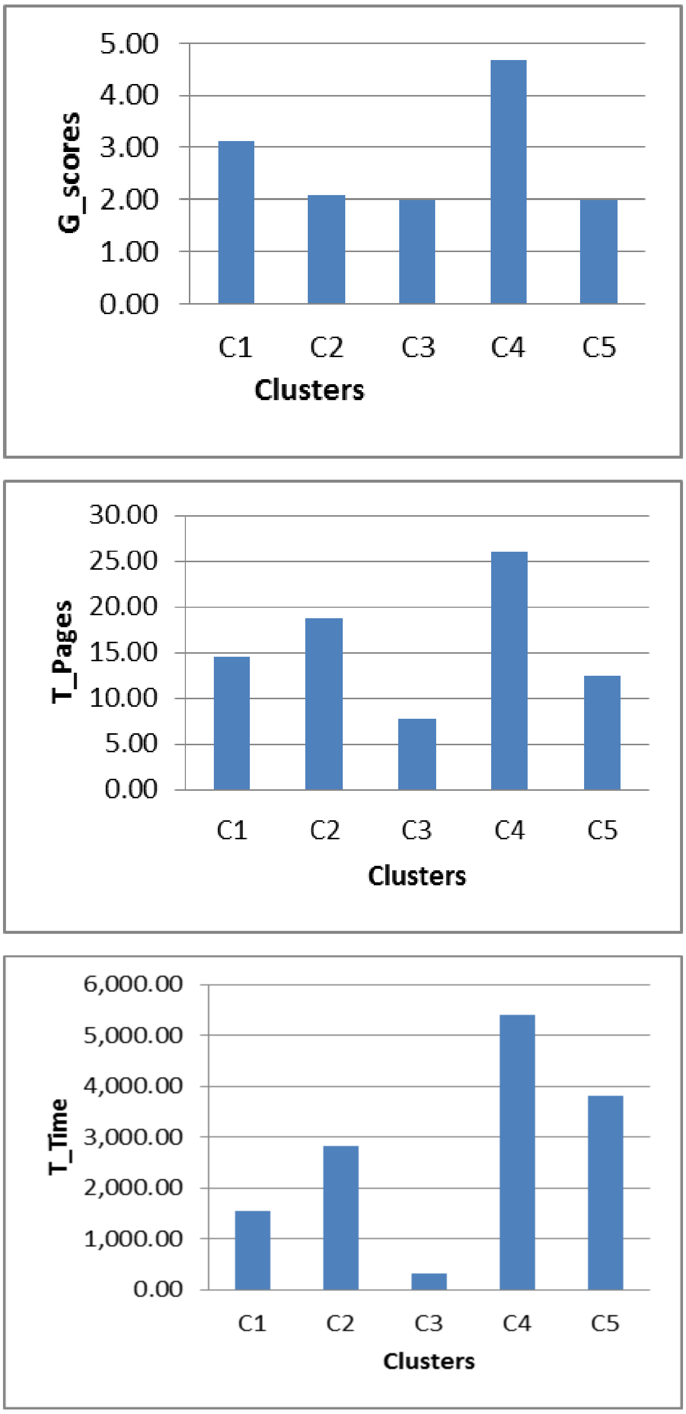


Figure 6-5: Hierarchical algorithm for four clusters and the three attribute values

6.4. Discussion and Conclusion

From the previous discussion, we can conclude that the g-score, t-pages and t-time attributes had a large effect on the performance level of the individual difference intersection. Additionally, there is a significant relationship between such attributes. These relationships can be encapsulated in the following rules:

1. Rule 1: *A participant who achieves a higher g-score after visiting fewer t-pages and spending less t-time in visiting pages compared to the global mean values,* is established to consider a learner with the *best performance*. Thus, the best performance is if a learner achieves a higher g-score than the global mean of all the participants' attribute values after they spent a time less than the global mean of all the participants in browsing the WBI pages and visited less pages than the global mean of all the participants' attribute values.

2. Rule 2: *A participant who achieves a lower g-score after visiting more t-pages and spending higher t-time in visiting pages compared to the global mean values,* is established to consider the learner's *worst performance*. Thus, the worst performance is if a learner achieves a lower g-score than the global mean of all the participants' attribute values after they spent a time more than the global mean of all the participants in browsing the WBI pages, and visited more pages than the global mean of all the participants' attribute values.

To investigate the performance level (High/Low) of the (Multi-ID) using Rule 1 and Rule 2, we compared the means of the attribute values (t-pages, t-time and g-score) of the individual difference intersection in each of our four analyses with the mean values of the three attributes shown in Table 6-2 (t-pages = 15.35, t-time = 2015.36 and g-score = 2.77). Table 6-11and Table 6-12 show the results of performance level in our four analyses. We can conclude the following:

According to Rule 1, we observe that, of the individual difference intersection, those who had shown in our four analyses that they had high performance level are female-field dependent-novice (FFDN). These findings are shown in Table 6-11.

Analyses	Clusters	Individual differences	g-score	t-pages	t-time
Analysis One	C1	FFDN	3.63	12.75	1,941.38
		MFIE	2.67	13.00	1,810.50
	C4	FFIN	5.00	1.00	804.00
		FFDN	3.33	6.00	676.67
Analysis Two	C1	FFIN	3.00	11.00	1,407.50
		FFDN	3.60	11.40	1,710.50
		MFIE	3.10	14.10	1,520.10
Analysis Three	C2	FFIN	5.00	1.00	804.00
		FFDN	3.33	6.00	676.67
	C5	FFDN	3.63	12.75	1,941.38
Analysis Four	C1	FFIN	3.000	11.000	1,407.500
		FFDN	3.60	11.40	1,710.50
		MFIE	3.10	14.10	1,520.10

Table 6-11: Comparison means of individual difference intersection in clusters of our analyses (high performance)

According to Rule 2, we found that some of the individual differences intersection, those who had shown in the four analyses that they had a low performance level are female-field dependent-expert (FFDE), male-field independent-expert (MFIE) and male-field dependent-expert (MFDE). These findings are shown in Table 6-12.

Analyses	Clusters	Individual differences	g-score	t-pages	t-time
Analysis One	C3	FFDE	1.00	16.00	2,974.14
		MFIE	1.75	21.50	2,844.75
		MFDE	0.50	16.50	2,489.00
Analysis Two	C2	FFDE	1.00	16.00	2,974.14
		FFDN	2.67	18.33	3,421.83
		MFIE	1.75	21.50	2,844.75
		MFDE	0.50	16.50	2,489.00
Analysis Three	C3	FFIE	1.00	17.00	3,225.00
		MFIE	2.00	19.00	3,180.00
	C4	FFDE	1.00	17.60	2,716.60
		MFIE	1.67	22.33	2,733.00
		MFDE	0.50	16.50	2,489.00
Analysis Four	C2	FFDE	1.00	17.60	2,716.60
		FFDN	2.25	20.75	3,051.25
		MFIE	1.75	21.50	2,844.75
		MFDE	0.50	16.50	2,489.00

Table 6-12: Comparison of means of individual differences' intersection in clusters of our analyses (low performance)

To conclude this chapter, our findings showed that attribute relationships had an impact on measuring learners' performance level. Those learners were defined using the intersection of the three individual differences. Additionally, a suggested relationship of such attributes was provided for optimal performance. The results obtained using clustering were compared to investigate attribute relationships which explored performance level. Research question RQ5 asked: "What are the relationships between attribute values in measuring the performance level of the individual differences' intersection?" We demonstrated that the relationship of the three attributes had a significant effect on the performance level of the individual differences' intersection. Moreover, we demonstrated two different rules in measuring the optimal and worst level of performance. We also found that the intersection of individual differences female-field-independent-novice (FFIN) and the intersection female-field-independent-expert (FFIE) had the best performance, whereas the intersection of the individual differences male-field-independent-expert (MFIE) had the worst performance.

Research question RQ6 asked: "How the behaviour of individual differences' intersection influenced a learner's performance using three performance measurement attributes?" We found that learners achieve optimal performance when they gain a higher score (post-test minus pre-test) after spending lower time browsing the WBI program and browsing fewer pages compared to the overall mean values of all learners for each of such attributes. Learners exhibit worst performance when they gain a lower score after they spent more time browsing the WBI program and browse more pages compared to the overall mean values for each of attributes.

6.5. Summary

In this chapter, we found that individual differences had a significant impact on learner behaviour using our WBI program. We noted that the relationship between attributes that measure performance played an influential role in exploring performance level, and that the relationship between such attributes induced potential rules in measuring levels of learners' performance. From these findings, we can acknowledge that those learners who have better performance tend to be those who improved better after using our WBI program, but they are not necessarily known as better learners (those who are identified as experts). This implies that a learner may use specific preferences accommodated in a WBI program, although it may not be helpful for improving their learning performance. These findings imply that "*what learners like may not be what they need"* (Minetou, et al., 2008). The other explanation is that performance and preferences are two different things (Minetou, et al., 2008).

CHAPTER SEVEN

CONCLUDING REMARKS

7.1. Overview

The literature on the effects of hypermedia systems on user performance focuses extensively on measurement attributes such as time spent using the system by a user, gained score and number of pages visited in the system. However, there is a dearth of studies which explore the relationship between such attributes in measuring performance level. Our findings showed that attributes relationships had an impact on measuring learners' performance level. Those learners were identified using the combination of the three individual differences. Moreover, we demonstrated two different rules in measuring the optimal and worst level of performance.

In particular, we built a WBI program based on existing designs (Chen, et al., 2006; Chen & Liu, 2008). We evaluated the proposed system by comparing its results with related studies. We also investigated the impact of related individual differences on learners' preferences and performance after interacting with our WBI program.We found that some individual differences and their combination had an impact on learners' preferences when choosing navigation tools. Consequently it has become clear that the related individual differences altered a learner's preferences and that designers of WBI applications need to consider the combination of individual differences rather than considering them individually.

Furthermore, it was clear that learning preferences were influenced by gender when combined with prior knowledge. Designers of hypermedia systems do not need to consider prior knowledge as a part of the design process - our results show that prior knowledge did not influence the navigational preferences of participants individually. Thus, the combination of individual differences needs to be considered. Moreover, our findings demonstrate that such multiple individual differences (Multi-ID) have an impact on learner's preferences, performance and perception of using a WBI system.

7.2. Research Overview and Summary

In **Chapter Two**, we presented a review of the previous literature investigating the effect of individual differences on users' preferences and performance in the use of Web-based applications. We identified three individual differences, including cognitive style, prior knowledge and gender differences. Also, the feature design of WBI applications and their impact on learners' interaction were highlighted. More specifically, individual differences and system features (navigation tools, display options and content scope) were reviewed and a number of significant links identified to understand their influence on the learners' performance level of learning behaviour using three measuring attributes (gain score, number of visited pages and time spent on these pages). Additionally, suitable data mining tools were identified for our research analysis.

In **Chapter Three** we described the nature of the experiment conducted, detailing the design, the materials used and the sample used. Additionally, we described the pilot study conducted, the data analysis used as well as our proposed framework.

In **Chapter Four**, we studied three important individual differences (gender, cognitive style and prior knowledge) as well as their interactions in the resulting learning performances. We combine three attributes to measure performance (gain score, number of visited pages and time spent on these pages) of the three interacting individual differences. On the other hand, we investigated three system features to see how they could help users acquire information to meet their individual needs, thereby resulting in an improvement in the learning performance. To understand learners' behaviour, we compared our results with related studies. Therefore, in this chapter, we evaluated our WBI program by examining the impact of gender, prior knowledge and cognitive style as individual differences on learning behaviour while interacting with our WBI program. We used a data mining technique which is the process of discovering interesting relationship between the three individual differences to understand how learners performed when interacting with our WBI program.

Following on from findings of Chapter Four, we did further investigations in Chapter Five to understand the effect of multiple individual differences (Multi-ID) on user preferences after interacting with our WBI program. Moreover, in Chapter Six we undertook further analysis to understand how Multi-ID affected learner's performance measured by three measurement factors.

Therefore, in **Chapter Five**, we investigate the influence of Multi-ID on learners' preferences using our WBI program which accommodates learning needs of using navigation tools. As our WBI program logs all the navigational activities of each user, we use the log file data to conduct our analysis. We used independent-sample t-test to analyze each of the individual differences individually and compared our findings with previous studies. Henceforward, we used ANOVA test to analyze several combinations of individual differences to investigate how each combination influence the learning preferences based on our individual tests. Statistical analysis was used on the questionnaire to understand learners' perception in order to explore their satisfaction.

In **Chapter Six**, the literature focuses extensively on the effects of hypermedia systems on user performance using measurement attributes such as time spent using the system by a user, gain score (g-score) and number of pages visited in the system. In this chapter, we investigated the relationship between attributes that measure performance to explore rules in measuring level of learners' performance. We use a data mining approach to analyze the results by comparing between two clustering algorithms (K-Means and Hierarchical) using two different numbers of clusters in each comparison.

7.3. Research Findings

This section presents the key findings from the corresponding study. We studied three important individual differences (gender, cognitive style and prior knowledge) as well as their interactions (Multi-ID) to understand learners' preferences, performance and perception. An investigation was done to understand how the three system features (navigation tools, display options and content scope) could help users acquire information to meet their individual needs thereby resulting in an improvement in the learning performance.

We started our analysis by evaluating our WBI program. That was done by examining the impact of gender, prior knowledge and cognitive style as individual differences on learning behaviour while interacting with our WBI program. To understand learner behaviour, we compared our results with related studies. Our comparison showed that we succeeded in implementing a hypermedia system that accommodated preferences of each of the individual differences which impacts learner's performance. Thus, we found that our WBI program did indeed affect learner's behaviour and matched the majority of existing study findings. Therefore, our findings clearly demonstrate that such individual differences have an impact on learner's preferences. Additionally, we also found that performance could be affected by the behaviour of individual differences when using our WBI program. Moreover, we found that the interaction between individual differences had an even higher impact on the learners' performance.

Following on from these findings, we did further investigations to deeply understand the effect of Multi-ID on user preferences and performance after interacting with our WBI program. We found that the Multi-ID had a significant impact on influencing learners' preferences when using the navigation tools. Designers of WBI applications thus need to consider the combination of individual differences rather than considering them individually. Moreover, we found that learning preferences were influenced by gender when combined with prior knowledge. Designers of hypermedia systems do not need to consider prior knowledge as a part of the design process - our results show that prior knowledge does not influence the navigational preferences of the participants individually. Finally, it is nice to note that our questionnaire results objectively show that learners were satisfied using our WBI program.

Moreover, we undertook further analysis to understand how Multi-ID affected learner's performance measured by three measurements attributes. We found that attribute relationships had an impact on measuring learners' performance level. Thus, we conclude that the combination of individual differences had a great effect on the performance of the learners. Thus, we provided two rules in measuring learning performance level by exploring relationships between measurement attributes that affect performance level. This was done by using Rule 1 and Rule 2, in understanding the performance level of each of the Multi-ID and exploring the best and worst performing learners. The suggested rules are:

Rule 1: *when a learner achieves a higher g-score after visiting fewer t-pages and spending less t-time in visiting pages compared to the global mean values,* we consider them to be a learner who had the *best performance*.

Rule 2: *when a learner who achieves a lower g-score after visiting more t-pages and spending higher t-time in visiting pages compared to the global mean values,* we consider them to be a learner who had the *worst performance*.

Therefore, we found that learners achieve optimal performance when they gain a higher score (post-test minus pre-test) after spending lower time browsing the WBI program and browsing fewer pages compared to the overall mean values of the all learners for each of such attributes. Those learners were found to be female-field independent-novice (FFIN) and female-field independent-expert (FFIE) learners. On the other hand, learners exhibit the worst performance when they gain a lower score after they spend more time browsing the WBI program and browse more pages compared to the overall mean values for each of attributes. Those learners were found to be male-field independent-expert (MFIE) learners.

We accept that the data underlying development of these rules, subject to scrutiny and further analysis might reveal further insights into the data, different perspectives of the data and generate added conclusions; however, we leave this interesting aspect of data analysis for future work.

7.4. Meeting the Research Objectives

The research objectives were presented in Section 1.3. These objectives are revisited and discussed below to demonstrate how they have been achieved in Chapters Four, Five and Six.

Objective One: *Understanding whether our developed WBI program affects learner's behaviour*. This objective was achieved in Chapter Four, where we investigated and evaluated the effect of using our WBI program on learners' behaviour. This investigation was done by comparing our findings with findings of existing studies thus evaluating its design.

Objective Two: *Investigating whether a learner's performance affected by relating individual differences*. This objective was achieved in Chapter Four by exploring whether the interaction between individual differences had a higher impact on the learners' performance. A data mining approach was used to investigate the influence of the interaction between individual differences on learner's performance.

In Chapter Five we achieved **Objective Three,** where *we investigated whether Multi-ID had an influence on learners' preferences using the navigational tools of our WBI program*, and **Objective Four**, *investigate which factor of the Multi-ID has a significant impact on learners' preferences in using navigation tools of our WBI program*, we studied the preferences of three individual differences (cognitive style, prior knowledge, and gender) separately. Then, we analyzed several combinations of individual differences (Multi-ID) to investigate how each combination influence the learning preferences based on our individual tests. Firstly, we used an independent sample t-test to study the preferences of our learners based on individual differences individually. Secondly, we used ANOVA to allow the testing of the differences of preferences for the combined two and three individual differences (Multi-ID) where these combination resulted into more than three independent groups to be tested.

Objective Five: *To understand the relationship between attributes values in measuring the performance level of the individual differences*. This objective was achieved in Chapter Six by investigating the relationships between measurement attributes (gain scores, number of pages visited in a WBI program and time spent on such pages) to explore the performance level. We found that the relationship between attributes that measured performance played an influential role in exploring the performance level; the relationship between such attributes induced optimal and worst performance.

Objective Six, *to understand the influence of the individual differences on learner's performance using three performance measurements attributes*. This objective was achieved in Chapter Six by investigating the effect of combined individual differences on learning performance level by exploring relationships between measurement attributes that affect performance level. This was done by using Rule 1 and Rule 2, in understanding the performance level of each of the Multi-ID and exploring the best and worst performing learners.

7.5. Contribution

Many studies have been engaged in understanding learners' preferences using web-based programs. Some studies have shown that user prior knowledge plays a significant role in the use of navigation tools in hypermedia learning systems (Chen, et al., 2006; Minetou, et al., 2008; Lee, et al., 2009). Many studies have shown that index tools are helpful for experts. On the other hand, map and menu tools have been shown to be beneficial for novice learners (Chen & Macredie, 2010; Chen, et al., 2006; Minetou, et al., 2008). However, others have argued that there is no significant difference between experts and novices in the use of a hierarchical map (Calisir & Gurel, 2003), where experts and novices opened equal number of nodes in a hierarchical document. The lack of significant differences is inconsistent with the findings of (McDonald & Stevenson, 1998) where it was found that experts opened more nodes than novices in hierarchical environment.

In this thesis, we explored those contradictions from the perspective of existing studies. Thus, we investigated the impact of prior knowledge on learner's preferences using our WBI program. We found that prior knowledge did not influence the navigational preferences of participants individually.

Previous findings have shown that a learner's cognitive style has an impact on learning preferences. Field independent users often prefer an alphabetical index, whereas field dependent users often use a hierarchical map (Chen, 2010; Chen & Liu, 2008; Farrell & Moore, 2001; Ford & Chen, 2000). While those studies have investigated the cognitive style alone, it is not clear how the cognitive style of learners would be influenced by gender and prior knowledge. Thus, in this thesis, we investigated the preferences of learners identified by using one of the individual differences and by identifying learners according to the combination of three individual differences (prior knowledge, cognitive style and gender). Designers of WBI applications need to consider the combination of individual differences rather than considering them individually which has a great impact to alter a learner's preferences. Few previous studies have been carried out to conduct a thorough investigation of the three attributes (g-score, t-pages and t-time) and what relationships between such attributes may affect learners' performance level using the combination of three individual differences (gender, cognitive style and prior knowledge).

We acknowledge that those learners who have better performance are those who improved after using our WBI program and are not necessarily known as better learners (those who are identified as experts). This implies that a learner may use specific preferences accommodated in a WBI program although it may not be helpful for improving their learning performance. These findings imply that "what learners like may not be what they need" (Minetou, et al., 2008).

The other explanation is that performance and preferences are two different things (Minetou, et al., 2008). Here, preference represents how much a learner prefers a given tool or not while performance means the ability of learners actually solve problems (Topi & Lucas, 2005). Superior performance requires not only knowledge and skills but also how to use knowledge and skills effectively (Mavis, 2001).

7.6. Significance of Thesis and Concluding Remarks

The significance of this thesis lies within three different aspects, including theory, practice and methodology.

With regard to *methodology*, this study implements existing designs using three system features provided by Chen, et al., (2006) and Chen & Liu (2008) in designing our WBI program. We extend their work to include gender into our analysis in order to understand their behaviour of using hypermedia systems. Additionally, we use our design in identifying cognitive style; more specifically field dependent and field independent learners.

With regard to *theory*, firstly, our investigation helps to understand the behaviour of different dimensions of the individual differences (gender, cognitive style and prior knowledge); few previous studies have been carried out to investigate the combination of such three individual differences and their impact on learners' behaviour. This investigation also helps to identify the interactions between individual differences, taking a step forward in understanding the combined effects of multiple individual differences and how this could affect their preferences, perception and performance. Moreover, this could help designers in developing their Web-based applications to ensure design effectiveness. Secondly, few previous studies have been carried out to investigate these three attributes (g-score, t-pages and t-time) and what relationships between such attributes may affect learners' performance level using the combination of the three individual differences.

With regard to *practice*, this research makes a unique contribution to practice through the rich experience it supplies to learners using hypermedia system. It provides learners with the knowledge they need in a way they prefer and aims to enhance their performance by improving their ability and productivity. That was clearly offered by three system features in designing a WBI program while meeting learners' needs.

7.7. Limitations and Future Work

There are some limitations in the current research that should be recognised. However, these limitations can provide a starting point for future research. These can be summarised as follows:

1. Our WBI program was designed using three system features, navigation tools, display options and content scope. As shown in Section 3.3.1, integrating the feature - display options in the design of our WBI program, more specifically in designing the topic pages of the program, is to have a table that presents the topic where one column to be used in presenting the detailed descriptions of a particular topic, while the other column provides the illustration with examples for that topic (Figure 3.3). A learner can read the topic content either from the detailed descriptions (left column) or from the illustration with examples (right column). Thus, a learner's choice of

reading the topic (either from the left or the right column) will not be registered in the log file as a learner's preferences. Thus, learner's behaviour, using the system feature - display options, was not recognised. That was one of the limitations in this research, where it would be interesting to investigate learners' preferences of using the system feature - display options.

2. Our experiment was conducted on a 91 undergraduate participants from the Computing Department of the Higher Institute of the Telecommunication and Navigation in Kuwait. We used only one course content of this department in designing the instructions of our WBI program. Other courses contents of this department or even other departments may take place in the instruction of the WBI program to give a solid understanding of learners' behaviour. Moreover, experimentations could be conducted in other educational organizations which could be governmental or private sectors where ages and background information may vary.
3. Classification of cognitive style into field-dependent and field-independent was done by using our system's log file (stated in Section 3.3.2). Using a validated test for classification into field-dependent and field-independent needs to be recognised as a limitation of the Thesis. It would be interesting to compare results between these two classification strategies to have more evidence for our systems' results in such identification of cognitive style. This will be a topic of future research.
4. The satisfaction questionnaire was positively-biased, because of the many positively phrased questions with only two negative questions out of the total of 20 and this might have influenced our results. Therefore, this could be a limitation of the research; we would need to explore learners' satisfaction in using our system in more depth to ameliorate this limitation.

The following are some important directions for future research in order to continue developing this research domain:

1. As a learner's behaviour, using the system feature - display options, was not recognized in the log file, it is important to design the page in the WBI program in a way to log their choice as it was one of the limitations mentioned above.

2. There is a need to analyze learners' performance using other data-mining approaches such as classification. The classification approach is used to understand existing data and to predict how new cases will behave (Chen & Liu, 2008). Thus, we can use classification to explore a learner's identification (its combination of individual diffrences) by understanding its behaviour using a predefined set of classes.
3. We need to consider more subjects and a larger sample to provide additional evidence in understanding learner's preferences and perception using our design of WBI systems.
4. Understanding behaviour of our WBI users in other organizations with different background knowledge would also be interesting future work which may give a solid understanding of a learner's behaviour.
5. There is a need to analyze learners' navigation behaviour using other individual differences such as cultural background in order to understand learners' preferences deeply.
6. It would be interesting to compare between results of identifying field-dependent and field-independent using two classification strategies, our system's log file and a validated test. Doing this may provide more support for our results.

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APPENDIX A: EXPERIMENT INFORMATION AND AGREEMENT SHEET

Date:

WBI experiment

[*Information Sheet*]

- **Purpose of this experiment:**

  This experiment should be held on the Higher Institute of Telecommunication and Navigation, which may help to enhance the educational level in such institute.

  This study is intends to investigate the impact of using a mechanism in our **Web Based Instruction** (**WBI**) program, which accommodates the intersection preferences of three individual differences (such as cognitive style, prior knowledge and gender) with three key design elements (such as navigation tools, display options and content scope) on the learners' preferences, performance and performance.

- **Phases of this experiment:**

  Participants will go through four phases in this experiment as follows:

  Phase 1: **Pre-test** will be produced to the participant to identify their prior knowledge to PowerPoint in order to be clear with the participants' natures.

  Phase 2: The participants will then be given an introduction about how to use the WBI program. After that, they should be asked to spend two hours maximum in interacting with the WBI program using a given **Task** sheet. The WBI program gives an introduction to how to use the PowerPoint, and the Task sheet contains exercises that should be applied on the PowerPoint application.

  Phase 3: A **post-test** should be provided to be used later to check the participants' performance.

  Phase 4: A **questionnaire** should be taken to check the participants' perception and satisfaction using our WBI.

- **Ethical issues:**

  The information provided will be held strictly and confidential and if you are interested in the results of this research, we will be happy to send you a result copy of this research.

Your cooperation is highly appreciated

[*Participants' Agreement Sheet*]

I have read and understood the **[*Information Sheet*]** in page 1. I agree to participate in this experiment and give my consent freely. I will try my best to ensure that the experiment will be carried out as described in the **[*Information Sheet*]** in page 1. I confirm that my agreement to solely participate is my decision.

Note: Please use the same spelling of your name (in English) in all the experiments phases.

	Name	Signature
1.		
2.		
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20.		

APPENDIX B: WBI TASK SHEET

Student Name:

Dear Students:

Thank you for volunteering to participate in this tutorial! You will be able to use a Web Page Instruction (WBI) to do a specific task. First, you have to start the PowerPoint XP application. Then, you have to start the WBI website (www.alothman.ws/rana2/p1.php). After that, you have to do the following:

1. You should create a New Presentation.
2. You should have 2 slides. Try to understand how to add and remove the slide.
3. You should save your presentation using Exam.ppt On the desktop.
4. In Slide 1, do the following:
    a. Change the slide Background to any Texture Fill Effect to this slide only.
    b. Use any of the existing Placeholders to write the following:

        "Enjoy the slide Content"

    c. Write "Your Name" using any WordArt.
    d. Use any effect to animate your name and try to discover the options there.
    e. Add any ClipArt about computer.
    f. Insert the following table:

My course	Multimedia Technology	
	CM. 126	
My topic	Introduction to PowerPoint	

g. Add any transition effect to move Slide 1 after 10 seconds

5. In Slide 2, do the following:
   a. Apply any Slide Design to this slide only.
   b. Discover the ways of changing the layout and change the layout of this slide to Blank.
   c. Add any picture.
   d. Add a button that takes you to the first slide.
   e. Add any AutoShape and change the filling of this AutoShape to any effect.
   f. Practice how to add a sound file and play it automatically.
   g. Practice how to add a movie file and play it automatically.

6. After you finish, click on the following node:

1.5 Getting Help

APPENDIX C: PRE-TEST

Student Name:

Choose the correct answer:

1. To write a text on a slide you can use:
   a) WordArt
   b) Text box
   c) All of the above
   d) None of the above
   e) I don't know

2. To add a new slide to your presentation, use the:
   a) Insert menu
   b) Drawing toolbar
   c) All of the above
   d) None of the above
   e) I don't know

3. The following are some views of the PowerPoint interface:
   a) Normal, Show, Action
   b) Sorter, Show, design
   c) Normal, Sorter, Show
   d) None of the above
   e) I don't know

4. You can find the command that change the Background from the following menu:
   a) Tools
   b) Format
   c) Insert
   d) File
   e) I don't know

5. You can find the insert a New Slide button on the following toolbar:
   a) Formatting
   b) Standard
   c) Task Pane
   d) None of the above
   e) I don't know

6. To delete a slide, you can find the Delete command under the following menu:
    a) Tools
    b) Edit
    c) Format
    d) None of the above
    e) I don’t know

7. The following can be known as a slide layout:
    a) Title Only
    b) Title and Text
    c) Blank
    d) All of the above
    e) I don’t know

8. The following can be known as a background fill effect:
    a) Blank
    b) Picture
    c) Ocean
    d) All of the above
    e) I don’t know

9. The following can be known as a slide Design:
    a) Clouds
    b) Ocean
    c) Balance
    d) All of the above
    e) I don’t know

10. You can insert an AutoShape using the following toolbar:
    a) Formatting
    b) Standard
    c) Drawing
    d) Task Pane
    e) I don’t know

11. To add a table to your slide, you can find the command under the following menu:
    a) Insert
    b) Tools
    c) Edit
    d) Formatting
    e) I don’t know

12. To add a picture to your slide, you can find the command under the following menu:
    a) Insert
    b) Tools
    c) Edit
    d) Formatting
    e) I don't know

13. To add a ClipArt to your slide, you can find the command under the following menu:
    a) Insert
    b) Tools
    c) Edit
    d) Formatting
    e) I don't know

14. You can change the AutoShape fill effect by applying:
    a) Texture
    b) Pattern
    c) Color
    d) All of the above

15. To add a Movie to your slide, you can find the command under the following menu:
    a) Insert
    b) Tools
    c) Edit
    d) Formatting
    e) I don't know

16. Slide transition can be known as:
    a) Animating the objects on the slide
    b) Changing a slide design
    c) Working on AutoShape Format
    d) None of the above
    e) I don't know

17. Custom Animation can be:
    a) Action Settings
    b) Emphasis
    c) Sorter
    d) None of the above
    e) I don't know

18. You can start your Custom Animation using:
    a) After previous
    b) On click
    c) With previous
    d) All of the above
    e) I don’t know

19. Action Settings is a hyperlink that can be used:
    a) As a connection from a slide to another
    b) To End Show
    c) To Link an object to a URL
    d) All of the above
    e) I don’t know

20. AutoShapes can be:
    a) Action Buttons
    b) Lines
    c) Block Arrows
    d) All of the above
    e) I don’t know

APPENDIX D: POST-TEST

Student Name:

Choose the correct answer:

1. WordArt can be
   - ☐ A slide design
   - ☐ Used to write a text on a slide
   - ☐ All of the above
   - ☐ None of the above
   - ☐ I don't know

2. You can add a new slide to your presentation using New Slide option which is located under the:
   - ☐ Insert menu
   - ☐ Task pane
   - ☐ All of the above
   - ☐ None of the above
   - ☐ I don't know

3. Normal and Sorter can be known as a:
   - ☐ Slide Design
   - ☐ Slide View
   - ☐ Slide Layout
   - ☐ None of the above
   - ☐ I don't know

4. Changing a slide background can be done using the:
   - ☐ Format Menu
   - ☐ Insert Menu
   - ☐ Tools Menu
   - ☐ Window Menu
   - ☐ I don't know

5. You can insert a new slide by:
   - ☐ Using New Slide button which is located on the Standard Toolbar
   - ☐ Using New Slide button which is located on the Formatting Toolbar
   - ☐ Using New Slide button which is located on the Drawing Toolbar
   - ☐ None of the above
   - ☐ I don't know

6. To remove a slide from an existing presentation you can apply the following instructions:
   - ☐ From the Slide Show menu, choose Hide Slide
   - ☐ From the Edit menu, choose Delete Slide
   - ☐ From the View menu, choose Delete Slide
   - ☐ None of the above
   - ☐ I don't know

7. Slide Layouts contains:
   - ☐ Placeholders
   - ☐ Clip art
   - ☐ Table
   - ☐ All of the above
   - ☐ I don't know

8. You can change the slide background to be:
   - ☐ A color
   - ☐ A picture
   - ☐ A texture
   - ☐ All of the above
   - ☐ I don't know

9. Ocean can be known as a:
   - ☐ Slide Design
   - ☐ Slide Layout
   - ☐ All of the above
   - ☐ None of the above
   - ☐ I don't know

10. AutoShapes are located on:
    - ☐ Task pane
    - ☐ Drawing toolbar
    - ☐ Standard toolbar
    - ☐ All of the above
    - ☐ I don’t know

11. To add a table to your slide you can apply the following instructions:
    - ☐ Using “Insert Table” button which is located on Drawing Toolbar
    - ☐ Using “Insert Table” button which is located on the Standard Toolbar
    - ☐ Using Table option which is located on the Tools Menu
    - ☐ Using Table option which is located on the Format Menu
    - ☐ I don’t know

12. To add a picture to your slide you can apply the following instructions:
    - ☐ Using “Insert Picture” button which is located on Standard Toolbar
    - ☐ Using “Insert Picture” button which is located on the Formatting Toolbar
    - ☐ Using “Picture From File” option which is located on the Tools Menu
    - ☐ Using “Picture From File” option which is located on the Insert Menu
    - ☐ I don’t know

13. You can find the option to add a ClipArt to your slide under the following menu:
    - ☐ File
    - ☐ Insert
    - ☐ Tools
    - ☐ Edit
    - ☐ I don’t know

14. The Fill Effect of the AutoShape can be:
    - ☐ Gradient and Picture
    - ☐ Black and Texture
    - ☐ Blue and Pattern
    - ☐ All of the above
    - ☐ I don’t know

15. To add a Sound to your slide you can use.
    - ☐ Edit Menu
    - ☐ Insert Menu
    - ☐ Tools Menu
    - ☐ Format Menu
    - ☐ I don't know

16. You can move from Slide to another by using some effect, this can be done by using:
    - ☐ Slide transition
    - ☐ Fill effect
    - ☐ Slide layout
    - ☐ None of the above
    - ☐ I don't know

17. "Emphasis" can be one of the:
    - ☐ Slide transition effects
    - ☐ Custom Animation effects
    - ☐ Font Format
    - ☐ None of the above
    - ☐ I don't know

18. One of the ways of how to start your Custom Animation is:
    - ☐ With Previous
    - ☐ Action Settings
    - ☐ Fill Effect
    - ☐ None of the above
    - ☐ I don't know

19. To Link an object to a URL (Uniform Resource Locator) you can use:
    - ☐ Action Settings
    - ☐ Custom Animation
    - ☐ Slide Transition
    - ☐ None of the above
    - ☐ I don't know

20. Action Buttons can be:
    - ☐ AutoShapes
    - ☐ Pictures
    - ☐ Text
    - ☐ All of the above
    - ☐ I don't know

APPENDIX E: SATISFACTION SURVEY

Your assistance is requested in a survey of your expertise of using Web Based Instruction (WBI) system. While we are asking for your name, please be assured that your responses will be kept in strictest confidence.

Name: ____

Email address: __________________________________

Group number: _________________________________

You are:

Female	☐
Male	☐

Given below are a number of statements about using WBI. Please tick only one box for each of the following statements that indicate your level of agreement or disagreement.

	Overall Satisfaction to the System- Subject Content	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
1.	This WBI is only useful for learners who have basic knowledge about PowerPoint.	☐	☐	☐	☐	☐
2.	This WBI is more helpful for novice learners.	☐	☐	☐	☐	☐
3.	It is easy to learn PowerPoint using the WBI without additional help.	☐	☐	☐	☐	☐
4.	After using the WBI I found it easy to use my knowledge to answer the multiple-choice posttest.	☐	☐	☐	☐	☐
5.	I find it is difficult to design a presentation using PowerPoint although I have taking the tutorial of WBI.	☐	☐	☐	☐	☐

	System Features-Functionality and Usability	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
6.	I like the fact that the WBI allows me to learn topics in specified frames.	☐	☐	☐	☐	☐
7.	I like the fact that I have the ability to control the pace of instruction using Hierarchal Map.	☐	☐	☐	☐	☐
8.	I like the fact that I have the ability to control the pace of instruction using Index.	☐	☐	☐	☐	☐
9.	I felt frustrated when having to follow the suggested route through the WBI.	☐	☐	☐	☐	☐
10.	I did not get lost when browsing the links in the WBI system.	☐	☐	☐	☐	☐
11.	I like the fact that I can see both the Hierarchal Map frame and the index frame.	☐	☐	☐	☐	☐
12.	I prefer to have every topic link I click a popup window of that topic is provided.	☐	☐	☐	☐	☐
13.	I like the fact that I can see the detailed descriptions and the illustration with examples shown within one table.	☐	☐	☐	☐	☐
14.	I like the fact that more details on a topic can be provided in another popup window.	☐	☐	☐	☐	☐

	Overall Satisfaction - General Perceptions	**Strongly Agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
15.	I like using the interface of this system.	☐	☐	☐	☐	☐
16.	It was simple to use this system.	☐	☐	☐	☐	☐
17.	I feel comfortable using this system.	☐	☐	☐	☐	☐
18.	Overall, I was very satisfied with the presentation of instructional material.	☐	☐	☐	☐	☐
19.	Overall, I was very satisfied with the system.	☐	☐	☐	☐	☐
20.	Overall, I had a very positive learning experience.	☐	☐	☐	☐	☐

Overall Perception

1. Please list all the things you liked most about the WBI system:

    a.

    b.

    c.

2. Please list all the things you disliked most about the WBI system:

    a.

    b.

    c.

Thank you for your participation

APPENDIX F: COLLECTED DATA

Participants	Pre-test	Post-test	gain score (g-score)	Number of pages visited using Map	Number of pages visited using Index	Total number of topics visited	Total time (in seconds) spent on topic pages	Gender (F: Female/ M: Male)	Prior knowledge (E: Expert/ N: Novice)	Cognitive Style (FD: Field-dependent / FI: Field-independent)
Participant-01	12	13	1	3	15	17	1567	F	E	FI
Participant-02	10	14	4	3	6	8	2633	F	E	FI
Participant-03	12	13	1	4	14	17	3225	F	E	FI
Participant-04	9	12	3	8	13	18	2740	F	E	FI
Participant-05	12	15	3	1	6	7	1002	F	E	FI
Participant-06	10	15	5	1	2	3	17	F	E	FI
Participant-07	13	14	1	1	2	3	146	F	E	FI
Participant-08	11	13	2	4	8	7	1145	F	E	FI
Participant-09	7	8	1	12	13	21	2011	F	N	FI
Participant-10	4	11	7	4	15	19	4832	F	N	FI
Participant-11	6	11	5	0	1	1	804	F	N	FI
Participant-12	10	8	-2	30	0	25	1493	F	E	FD

Participants	Pre-test	Post-test	gain score (g-score)	Number of pages visited using Map	Number of pages visited using Index	Total number of topics visited	Total time (in seconds) spent on topic pages	Gender (F: Female/ M: Male)	Prior knowledge (E: Expert/ N: Novice)	Cognitive Style (FD: Field-dependent / FI: Field-independent)
Participant-13	11	9	-2	13	7	17	2618	F	E	FD
Participant-14	14	15	1	8	0	6	1682	F	E	FD
Participant-15	13	14	1	25	2	21	2618	F	E	FD
Participant-16	13	15	2	13	2	12	1713	F	E	FD
Participant-17	15	16	1	20	1	20	2727	F	E	FD
Participant-18	10	12	2	14	7	17	1775	F	E	FD
Participant-19	10	7	-3	7	3	6	1017	F	E	FD
Participant-20	10	15	5	15	1	14	2897	F	E	FD
Participant-21	9	7	-2	14	3	14	5790	F	E	FD
Participant-22	13	15	2	19	0	15	3678	F	E	FD
Participant-23	10	10	0	7	3	9	3558	F	E	FD
Participant-24	14	14	0	13	0	7	314	F	E	FD
Participant-25	15	16	1	6	0	5	2134	F	E	FD
Participant-26	10	13	3	13	11	18	705	F	E	FD

Participants	Pre-test	Post-test	gain score (g-score)	Number of pages visited using Map	Number of pages visited using Index	Total number of topics visited	Total time (in seconds) spent on topic pages	Gender (F: Female/ M: Male)	Prior knowledge (E: Expert/ N: Novice)	Cognitive Style (FD: Field-dependent / FI: Field-independent)
Participant-27	15	19	4	12	0	3	523	F	E	FD
Participant-28	14	14	0	16	4	16	2723	F	E	FD
Participant-29	5	9	4	22	1	20	1790	F	N	FD
Participant-30	8	15	7	23	2	21	2854	F	N	FD
Participant-31	6	12	6	7	2	9	2159	F	N	FD
Participant-32	7	8	1	16	0	11	1754	F	N	FD
Participant-33	6	9	3	11	0	6	456	F	N	FD
Participant-34	5	12	7	19	0	13	2115	F	N	FD
Participant-35	8	9	1	16	4	13	2080	F	N	FD
Participant-36	6	10	4	17	6	22	1725	F	N	FD
Participant-37	5	8	3	9	1	7	795	F	N	FD
Participant-38	6	8	2	8	2	5	2097	F	N	FD
Participant-39	8	8	0	19	13	27	2992	F	N	FD
Participant-40	2	6	4	7	2	5	779	F	N	FD

Participants	Pre-test	Post-test	gain score (g-score)	Number of pages visited using Map	Number of pages visited using Index	Total number of topics visited	Total time (in seconds) spent on topic pages	Gender (F: Female/ M: Male)	Prior knowledge (E: Expert/ N: Novice)	Cognitive Style (FD: Field-dependent / FI: Field-independent)
Participant-41	8	9	1	22	0	20	3043	F	N	FD
Participant-42	1	5	4	9	0	9	1811	F	N	FD
Participant-43	7	16	9	51	1	45	5547	F	N	FD
Participant-44	5	6	1	18	0	15	3316	F	N	FD
Participant-45	3	8	5	10	7	13	3972	F	N	FD
Participant-46	3	5	2	26	0	14	4354	F	N	FD
Participant-47	13	15	2	7	15	19	2458	M	E	FI
Participant-48	12	13	1	9	14	20	3017	M	E	FI
Participant-49	9	8	-1	1	12	12	1926	M	E	FI
Participant-50	9	13	4	4	12	14	1703	M	E	FI
Participant-51	9	9	0	5	6	10	2076	M	E	FI
Participant-52	10	12	2	9	25	28	2724	M	E	FI
Participant-53	11	13	2	9	15	19	3180	M	E	FI
Participant-54	9	14	5	1	4	4	2049	M	E	FI

Participants	Pre-test	Post-test	gain score (g-score)	Number of pages visited using Map	Number of pages visited using Index	Total number of topics visited	Total time (in seconds) spent on topic pages	Gender (F: Female/ M: Male)	Prior knowledge (E: Expert/ N: Novice)	Cognitive Style (FD: Field-dependent / FI: Field-independent)
Participant-55	5	9	4	4	12	13	2084	M	N	FI
Participant-56	8	12	4	5	25	23	2235	M	N	FI
Participant-57	10	14	4	17	0	13	2402	M	E	FD
Participant-58	9	13	4	12	6	17	1826	M	E	FD
Participant-59	13	10	-3	17	7	20	2576	M	E	FD
Participant-60	13	13	0	33	0	25	555	M	E	FD
Participant-61	10	11	1	14	0	10	1501	M	E	FD
Participant-62	1	8	7	20	0	17	2479	M	N	FD
Participant-63	3	3	0	16	9	20	2829	M	N	FD
Participant-64	6	11	5	37	0	33	3294	M	N	FD
Participant-65	2	6	4	10	0	10	2711	M	N	FD
Participant-66	5	7	2	9	1	7	713	M	N	FD
Participant-67	8	9	1	20	7	15	1851	M	N	FD
Participant-68	8	9	1	16	3	11	3547	M	N	FD

Participants	Pre-test	Post-test	gain score (g-score)	Number of pages visited using Map	Number of pages visited using Index	Total number of topics visited	Total time (in seconds) spent on topic pages	Gender (F: Female/ M: Male)	Prior knowledge (E: Expert/ N: Novice)	Cognitive Style (FD: Field-dependent / FI: Field-independent)
Participant-69	5	18	13	12	20	27	1450	M	N	FI
Participant-70	10	10	0	14	8	18	1721	M	E	FD
Participant-71	2	8	6	7	12	17	1699	M	N	FI
Participant-72	12	13	1	7	1	8	269	M	E	FD
Participant-73	8	14	6	1	13	14	2302	M	N	FI
Participant-74	12	13	1	20	12	19	1074	M	E	FD
Participant-75	7	8	1	0	19	19	925	M	N	FI
Participant-76	9	13	4	4	10	12	1023	M	E	FI
Participant-77	5	8	3	6	16	18	1452	M	N	FI
Participant-78	9	17	8	0	22	20	1233	M	E	FI
Participant-79	8	11	3	3	18	16	1467	M	N	FI
Participant-80	8	12	4	9	10	13	1355	M	N	FI
Participant-81	6	9	3	5	18	18	1186	M	N	FI
Participant-82	3	12	9	6	17	20	1031	M	N	FI

Participants	Pre-test	Post-test	gain score (g-score)	Number of pages visited using Map	Number of pages visited using Index	Total number of topics visited	Total time (in seconds) spent on topic pages	Gender (F: Female/ M: Male)	Prior knowledge (E: Expert/ N: Novice)	Cognitive Style (FD: Field-dependent / FI: Field-independent)
Participant-83	11	14	3	2	9	11	920	M	E	FI
Participant-84	7	9	2	0	23	23	1415	M	N	FI
Participant-85	6	13	7	1	19	18	2134	M	N	FI
Participant-86	9	15	6	3	19	22	1338	M	E	FI
Participant-87	11	11	0	6	17	20	1162	M	E	FI
Participant-88	7	10	3	7	21	23	1887	M	N	FI
Participant-89	5	12	7	3	24	23	1289	M	N	FI
Participant-90	9	11	2	3	17	16	1771	M	E	FI
Participant-91	13	14	1	16	9	21	1833	M	E	FD

APPENDIX G: SATISFACTION RESULTS OF MULTI-ID

Q1: This WBI is only useful for learners who have basic knowledge about PowerPoint.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	0	3	4	2	1	1	1	12
Disagree	1	0	2	2	1	1	0	0	7
Neutral	1	0	1	2	2	1	3	1	11
Agree	3	1	5	6	3	5	2	3	28
Strongly Agree	3	2	6	4	6	7	3	2	33
Total	8	3	17	18	14	15	9	7	91

Q2: This WBI is more helpful for novice learners.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	0	1	1	0	1	0	0	3
Disagree	0	1	1	1	0	1	1	0	5
Neutral	0	0	0	3	2	2	0	1	8
Agree	2	1	6	2	4	4	2	1	22
Strongly Agree	6	1	9	11	8	7	6	5	53
Total	8	3	17	18	14	15	9	7	91

Q3: It is easy to learn PowerPoint using the WBI without additional help.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	0	0	1	0	1	0	0	2
Disagree	0	0	1	0	0	0	0	0	1
Neutral	1	1	1	3	5	4	1	1	17
Agree	2	0	5	4	6	5	4	2	28
Strongly Agree	5	2	10	10	3	5	4	4	43
Total	8	3	17	18	14	15	9	7	91

Q4: After using the WBI I found it easy to use my knowledge to answer the multiple-choice posttest.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	1	1	0	0	0	0	0	2
Neutral	3	0	4	6	3	1	0	3	20
Agree	3	1	3	4	9	7	6	3	36
Strongly Agree	2	1	9	8	2	7	3	1	33
Total	8	3	17	18	14	15	9	7	91

Q5-R: I find it is not difficult to design a presentation using PowerPoint although I have taking the tutorial of WBI.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	0	0	2	0	0	0	0	2
Disagree	0	0	2	1	4	2	0	2	11
Neutral	3	2	3	3	1	0	2	1	15
Agree	2	0	1	5	6	7	1	4	26
Strongly Agree	3	1	11	7	3	6	6	0	37
Total	8	3	17	18	14	15	9	7	91

Q6: I like the fact that the WBI allows me to learn topics in specified frames.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Disagree	0	0	0	0	1	0	1	0	2
Neutral	1	1	1	3	2	3	1	2	14
Agree	4	0	7	8	3	5	6	3	36
Strongly Agree	3	2	9	7	8	7	1	2	39
Total	8	3	17	18	14	15	9	7	91

Q7: I like the fact that I have the ability to control the pace of instruction using Hierarchal Map.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Disagree	0	0	0	0	0	1	0	0	1
Neutral	0	1	3	3	2	6	1	0	16
Agree	2	0	5	9	8	4	3	2	33
Strongly Agree	6	2	9	6	4	4	5	5	41
Total	8	3	17	18	14	15	9	7	91

Q8: I like the fact that I have the ability to control the pace of instruction using index.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Disagree	0	0	0	2	0	0	0	0	2
Neutral	1	0	3	4	2	3	0	1	14
Agree	3	2	7	6	7	7	5	4	41
Strongly Agree	4	1	7	6	5	5	4	2	34
Total	8	3	17	18	14	15	9	7	91

Q9-R: I did not feel frustrated when having to follow the suggested route through the WBI.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	0	1	2	0	0	0	0	3
Disagree	0	0	4	1	3	2	1	1	12
Neutral	1	0	1	6	3	0	2	2	15
Agree	4	1	5	3	3	10	4	4	34
Strongly Agree	3	2	6	6	5	3	2	0	27
Total	8	3	17	18	14	15	9	7	91

Q10: I did not get lost when browsing the links in the WBI system.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	0	1	0	0	1	0	0	2
Disagree	0	0	3	3	3	0	1	1	11
Neutral	1	0	4	4	2	0	2	1	14
Agree	4	1	2	3	7	10	4	3	34
Strongly Agree	3	2	7	8	2	4	2	2	30
Total	8	3	17	18	14	15	9	7	91

Q11: I like the fact that I can see both the navigation frame and the index frame.

	Multi-ID								
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	Total
Disagree	0	0	0	0	0	0	0	1	1
Neutral	1	0	3	5	4	5	0	0	18
Agree	2	0	5	4	4	5	4	4	28
Strongly Agree	5	3	9	9	6	5	5	2	44
Total	8	3	17	18	14	15	9	7	91

Q12: I prefer to have every topic link I click a popup window of the detail of that topic is provided.

	Multi-ID								
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	Total
Strongly Disagree	0	0	1	0	0	0	0	0	1
Disagree	0	0	0	0	0	0	1	0	1
Neutral	2	0	0	0	2	1	0	1	6
Agree	3	1	7	8	6	7	2	3	37
Strongly Agree	3	2	9	10	6	7	6	3	46
Total	8	3	17	18	14	15	9	7	91

Q13: I like the fact that I can see the detailed descriptions and the illustration with examples shown within one table.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	0	0	0	0	1	0	0	1
Disagree	0	0	0	0	0	1	0	0	1
Neutral	1	0	2	0	0	1	1	0	5
Agree	2	1	5	7	8	8	2	3	36
Strongly Agree	5	2	10	11	6	4	6	4	48
Total	8	3	17	18	14	15	9	7	91

Q14: I like the fact that more details on a topic can be provided in another popup window.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	0	1	0	0	0	0	0	1
Disagree	0	0	1	0	0	1	0	0	2
Neutral	2	0	0	0	2	1	0	0	5
Agree	1	1	6	6	6	7	3	4	34
Strongly Agree	5	2	9	12	6	6	6	3	49
Total	8	3	17	18	14	15	9	7	91

Q15: I like using the interface of this system.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Disagree	0	0	1	0	1	1	0	0	3
Neutral	4	0	1	3	2	5	0	1	16
Agree	2	1	8	10	8	5	7	3	44
Strongly Agree	2	2	7	5	3	4	2	3	28
Total	8	3	17	18	14	15	9	7	91

Q16: It was simple to use this system.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	0	0	0	0	1	0	0	1
Disagree	0	0	1	1	0	0	0	0	2
Neutral	0	0	2	4	3	1	0	0	10
Agree	4	2	3	5	7	9	5	3	38
Strongly Agree	4	1	11	8	4	4	4	4	40
Total	8	3	17	18	14	15	9	7	91

Q17: I feel comfortable using this system.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Disagree	0	0	0	1	1	0	0	0	2
Neutral	0	0	4	5	2	0	2	1	14
Agree	4	1	4	4	9	6	3	2	33
Strongly Agree	4	2	9	8	2	9	4	4	42
Total	8	3	17	18	14	15	9	7	91

Q18: Overall, I was very satisfied with the presentation of instructional material.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	0	0	1	0	0	0	0	1
Disagree	0	0	1	0	0	1	0	0	2
Neutral	1	0	2	1	3	1	1	1	10
Agree	2	1	7	9	6	7	2	2	36
Strongly Agree	5	2	7	7	5	6	6	4	42
Total	8	3	17	18	14	15	9	7	91

Q19: Overall, I was very satisfied with the system.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	0	0	1	0	0	0	0	1
Disagree	0	0	1	0	1	0	0	0	2
Neutral	1	1	3	1	1	4	0	2	13
Agree	1	0	5	9	8	7	4	3	37
Strongly Agree	6	2	8	7	4	4	5	2	38
Total	8	3	17	18	14	15	9	7	91

Q20: Overall, I had a very positive learning experience.

	Multi-ID								Total
	FFIE	FFIN	FFDE	FFDN	MFIE	MFIN	MFDE	MFDN	
Strongly Disagree	0	0	1	0	0	0	0	0	1
Disagree	0	0	0	1	0	0	0	0	1
Neutral	0	0	0	0	2	0	0	0	2
Agree	0	1	7	6	4	7	4	2	31
Strongly Agree	8	2	9	11	8	8	5	5	56
Total	8	3	17	18	14	15	9	7	91