Enhancing Online Course Materials for Self-Revision in Higher Education

by

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Thesis

Submitted to the University of Warwick

for the degree of

Doctor of Philosophy in Computer Science

Department of Computer Science

September 2016

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Acknowledgments

First of all, I would like to express my gratitude to my supervisor, Dr. Mike Joy, for his guidance and support throughout the PhD journey. I am really grateful to Dr. Jane Sinclair for her expert advice on every annual report, as well as Dr. Mike Wald for his useful feedbacks after the viva.

This project would have been impossible without the support of the Faculty of Information and Communication Technology (ICT), Mahidol University. It was a great honour for me to receive a full scholarship to further my study, both Masters and Doctoral degrees in the UK. I would like to thanks all the members of the ICT faculty particularly to Dr. Jarernsri Mitrpanont who always believes in me and teaches me the value of hard working.

To my family, particularly my parents, thanks for believing in me and encouraging me to pursuit my dream. All their continuing support at all circumstance is the greatest gift. Thank you to my grandparents, Niyom Sajjacholapunt and Suwin Sajjacholapunt who look after me since I was young, for their guidance in many aspects of life.

To all my friends, thanks for listening, sharing and supporting me through the study process especially to Reem Al-Fayez, Yiwei Zhou, and Lei Shi for the great friendship since I started my PhD. Special thanks also go to Watthanan Jatuviriya-pornchai for her constant support.

Declarations

This thesis is presented in accordance with the regulations for the degree of Doctor of Philosophy. It has been composed by myself and has not been submitted in any previous application for any degree. The work in this thesis has been undertaken by myself under the supervision of Dr. Mike Joy. Some parts of this thesis are written based on previously published papers (as first author). Detail of all publications are described below.

- The conceptual revision framework proposed in chapter 3 is designed based on the survey results and literature review published in:
  - **Sajjacholapunt, P.** and Joy, M. "Exploring Patterns of Using Learning Resources as a Guideline to Improve Self-revision" INTED2014 Proceedings, IATED, 2014, 5263-5271.
- Some analysis of accuracy comparison result between classical term weighting scheme and proposed term weighting schemes when applied with lecture slide and past exam paper materials are published in:
  - **Sajjacholapunt, P.** and Joy, M. "Analysing Features of Lecture Slides and Past Exam Paper Materials - Towards Automatic Associating E-materials for Self-revision" CSEDU2015 Proceedings, SCITEPRESS, 2015.
- The SRECMATs software framework proposed in Chapter 4 is designed based on the survey results in chapter 3. Results of a usability evaluation regarding features of SRECMATs framework are published in:

- **Sajjacholapunt, P.** and Joy, M. “SRECTMATs - An Intelligent Tutoring System to Deliver Online Materials for Student Revision” CSEDU2016 Proceedings, SCITEPRESS, 2016.

- In addition, the conference paper was selected to be extended and included in a book of selected papers of the CCIS Series published by Springer.

  - **Sajjacholapunt, P.** and Joy, M. “Research on Potential Features to Enhance On-line Course Materials for Student Revision” (submitted) in Springer (LNCS), communications in computer and information science (CCIS) series.

Abstract

Revision is an important process for learning in higher education. At present, many universities provide online course materials including guidelines to support ubiquitous revision. Most of the traditional course websites, however, simply provide online materials for students to download. The main aim of this thesis is, therefore, to enhance these materials on a course website to facilitate student self-revision.

We firstly present a brief review of some aspects of exam revision. Subsequently, we conduct a questionnaire survey to identify patterns of students' revision, difficulties during revision, and potential approaches to address those difficulties. From the survey, many students have concerns about the amount of learning materials to be reviewed in a short period of time. We thus designed a novel software framework ("SRECMATs") that aims to reduce students' workload by enabling them to have direct access to learning materials, gaining quick overviews and related material recommendations.

In the second part of the thesis, we develop, launch, and evaluate the first prototype of the SRECMATs software framework. The prototype system was introduced to students on a level 1 Data Structures and Algorithms module in the summer term of 2014/2015. Many of them were willing to use the system and engaged with it constantly during their revision. The usability evaluation of each feature is positive, and students reported that all provided features are simple to use and some are effective for them.

The first prototype used TF-IDF as a term weighting scheme to calculate cosine similarity between learning materials. To improve retrieval accuracy, we have proposed a new technique to adjust the weight of the TF-IDF scheme with term important (TI) and term location (TL) components. The results illustrated that using the TI component with the TF-IDF scheme yields the best result for all datasets while the TL technique can improve accuracy on some datasets.

Finally, our results contribute to an understanding of students' revision difficulties and how to improve the existing online course materials to maximise the benefits for students.

Abbreviations

ATE	Automatic Term Extraction
CMS	Course Management System.
CSS	Cascading Style Sheets.
HTML	Hyper Text Markup Language.
LMS	Learning Management System.
NLP	Natural Language Processing.
POS	Part-of-Speech.
RDF	Resource Description Framework
SQL	Structured Query Language.
SRECMATS	Self-Revision Electronic Course MATerials.
TF	Term Frequency.
IDF	Inverse Document Frequency.
TI	Term Importance.
TL	Term Location.
VOD	Video on Demand.
WYSIWYG	What You See Is What You Get.

Chapter 1

Introduction

1.1 Background and Research Motivation

Examinations are official tests of students' learning. Revision is the key to success in any examination: students must put together everything they have learnt in classes and prepare themselves for the examination. However, evidence shows that students can capture only 20 to 40 per cent of a lecture's main ideas in their notes Kiewra [80, p. 72]. If they do not immediately review what they have learnt in a lecture, they may remember less than 10 per cent after three weeks Bligh [19, p. 40]. The revision process is therefore significant for the learner when it comes to recalling previous knowledge. While revising, students must read a plethora of learning materials in a short period of time. Most students work hard at this stage, but not all of them work effectively.

Learning resources are a vital component of exam revision. In recent years, the use of digital content, especially electronic learning materials, has increased in formal education [35]. Universities have started to provide students with ubiquitous access to e-learning materials on course websites [86]. Course management systems (CMS) have been applied as web application platforms to support lecturers in the creation and modification of content on course websites. CMS allow students to access online course materials and assignments, to engage in forums and discussions, and to use collaboration tools [151]. CMS commonly used in universities include Blackboard, WebCT, Drupal, TerminalFour and Site Manager. Although CMS were introduced to reduce lecturer workloads in terms of creating online learning environments, many features of CMS are often under-utilised [156]. Lecturers sometimes use CMS only as a tool to deliver course materials, without considering other core features, while Forsyth [55] states that many universities provide online learning materials simply to support their claims to be leading universities. Consequently, many e-materials are simply put online, with no features to encourage rich learning or to support students' self-regulation skills. Furthermore, current CMS do not provide advanced features for specific purposes such as delivering course materials to support student revision. Developing such features requires programming skills and time, which many lecturers are unwilling or unable to provide. These issues may hamper teaching and learning outcomes.

In the past few years, many studies have examined potential improvements to online course materials to support self-study, especially in the form of lecture slides. Most have focused on improving search techniques with regard to lecture slide archives in order to reduce the time that students spend looking for particular slides [60, 129, 155, 160, 161]. Other research has investigated improving lecture slide materials by synchronising them with the lecturer's speech using video on demand (VOD), as well as providing lecture slides to support students who miss a class, and even other people interested in the course, as if they had attended the lecture [29, 107, 137]. However, few studies [4, 63, 104] have considered improvements to other course materials, such as past examination papers, laboratory sheets and assignments. Furthermore, research on related learning materials has focused mainly on additional Internet resources, rather than on internally provided materials [1, 2]. Some have relied on "folksonomy", whereby students tag learning materials to inform later recommendations [12]; however, if students do not use a system heavily, there may be insufficient data to make recommendations. In addition, guidelines to improve students' revision are well publicised on many university course websites [48, 142, 143, 144, 154], but have not as yet matured into more formal publications. Such issues present challenges to academic staff, and provide motivation for examining how to enhance online course materials to support student revision.

Different students prefer different revision strategies. Supporting them requires the design of an e-learning environment that addresses student diversity [156]. Therefore, understanding how students use learning materials during their revision is an important avenue for research that may lead to better-quality e-learning materials. The research conducted for this thesis examined issues that may prevent students from revising effectively, including the identification of student needs in terms of support during revision. The results were used to develop a revision framework and a software framework called "SRECMATs". The first prototype of the framework was launched and evaluated through the Design of Information Structure (CS126) course at the Department of Computer Science, University of Warwick. The results of the evaluation revealed issues regarding features of the SRECMATs framework that required improvement, which led to engagement in further research.

The remaining sections of this chapter present the research questions addressed by the research described in the rest of this thesis, followed by an explanation of the research methodology and details of the thesis structure.

1.2 Research Questions

The main research question for this study is how can e-learning resources on a course website be enhanced to facilitate students' independent revision? To provide the research with direction regarding the main research question, the following key research questions are addressed:

- **RQ1**) How can difficulties faced by students during revision be addressed?
  - RQ1.1) What is the pattern of student participation in the use of learning resources for revision?
  - RQ1.2) What are the potential issues involved in supporting student revision?
- **RQ2**) How can online course materials to support students' revision be enhanced?
  - RQ2.1) Can a traditional course website benefit from the SRECMATs software framework in term of increasing students' satisfaction?
  - RQ2.2) Are keyword browsing, keyword searching, gaining a quick overview though a set of keywords and material recommendations features simple to use and useful to students?
- **RQ3**) How can the accuracy of the recommendations features in the new framework be improved?
  - RQ3.1) How can classical term-weighting methods to calculate similarity between lecture slides and past exam papers be improved?
  - RQ3.2) Can term-location techniques (TL) and term-importance techniques (TI) be used with classical term-weighting methods to improve retrieval effectiveness in terms of online material recommendations?

1.3 Research Methodology

This section discusses the research methodology underlying this research, including the research methods used to answer the research questions.

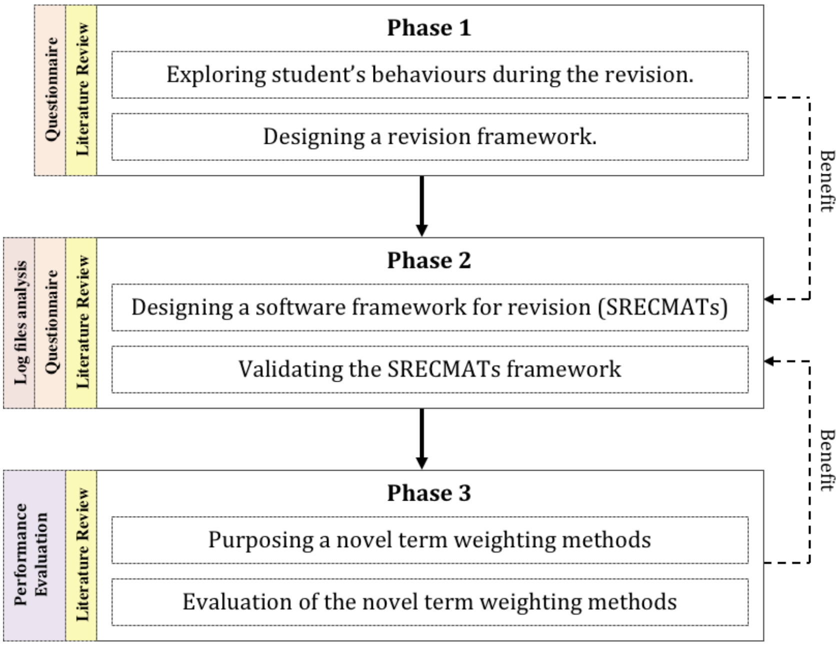


Figure 1.1: Three main phases of research methodology. Components in the horizontal boxes represent tasks conducted, while components in the vertical boxes represent methods used in the research. Solid arrows indicate flows in the experimental process, while dashed arrows indicate the direction of benefit from results to tasks.

An inductive approach was adopted to the research for this thesis, with the intention of proposing a conceptual framework of ways to enhance e-learning resources on a course website to support independent student revision. The main reason for applying an inductive approach was that a review of the literature showed that methods to improve e learning resources to support students during their revision had not previously been explored. The research therefore began with the research questions mentioned in the previous section to narrow the scope of the study. To answer the research questions, the research was divided into three phases, as shown in

Figure 1.1. In each phase, different research approaches and methods were applied based on the research questions.

1.3.1 Phase 1

RQ1 deals with how difficulties faced by students during revision might be addressed. To answer the main research question (RQ1), sub-research questions RQ1.1 and RQ1.2 were formulated in order to gain an understanding of students' behaviour during their revision and examine issues that might be supported by current technology. To answer these research questions, the first stage was to review the literature on common revision strategies, learning materials and cognitive tools. The results of the literature review revealed current research on revision strategy, as well as classifications of learning materials and types of cognitive tools used during revision.

Descriptive research based on a questionnaire survey was used to discover the pattern of student use of e-resources for their revision. This method was appropriate for capturing frequencies, preferences and similar data. In addition, owing to time limitations and a lack of human support and resources, the first phase was limited to exploring a case study using a questionnaire survey administered to a random sample of students from the University of Warwick. The results of the survey elicited difficulties faced by the students during their revision, revealing a common pattern with regard to students' use of e learning resources, including potential issues in the support available. These results contributed to answering RQ1.1 and RQ1.2.

Finally, conceptual research was conducted to develop a revision framework, explaining how the results of the survey regarding how students use e-resources for their revision are relevant to the classification of cognitive tools.

1.3.2 Phase 2

In the second phase, the results of the survey and the revision framework devised in Phase 1 were used to design a software framework entitled "SRECMATs". Action research was applied to find solutions to difficulties faced by students during their revision. At this stage, action research was considered because the SRECMATs system was launched and evaluated only for the Design of Information Structures (CS126) course of the Department of Computer Science, University of Warwick. To answer RQ2 regarding whether SRECMATs features were simple to use and useful for students, information from the questionnaire survey alone might have been insufficient. A log activity analysis capturing students' activity while using the SRECMATs system was conducted to strengthen the results. In addition, a questionnaire survey to evaluate usability was designed based on the 5Es usability scheme [127], which is a standard usability scheme.

1.3.3 Phase 3

The results of the usability evaluation of Phase 2 revealed that the recommendations feature needed improvement. A further literature review was therefore conducted to identify issues that might affect accuracy in order to answer RQ3.1. The results of this literature review suggested that adjusting the term-weighting techniques might improve the accuracy of the results of the recommendations feature. Empirical research was conducted to determine whether adjusting the term weighting would affect the accuracy of the results of the recommendations feature. Two potential term-weighting techniques to adjust the classical term-weighting scheme were used in an experiment to compare performance between the proposed approach and the classical term-weighting approach, in order to answer RQ3.2. To improve the generalisability of the results, the experiment was conducted with two sources of learning materials from different universities but similar courses (Data Structure), and one source of learning materials from the same university but a different course.

1.4 Thesis Outline

This thesis consists of seven chapters. The remainder of the thesis is structured as follows.

Chapter 2 provides a review of the literature on revision strategies, the use of traditional course websites, and learning resources and cognitive tools for revision. It begins by explaining different types of student understanding and approaches to learning that may lead to different revision strategies, and then examines existing research on revision behaviour in higher education. This information provides a better understanding of related components in the revision processes, forming a basis on which to design a software framework to support revision. The following section discusses current tools used by traditional course websites, including issues that prevent effective revision. In addition, types of learning resources were studied in order to develop an understanding of currently available resources for revision. This revealed that further study on the use of learning resources for revision would be of benefit. The final section explains currently available cognitive tools designed to support the revision process.

Chapter 3 discusses the results of a questionnaire survey of a sample of students using learning resources while preparing for examinations. The survey was conducted with postgraduate students at the University of Warwick. The results of the survey reveal issues and common strategies emerging during student revision, and students' requirements in terms of tools needed to support their revision. This chapter also proposes a revision framework developed from the survey results.

Chapter 4 discusses the process of designing a software framework, SRECMATs, to support independent revision through online course materials. The SRECMATs framework was designed on a web-based architecture similar to traditional course websites. The design of the user interface and the features provided were based on the literature review described in Chapter 2 and the survey results reported in Chapter 3. This chapter also discusses details of the back-end services, including the technologies behind the framework.

Chapter 5 evaluates the SRECMATs framework proposed in Chapter 4. The SRECMATs prototype was built and launched with the help of first-year undergraduate students in the Department of Computer Science at the University of Warwick. The evaluation process examined three major aspects: (i) students' behaviour while using SRECMATs, (ii) students' perceptions of the tool, and (iii) the usability of the proposed features. The results of the evaluation were used to understand aspects that required improvement.

Chapter 6 describes actions taken to improve the accuracy of the recommendation features of the SRECMATs framework. In order to accomplish this, consideration was given to improving the classical term-weighting method, TF-IDF, based on two proposed techniques: term location (TL) and term importance (TI). A comparative study was carried out to evaluate the performance of the proposed techniques.

Chapter 7 provides conclusions regarding the contribution of all the research conducted for this thesis. The limitations of the research are also discussed, as well as recommendations for future research.

Chapter 2

Overview of Revision in Higher Education

2.1 Introduction

The term "higher education" commonly refers to university-level education leading to bachelor's, master's or doctorate degrees. At this level of education, students require strong determination and self-discipline in their studies to pass examinations and obtain a degree. Revision is one of the most important processes during the examination period, and most universities provide general "how to survive" revision guides for their students. This chapter provides a background to major elements relating to the revision process in university education, including revision strategy, the use of traditional course websites, learning resources, and cognitive tools. An understanding of these elements is fundamental to understanding the designs and research discussed in the remainder of this thesis.

2.2 Revision Strategy

In classroom learning, “revision” is defined by the Cambridge Advanced Learner’s Dictionary Mclntosh [100, p. 1322] as “a study of work you have done, in order to prepare for an examination”.

Examinations are tools to measure students’ performance and their understanding of what they have studied in class. At the revision stage, students must plan their revision based on their current level of knowledge, their previous experience and their understanding of the course content. Since students have differing levels of understanding, they prepare themselves for examinations in a style that suits their preferences [51, 58]. These different styles of preparation are called “revision strategies”.

Chikwiriro et al. [30, p. 1] argue that “effective revision is an ongoing process, not a cramming session just before the examinations”. Although a good revision plan is essential and may produce good results, it is difficult to define what good revision is and which revision techniques are appropriate for particular students. Dunlosky et al. [41] investigate and discuss ten effective learning techniques, and make recommendations on their relative use for improving students’ learning. Their findings reveal that. for various reasons, summarising, highlighting, keyword mnemonics, use of imagery for text learning and re-reading techniques have relatively low utility. For example, they are difficult to implement in some contexts, and may be of benefit only for certain materials. However, practice tests and distributed practice techniques (techniques of breaking up exercises into small units for practice) appear to have high utility because they boost the performance of students of different ages and abilities.

Revision strategy cannot be isolated from other parts of the learning process. What students do when they begin their revision depends on what they have done previously [46, 165]. It is essential to understand how revision strategy relates to the learning process. Many studies [17, 44, 45, 46, 47, 94] have attempted to examine and classify types of learning process in terms of student behaviours. A review of the literature on classifying learning approaches is provided in the next section.

2.2.1 Approaches to learning

In 1975, Marton [93] conducted empirical research to investigate interactions between students and sets of learning tasks. His results indicate that students' approaches to a task determine their level of engagement with the subject and affect learning outcomes. Marton and Säaljö [94] later classified these results into two learning approaches, "surface" and "deep". A surface learning approach involves simply learning by memorising, whereby students acquire knowledge uncritically. A deep learning approach is a way of learning by exploring knowledge before memorising, as well making associations between items of knowledge. Entwistle and Ramsden [47] elaborated on these types of learning and proposed a third approach, which they called the strategic learning approach. In this approach, students are motivated by high levels of achievement, including competition and ego-enhancement, to obtain better results, as appears to occur while revising before examinations. Biggs [17] later proposed a similar learning approach, referring to the strategic approach as the "achieving" approach.

These classifications illustrate that approaches to learning depend on motivation and learning objectives. Modifying Bloom's classification [20], Anderson et al. [8] proposed six classifications of learning objectives for the development of knowledge: remembering, understanding, applying, analysing, evaluating and creating. In this classification, each learning objective depends on the previous stage; for example, understanding requires remembering.

The proposed learning objectives can be mapped with the learning approaches, as presented in Table 2.1. The surface approach relates to remembering and understanding, where students learn by memorisation and are able to repeat the content of materials. The deep approach corresponds with applying and analysing, where students understand knowledge, can connect it with other knowledge, and can use it for construction or implementation. Finally, the strategic approach relates to all learning objectives, including evaluating and creating, where students are able to make judgments based on criteria and put concepts together to generate new knowledge. These theories have been accepted by and referred to in many research studies. However, in examinations, the skills of evaluating and creating are rarely required. Table 2.1 extends and combines studies by Biggs [17], Anderson [8] and Entwistle [47] to present the strategies for each learning approach based on learning objectives.

Table 2.1: Mapping of learning objectives and strategies against learning approaches.

Approach	Learning Objective	Strategy
Surface	The intention is just to pass or meet minimal requirements. (Remembering and Understanding)	This approach focuses only on basic essential knowledge and rote learning.
Deep	The intention is to gain actual understanding of concepts and competence in particular subjects. (Applying, and Analysing)	This approach focuses on active learning processes and connection of relevant knowledge.
Strategic/ Achieving	The intention is to achieve the highest score. (Evaluating, and Creating)	This approach focuses on organising study methods in terms of time, space, and learning materials for learning.

These learning approaches are interrelated. While revising, students may apply one or more approaches to learning based on their preferences. However, following these learning approaches does not guarantee that students will get good results.

Zimmerman [170] defines self-regulation as "self-generated thoughts, feelings, and actions for attaining goals". His research shows that self-regulation has an effect on students' academic achievement [138, 170, 174]. Other evidence shows that students who use a strategic approach for revision with self-regulation perform better in examinations than those who only set a goal and do not use self-regulation [158, 171, 172]. Moreover, research also reveals that self-regulated learners who often engage in self-evaluation are able to improve their learning outcomes after adjusting their study habits [82]. The term self-evaluation refers to "a comparison of outcome of performance with a standard and goal" [173].

Biggs [16] argues that poor teaching may pressurise students into taking a surface learning approach, while good teaching may lead them toward a deep learning approach. The next section will discuss teaching approaches and how they may affect revision strategy.

2.2.2 Teaching approaches

Choosing appropriate teaching methods is a crucial task in education. Research has shown that teaching methods that match a student's learning style may lead to better learning than mismatched methods [6, 50]. Westwood [164] argues that, when selecting teaching methods, lecturers should consider not only the nature of the subject matter but also how students learn. This indicates that teaching approaches are relevant to approaches to learning.

Traditional methods of teaching are based on teacher-centred approaches, where lecturers talk and students listen. These teaching approaches are sometimes known as direct instruction and whole-class interactive teaching. In universities, lecture-based teaching forms part of a teacher-centred approach in which students learn by being told [103]. Johnson et al. [72] state that the purpose of a lecture-based method is to convey information to a large group of people within a fixed period of time. The main advantage of this method is that lecturers can organise and deliver intrinsic knowledge on a subject to students, which benefits those who learn by listening [22]. The lecture-based method is sometimes considered to be ineffective because it presumes that all students have the same level of understanding. It is often passive, making it hard to know whether students are actually engaged with the material; therefore, the lecturer may encourage students to be more active by using a lecture-discussion method [32]. The lecture-discussion method allows students to interact with the lecturer through in-class question-and-answer sessions. Charlton [28] suggests that "lectures can be the best teaching method in many circumstances and for many students". They are appropriate for lecturers who know what to teach, and for students who know what is worth learning.

The constructivist paradigm led to the emergence of the student-centred approach, where the instructional environment focuses more closely on students. The general concepts of constructivism in a learning context are that it is an active process in which students use present and past knowledge, including their experience, to construct new concepts and ideas [32]. The notion of constructivism in the student-centred approach can be classified into two types: cognitive constructivism and social constructivism. Cognitive constructivism was first introduced by Piaget [120], who believed that new concepts or knowledge are constructed internally by students, rather than by external sources such as colleagues or lecturers. Social constructivism was later introduced by Vygotsky [157], who believed that social interactions with other students help the learner to develop better understanding. Some teaching methods belong to both types of constructivism. Common teaching methods relating to these types of constructivism are listed below.

- **Discover learning** [23]: This is a self-directed learning method in which lecturers pose a problem to which students must find answers. Students are motivated to search for information themselves from external sources such as university libraries or the Internet, with or without assistance from lecturers. Other methods that rely on discovery learning include problem-based learning and WebQuest. In problem-based learning [49], the lecturer gives students real-world problems to solve, and there are normally many possible solutions to these problems. WebQuest [40] is another example of discovery learning in which the lecturer sets up a classroom inquiry activity. WebQuest focuses more on how students use both internal and external resources, rather than trying to support them in deep analysis.

- **Hands-on learning** [14]: This method uses the concept of discovery learning but focuses more closely on a practical form of learning, which may be considered as "learning by doing". For example, in laboratory work where students are given a task to complete, the lecturer or demonstrator will act as a facilitator who provides guidelines but not answers. This motivates students' learning and helps them to gain a deep understanding of the subject. Hands-on learning methods can be used with both individuals and groups of students.

- **Learning through discussion and debates** [18, 141]: This method is a social learning approach in which students are grouped to discuss topics given by the lecturer. The lecturer acts as an experienced or expert member of the group. This method allows and motivates students to think and use their existing knowledge, and to co-operate with other students. A major factor affecting this kind of learning is group size.

Although the constructivist approach appears to be a promising paradigm for encouraging students to be active learners, Hoover [65] argues that some students may become confused because not all students have the same prior knowledge. In using the constructivist approach, lecturers must ensure that they engage students' learning and bring their current understanding to the forefront [65]. In practice, the various teaching methods are usually blended together for use in higher education. Lecturers must therefore consider how students learn and balance their teaching approaches.

How teaching and learning methods affect revision strategy does not appear to have been investigated previously. However, by considering the outcomes of teaching and learning theories, some relationships between them can be deduced. For example, assume that there are two groups of students who all have the same capability to learn and gain knowledge. The first group is only exposed to the lecturer-based method, where students learn by being told in class. This group of students will obtain limited knowledge from the lecturer, through application of a surface approach. Although the lecturer may tell them to study further by themselves, this may only motivate certain students. Kiewara's [80] research indicates that students can capture only 20 to 40 per cent of a lecture's main ideas in their notes. If they do not review the lecture material, after three weeks they can remember less than 10 per cent [19]. Therefore, this group of students is likely to need to revise intensively during the examination period. The second group learns by both the lecturer-based method and hands-on (laboratory) learning. Although this group of students will obtain less knowledge in class, they will have better problem-solving skills, such as analysis and critical thinking, as both surface and deep approaches are applied. Aleven and Koedinger [5] state that engaging students through problem solving helps strengthen their long-term memory. Therefore, this group of students will tend to spend less time on revision than the first group because they are likely to have a better understanding of the material. They may simply need to revise some parts, such as definitions, or may immediately practise on past examination papers.

This thesis focuses only on supporting students during their revision, leaving the teaching stage for future study. The basic teaching and learning theories are used as guidelines to design the framework for revision described in Chapter 2. The next section discusses existing research on revision behaviour.

2.2.3 Revision behaviour

Research on supporting students' revision is as yet immature; few studies have examined revision strategy or revision behaviour directly [43, 45, 119]. Many UK universities provide guidelines on effective revision, devised as a result of consultations with students [142].

A random review of the revision guidelines of six universities in the UK [48, 142, 144, 149, 153, 154] reveals that common guidelines for effective revision are to begin by planning a timetable for revision and organising a list of subjects to be revised. Revision time can be planned more effectively by starting earlier (five to six weeks before an examination is recommended). In fact, students should plan revision all year round, not just a few weeks before an examination. Students should also organise a list of subjects, specifying which should be revised first and how long should be spent on them. The guidelines of the universities of Bath [144] and Reading [149] mention that students should first think about their own understanding of each subject, to help them further plan how much time should be spent on each subject. Students may allocate more time to a subject about which they are unsure. In addition, the universities of Bath [144] and Leicester [142] consider where to revise in more detail. They argue that different stages of revision (time) may fit into different contexts (places), so students should choose the most appropriate locations.

In addition, the most common revision strategies suggested by most universities are note-taking, memorising and practising on past examination papers [48, 142, 144, 149, 153, 154]. At this stage, students may remember more by making short notes and jotting down only important information in bullet points. Universities tend to advise students to use other techniques to memorise large amounts of material, such as mind maps, diagrams and colour to link relevant information together. Practising on past examination papers is like a mock test, where students can analyse and get used to the questions before the real examination.

Some studies have examined students' behaviour while revising, which reflects their preferences and styles and leads to the selection of revision strategies. To identify common revision strategies, these studies have focused on interviewing students and observing common patterns of revision behaviour [43, 45, 46, 119, 158]. The major components that have been observed include students' behaviour, time spent and their use of learning materials. This emphasises examining students' behaviour to elicit the common steps in revision.

Entwistle [43, 44, 45, 46, 47] focused on exploring a different form of understanding and on understanding students' behaviour during the revision period, in order to confirm previous work by Ference Marton and Beaty [53] on the importance of contrasting conceptions of learning. He identified a revision process and strategy by transcribing interviews with 13 students who had just completed their degrees, and analysing written responses from 11 students [45]. His results concerning the revision process and strategy consist of four stages. First, students learn from their original notes; second, they memorise parts of their notes; third, they copy their notes in order to maintain concentration; and fourth, they summarise and condense their notes. This final stage is carried out in order to remember the lecture structure, check their understanding, and trigger memories of details and schematics. Entwistle [43] also argued that students develop understanding through provided learning materials, friends and tutors. He extended his work [45] and proposed some steps in a revision strategy [46] by conducting interviews with 28 students. The results of these interviews suggest the following common steps in revision:

- Commenting on the understanding they achieved;
- Preparing a review of all notes;
- Producing summary notes;
- Checking understanding of those notes, memorising both the structure of their understanding and the detail to support it.

The results of Entwistle's [43] interviews conform with guidelines commonly provided on university websites, which recommend that students start their revision by thinking about the level of understanding they have achieved, then review and summarise all of their notes, before re-checking their understanding and trying to memorise key elements of their notes. These results provide an overview of the common steps in revision; however, they still lack detail pertaining to the use of provided learning materials. For instance, how do students prepare a review of all notes? What common behaviours do they adopt to summarise their notes? And how do they use other provided materials to construct their notes? These details require further exploration to support the findings.

2.3 Use of Traditional Course Websites

The results of the Gartner Research Survey 2002 [122] reveal that over 95 per cent of colleges and universities have online course websites to support teaching and learning. Furthermore, a review of harnessing technology conducted in 2008 [38] describes important cases of using online learning environments to support education. The main purposes of a course website are to provide course information and learning resources, and increase collaboration between and feedback from students [105]. In the past, creating a university course website required some programming knowledge, for instance hypertext markup language (HTML), cascading style sheets (CSS) and database systems [166].

Since the introduction of course management systems (CMS), lecturers no longer need to worry much about programming skills. CMS are collections of tools that aim to support teaching and learning. Although there are many types of CMS tools, each is a little different. West et al. [163] identify three common features of CMS:

- **A central repository**: a feature whereby lecturers provide course information and upload related materials for students' revision. CMS provide a WISYWIG editor, which allows lecturers to input course content and upload learning materials through an attractive graphical user interface (GUI).
- **An online discussion board**: a feature used by lecturers to communicate and discuss with students. Rogers [128] reports that some lecturers use discussion boards as a drop box for students to submit their homework or share reports or articles.
- **Gradebook**: a feature enabling students to view their own grades. Although CMS provide a simple GUI for lecturers, there is some evidence that lecturers are slow to adopt complex features of CMS, such as discussion and quiz tools [105].

With increasing use of these tools in higher education, many studies have examined use of these features and their potential impact on learning outcomes [67, 83, 105, 95, 167]. However, there has been little direct research on ways of maximising the capability of learning materials provided by the features of a central repository.

Many universities in the UK use commercial content management tools to deal with course websites, as presented in Table 2.2. These tools aim simply to enable university members (mainly lecturers) to create and put information on websites quickly and easily, but leave the quality of the materials' content to the lecturers. Because students have different ways of learning, it is important to examine how the quality of information that lecturers put on websites, particularly learning materials, might be enhanced to support the diversity of students' preferences in using learning materials.

Table 2.2: List of CMS tools used by the top 10 UK universities ranked by University League Tables [148].

University League Table			
2016	**Top 10 UK University**	**CMS tools**	**Type**
1	Cambridge	Drupal, Falcon	Open Source
2	Oxford	Drupal	Open Source
3	London School of Economics	Contensis	Commercial
4	Imperial College London	t4 Site Manager	Commercial
5	St Andrews	t4 Site Manager	Commercial
6	Durham	CIS web	University own's bespoke system
7	Warwick	SiteBuilder, Moodle	University own's bespoke system,Open Source
8	Surrey	Drupal	Open Source
9	Lancaster	t4 Site Manager	Commercial
10	Exeter	t4 Site Manager	Commercial

2.4 Learning Resources for Revision

Learning resources are an important component of revision which students use to recall what they have learnt in class. The Education Regulations, 2015 [136] define a learning resource as "a resource used for educational purposes in any format, real or virtual, that: (a) illustrates or supports one or more elements of a course or course of study; and (b) may enrich the learning experience of the pupil or teacher".

A human subject may also sometimes be considered as a learning resource [37]. Wade et al. [158] studied the behaviour of engineering students on a Dynamic Modelling Course at West Point regarding their use of learning materials. His research focused on which materials and activities were more effective for students' success in a given course. In this study, Wade classified learning materials into eight types:

- **Course text**: a course textbook used by the lecturer as a supplementary teaching material.
- **Notes**: notes jotted down by students during a classroom lecture.
- **Instructor**: some universities provide additional instructors (also called tutors) whom students can consult outside of the classroom when needed.
- **Old tests and homework** (sometimes called past examination papers): universities usually change the tests and homework each semester. However, sometimes they recycle tests, using an old test structure but changing the numbers.
- **Current semester quizzes**: a set of questions for practising and supporting class concepts in preparation for a test.
- **Workbooks**: additional material with sample problems for practising and understanding materials.
- **Study groups**: students socialise for a class assignment. This collaboration aims to encourage students to work on assignments.
- **Daily quizzes**: sets of questions asked in daily classes, with solutions posted on the course website for later reference.

However, Wade et al. [158] did not examine the use of electronic materials in their study. Advances in technology mean that most paper-based materials are now converted and provided in digital format in the form of electronic materials and tools. Therefore, students have alternative ways of engaging in independent study. Hogarth [63] studied the usefulness of various online learning resources by surveying a group of third-year undergraduate students at Glasgow Caledonian University. The overall results suggest that, although students were happy with traditional teaching methods, they were also willing to try a blended approach by revising with technology. Hogarth [63] therefore proposed a blended e-revision pack comprising content such as podcasts, vidcasts, guidance notes and face-to-face sessions to support university students during the revision period. However, a prototype of this framework has not yet been developed and validated.

Although many electronic resources are available to students, there are issues regarding differences in use compared with non-digital materials, for instance between e-books and hard copies. A book is a three-dimensional object; readers can feel its texture and interact physically with it, for instance by underlining text or folding the edge of a page. E-books do not offer the same sensual experience; they belong only to the visual domain. Readers who are unfamiliar with visual experiences find it difficult to take notes or spend a long time reading on-screen. However, Polsani [123] believes that this fundamental differentiation from the material book may develop and enhance the format of e-books. E-books may generate new and different experiences for the reader compared with material books, including multimedia elements with which a user can interact.

While Wade et al. [158] were concerned with paper-based materials, including human subjects as learning resources (e.g. teachers and colleagues), this thesis focuses on both paper- and electronic-based materials which are commonly provided by universities. Wade et al.'s [158] list of currently available learning resources is redesigned, with the incorporation of additional electronic resources from Hogarth [63], while ignoring human resources such as lecturers and tutors.

The extended list of nine learning materials is as follows:

- Lecture notes;
- Lecture slides (read directly from the PowerPoint file);
- Lecture slide hand-outs (printed from PowerPoint slides);
- Textbooks;
- E-Books;
- E-learning websites, both formal and informal (e.g. Udacity, Wikipedia, Blog);
- VOD streaming (e.g. YouTube, course website);
- Course assignments/essays, including students' own notes;
- Past examination papers.

Since all university departments tend to provide online materials to their students, it is important for the lecturer of each module and the students to think about the appropriateness of the materials used. Murphy [108] suggests six issues that lecturers need to consider when putting materials online: the purpose of the website, the authority, content, design and readability of the material for a specific audience, and the implementation of a system to deliver the material. Furthermore, Boklaschuk and Caisse [21] suggest that educational websites should be evaluated based on audience, credibility, accuracy, objectivity, coverage, currency, aesthetic and visual appeal, navigation and accessibility. Students should also consider choosing appropriate learning materials for their revision. They should think ahead before using these resources so as not to waste time and energy.

2.5 Cognitive Tools for Revision

Cohen et al. [32] state that “It is impossible to introduce learning and its constructivist base without mentioning cognition - thinking, learning, understanding, how we perceive, learn and know something”. These cognitive activities are relevant to the working memory, which is significant for learning. De Jong [39] suggests that cognitive capacity in working memory is limited; it can be overwhelmed if learning activities need too much capacity. This idea is referred to as “cognitive load theory”. Cognitive load is classified into three types based on De Jong [39]:

- **Intrinsic cognitive load**: In education, intrinsic cognitive load refers to the difficulty of the learning material itself [34]. The level of difficulty is judged by the number of interactive elements in the material, where a high number of interactive elements indicates higher difficulty and the need for more cognitive resources than a lower number of interactive elements. An example of low interactive materials given by Sweller and Chandler [147] is a vocabulary book, where each term can be learnt independently. A grammatical syntax book would be considered as a high interactive material because elements of syntax are interrelated.

- **Extraneous cognitive load**: This is a load that is unnecessary for learning [98]. such as the cognitive load from the separate presentation of information that requires simultaneous processing, where students must retain some information in their memory while searching for other pieces of related information [39].

- **Germane cognitive load**: This is a load that is a beneficial for learning. De Jong [39] mentions that a load that involves the processes of interpreting, exemplifying, classifying, inferring, differentiating and organising, as stated by Mayer [97], is considered a germane cognitive load.

Eliminating intrinsic and extraneous cognitive load will help students to focus only on the processes that matter [39]. Since learning materials designed by lecturers are difficult to control, reducing intrinsic cognitive load is not considered here. Instead, this thesis aims to reduce the extraneous cognitive load of students using online materials for their revision, while preserving the germane cognitive load. To achieve this, the concept of cognitive tools is studied to identify potential gaps.

Cognitive tools have emerged to help students with their cognitive load, for example by supporting them with learning activities or helping them to construct knowledge themselves. Kim and Reeves [81] define cognitive tools as "technologies that learners interact and think within knowledge construction, designed to bring their expertise to the performance as part of the joint learning system". Moreover, a cognitive tool is considered as a means of supporting different learning processes in independent study, such as reflective thinking. When designing such tools, it is necessary to remember that they should be easy-to-use, and should help users to manage, but not increase, their cognitive load.

2.5.1 Types of cognitive tools

Iiyoshi et al. [68] classify five functions of cognitive tools in a student-centred learning environment. These five functions and their definitions are:

- **Knowledge Organisation**: enables a student to identify and establish relationships between information. In the revision process, this will help students who have problems with memorising things without understanding (surface learning approach). It may help students perceive relevant knowledge through organised information such as mind-mapping tools. For instance, Evernote[1] may support students by allowing them to summarise and reorganise knowledge in their own way. Spreadsheet software such as Excel also allows students

[1] `https://evernote.com`

to organise and analyse data in tabular form.

- **Information Presentation**:

  allows students to represent data in meaningful ways, such as selecting relevant information while ignoring irrelevant information. Students sometimes have problems with understanding content. This tool may support them by representing data in different forms. For example, Nardoo [59], which is a system for learning about general ecology, allows students to view and compare information in different forms (e.g. graphics, video and audio). The Google Chart API also supports information representation, allowing students to present data in different charts. This kind of tool may be useful and appropriate when dealing with a large amount of information that needs to be filtered [68].

- **Information Seeking**: allows students to locate, retrieve and store information to answer a question. When students do not understand something, they may find and collect information from many places to answer their query. Examples of these tools include search engines and databases.

- **Knowledge Integration**: allows students to connect new knowledge with existing knowledge. This tool is appropriate when students want to learn something new but struggle to link knowledge. For example, Freemind[2] is a tool that allows students to organise ideas and integrate them to develop their understanding.

- **Knowledge Generation**: allows students to construct and exhibit new ideas or knowledge meaningfully. This tool is appropriate for students who have difficulty forming ideas. For example, collaborative tools, such as Google Docs, which allow students to discuss their ideas with friends are also knowledge generation tools.

[2] `http://freemind.sourceforge.net`

These types of tool functionality allow existing tools to be classified. This is useful to identify issues encountered in using tools for revision, for instance to examine which types of tool need improvement, and to design revision applications that conform to the classification.

2.5.2 Cognitive tools to support revision

How can cognitive tools support revision? This question depends on students' revision issues and how they can be supported. Since revision is part of the learning process, this section discusses how cognitive tools support approaches to learning, which is a fundamental objective of revision.

Surface Learning

Shim and Li [140] argue that cognitive tools should reduce students' cognitive load by covering lower cognitive skills such as search and integration skills, so that only higher-order thinking skills remain to be considered. Hence, cognitive tools such as knowledge organisation, information presentation and information seeking may motivate and enhance student revision through a surface learning approach when they need to memorise a lot of learning material. Seeking information through a search engine may save students' time in finding relevant information. Moreover, reorganising and representing information may expose hidden issues that students do not understand.

Deep Learning

Kommers et al. [84] state that cognitive tools should support students in activating metacognitive learning strategies by helping them to memorise things, connect knowledge and construct schemata when they are faced with new information. Since metacognitive learning strategies form one component of the deep learning approach, all cognitive tools that support surface learning approaches, including knowledge integration tools, are useful at this level. Students who have problems with connecting knowledge may benefit most.

Strategic Learning

The strategic learning approach focuses more on time, space and resource management. Therefore, knowledge organisation and knowledge generation tools, which allow students to access learning materials easily and collaborate effectively with their friends for revision, benefit most from this approach.

2.6 Summary

This chapter has explained the theories and components relating to revision in higher education. It has provided an overview of the revision process and related principles. Four major components relating to the revision process have been described, including revision strategy, and the use of traditional course websites, learning resources and cognitive tools. These components are interrelated. Students pursue their revision strategy through learning resources, and these resources are sometimes provided on course websites. Current course websites only deliver static materials for students to download for revision. This may increase their extraneous cognitive load in searching for relevant information. To improve the capability of these learning materials, cognitive tools have been considered.

Section 2.2 has discussed learning and teaching theory, including existing systems regarding revision behaviour that may affect revision strategy. Three approaches to learning have been considered: the surface approach (memorising), the deep approach (understanding) and the strategic approach (organising). The revision process is considered to be a strategic approach when a student's intention is to achieve a high score. A strategic approach encompasses the skills necessary for both surface and deep approaches. However, teaching methods may affect revision strategy. If a lecturer uses methods such as discovery learning, which increase students' problem-solving skills, they are likely to revise less. Furthermore, a review of university guidelines on effective revision also confirms the results of previous research, that common revision behaviour involves students thinking about how much past knowledge they understand, taking notes of important points and re-checking their understanding.

Section 2.3 has provided an overview of common tools used for university course websites in the UK and how learning materials are provided, while Section 2.4 has discussed types of learning materials that are used at university level, classified according to previous research. The current classification has also been extended by including additional electronic learning resources, while ignoring human resources such as lecturers and tutors. Finally, Section 2.5 has examined the concept of cognitive load theory, including three types of cognitive load: intrinsic (the material itself), extraneous (unnecessary for learning) and germane (beneficial to learning). Six types of cognitive tools and their benefits for revision have also been discussed, providing an understanding of potential approaches that may improve current online materials to support students' revision.

The results of the literature review indicate that most existing course websites are used simply as a repository for learning materials. This may cause extraneous cognitive load for some students when trying to search for relevant information. Furthermore, existing research pertaining to revision strategy has proposed only a big picture of revision steps, leaving further challenges to explore how students actually use learning resources.

The next chapter will present further exploration of the use of learning resources. Background information from this chapter will be used for discussion, which will help in the construction of a revision framework.

Chapter 3

Students' Experience of E-Materials for Self-Revision

3.1 Introduction

Chapter 2 highlighted a gap in the literature regarding exploration of the student experience of using learning resources during revision. The literature review revealed not only the relationship between students' activities and learning resources, but also students' need for support regarding which current technology can be applied to enhance their activities.

This chapter presents the results of a questionnaire survey conducted with post-graduate students at the University of Warwick. The results of the survey are used to identify patterns of student participation in the use of learning resources, their revision strategies, and the difficulties they face during revision. The results of this chapter have previously been published [131].

3.2 Survey of Student Use of E-Materials for Revision

This research arises from identification through the literature review that existing research has provided only an overview of revision strategies, such as memorising sections of notes, copying and summarising notes, and checking understanding of notes. However, these activities have not yet been observed in detail, especially regarding how students use learning resources for revision, what learning resources they commonly use, and what learning resources they usually focus on first.

Why is it necessary to understand students' use of learning resources? The main reason is to understand different kinds of tools that have the potential to support students' revision. However, in order to provide tools to support students, a better understanding is required of how they use learning resources and which resources or strategies work well for them. Students' engagement with learning resources is of interest from both educational and technological perspectives.

From an educational perspective, different ways of using learning resources may affect students' performance. For example, students who spend more time on past exam papers may achieve better results than students who spent more time on textbooks. However, this aspect was not explored in the current study because of the difficulty of accessing student information. From a technological perspective, it sought to gain insights into what kinds of tools students prefer to use to support their learning.

The questionnaire survey revealed strategies for using learning resources for revision, as well as potential issues that needed to be addressed. The two underlying goals were to develop a fundamental revision framework of common steps in using learning resources during the revision period, and to understand how cognitive tools might be applied within the framework.

3.3 Methodology

This research was descriptive in nature, using a questionnaire to conduct a survey (see Appendix A for details). The questionnaire method was selected because it allowed a number of students from different departments to be reached more simply and efficiently than using the interview method [114]. The design of items in the questionnaire was based on the previous literature review (see Chapter 2), including articles and university guidelines on causes of exam stress, study problems and revision techniques [126, 143, 87, 48, 144, 142, 154, 153]. The sample was selected using two methods. First, a link to an online questionnaire was emailed to all students in each department, resulting in 49 student responses. Second, 20 students in the library were approached at random and asked to fill in a paper questionnaire to eliminate voluntary response bias (only one questionnaire was not completed). Details of the sample, measures and procedures are discussed in the next sub-sections.

3.3.1 Sample

The population of interest in this study were all students at the University of Warwick. However, only master's students were accessible because undergraduate students were not on campus in August when the survey was conducted. In this study, a sample of 68 participants was collected from five departments: 44% from Warwick Business School (WBS), 34% from Warwick Manufacturing Group, and the remaining 22% from three other departments, the Economics Department, the Computer Science Department and the Mathematics Institute. These five departments were selected because the courses included examinations and the departments granted access to carry out the survey. The participants were 43 per cent male and 57 per cent female. Sixty-eight per cent were Asian, with 26 per cent European and six per cent African.

The sample for this study cannot be considered representative of the population of interest. The revision behaviour captured in this study can only be generalised to other universities that have students with similar backgrounds on similar courses. Details of the methods and data analysis are discussed in the next sub-section.

3.3.2 Measure

Three types of measures were used in this study. First, frequency tables were used for the following eight questions regarding the use of learning resources for revision:

(i) What are the difficulties?

(ii) What are the commonly used resources?

(iii) Which resources do students prefer to use first when starting revising?

(iv) What actions do students take?

(v) What do students do when they do not understand?

(vi) What do students need?

(vii) Do students normally prefer self-study revision or peer group revision?

(viii) Would students be happy to share their notes with friends?

The results from the frequency table were visualised in pie-chart and bar-chart formats for easier understanding.

Second, cross-tabulation was used to display multivariate frequency distributions, as well as to determine relationships between the results of the eight questions and background information such as gender, ethnicity and department of study. Since most of the data in this section came from multiple-choice questions, the traditional Pearson's chi-square test could not be used because of within-subject dependence in the responses; instead, the multiple marginal independence test (MMI) based on traditional Pearson's chi-square was used [150]. Third, cross-tabulation with Pearson's chi-square test for independence was also used to determine relationships between the results of the eight questions; these were grouped into categorical data (based on frequency), where a chi-square test would normally be used rather than correlation [74].

For both chi-square (MMI) tests and Pearson's chi-square test of independence, the hypotheses were as follows.

- H_0: Assume that there is no relationship between the two variables (for all cross-tabulated data).
- H_a: Assume that there is a relationship between the two variables (for all cross-tabulated data).

In order to reject the null hypothesis (H_0) and accept the alternative hypothesis (H_a), the p-value had to be less than the chosen significance level. In this case, a p-value of less than 0.05 was accepted as statistically significant, which is a standard choice of significance level. All statistical calculations were performed using IBM SPSS Statistics Version 22.

3.3.3 Procedure

Students from the five departments completed the surveys during August 2013 after their final examinations. They were asked to think about their experiences during their studies in general, rather than focusing on their experience of a particular course. Ethical consent was obtained from the University's BSREC committee (approval REGO–2013–413).

3.4 Result and Discussion

This section discusses the results of data analysis from the frequency tables. Data pertaining to research questions RQ1.1 and RQ1.2 were collected and analysed.

The following sections present the analysed results, and describe students' difficulties, commonly-used resources, patterns of learning strategy, activities undertaken when they did not understand the material, and their preferred support systems. The results in each section would subsequently be used to construct a revision framework to demonstrate the potential to improve students' revision process through the application of appropriate tools.

3.4.1 What are the difficulties?

This study began by investigating issues faced by students during the revision period. The results of the student responses are presented in Figure 3.1.

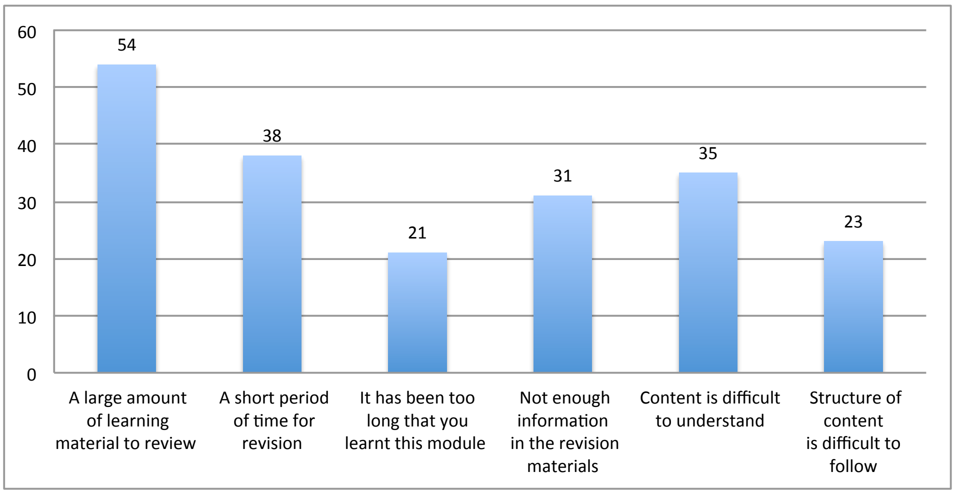


Figure 3.1: Number of difficulties and issues experienced by students that might prevent them from carrying out effective revision.

Figure 3.1 reveals that the most pressing issue that students were worried about was the large amount of learning resources provided by the lecturer (54/79%). This result supports Sweller and Chandler [147, p. 185] finding that learning materials containing a large amount of information are harder to learn. This may indicate that students needed a good technique to help them organise their learning resources. Other difficulties that concerned students were the short period of time for revision (38/55%) and difficulty in understanding the content (35/51%). The remaining difficulties were of concern to less than half of the respondents.

Relationship between difficulties and gender

This section focuses on the relationship between difficulties that students faced during revision and their gender. A cross-tabulation of these two variables is presented in Table 3.1, which shows that most difficulties that students faced were experienced by approximately the same percentage of each gender. The greatest difference between male and female was only 17.6 per cent with regard to difficulty understanding the content. However, a chi-square (MMI) test (Table 3.2) shows that this result is not significant at the 0.05 level $\chi^2_{MMI}(6, N = 68) = 8.562, p = 0.200$, indicating acceptance of the null hypothesis, and that gender was independent of the difficulties that students faced during revision.

Relationship between difficulties and ethnicity

This section presents analysis of the relationship between difficulties that students faced during their revision and their ethnicity (see Table 3.3). It is clear that a greater percentage of Asian respondents faced difficulties in all categories apart from the issue of a lot of learning materials. This result is statistically significant at the 0.05 level, ($\chi^2_{MMI}(12, N = 68) = 39.65, p < 0.001$), as shown in Table 3.4. The null hypothesis is rejected, indicating that the difficulties students faced during revision were related to ethnicity.

Table 3.1: Cross tabulation of difficulties faced by students and gender

			Gender		Total
			Male	Female	
Difficulties that students faced during the revision. [a]	A large amount of learning material to review.	Count	22	32	54
		% within Gender	75.9%	82.1%	
	A short period of time for revision.	Count	16	22	38
		% within Gender	55.2%	56.4%	
	It has been too long that you learnt this module.	Count	7	14	21
		% within Gender	24.1%	35.9%	
	Not enough information in the revision materials.	Count	12	19	31
		% within Gender	41.4%	48.7%	
	A content is difficult to understand.	Count	12	23	35
		% within Gender	41.4%	59.0%	
	Structure of content is difficult to follow.	Count	11	12	23
		% within Gender	37.9%	30.8%	
Total		Count	29	39	68

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.2: Results of chi-square (MMI) test calculated from Table 3.1.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	8.562
	df	6
	Sig.	.200

Table 3.3: Cross-tabulation between difficulties faced by students and ethnicity.

			The ethnic groups			
			European	Asian	African	Total
Difficulties that students faced during the revision.[a]	A large amount of learning material to review.	Count	15	36	3	54
		% within Group_of_Ethnic	83.3%	78.3%	75.0%	
	A short period of time for revision.	Count	8	28	2	38
		% within Group_of_Ethnic	44.4%	60.9%	50.0%	
	It has been too long that you learnt this module.	Count	3	17	1	21
		% within Group_of_Ethnic	16.7%	37.0%	25.0%	
	Not enough information in the revision materials.	Count	7	24	0	31
		% within Group_of_Ethnic	38.9%	52.2%	0.0%	
	A content is difficult to understand.	Count	5	30	0	35
		% within Group_of_Ethnic	27.8%	65.2%	0.0%	
	Structure of content is difficult to follow.	Count	5	18	0	23
		% within Group_of_Ethnic	27.8%	39.1%	0.0%	
Total		Count	18	46	4	68

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.4: Results of chi-square (MMI) test calculated from Table 3.3.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	39.650
	df	12
	Sig.	.000

Relationship between difficulties and department

The difficulties that students faced were also considered in terms of their department. The results of cross-tabulation between these two factors are presented in Table 3.5. Fewer students from WMG and WBS than from other departments reported difficulty regarding the length of time since they had learnt the module content. With regard to the issue of the content being too difficult to understand, 73.3 per cent of WBS students responded on this issue, compared with 26.1 per cent for WMG and 46.7 per cent for students from other departments. These results are statistically significant at the 0.05 level ($\chi^2_{MMI}(12, N = 68) = 37.872, p < 0.001$), as illustrated in Table 3.6. The null hypothesis is rejected, indicating that the difficulties that students faced during revision depended on their department.

Table 3.5: Cross-tabulation between difficulties faced by students and their department.

			Group_Department			Total
			WMG	WBS	Other	
Difficulties that students faced during the revision.[a]	A large amount of learning material to review.	Count	18	23	13	54
		% within Group_Department	78.3%	76.7%	86.7%	
	A short period of time for revision.	Count	14	17	7	38
		% within Group_Department	60.9%	56.7%	46.7%	
	It has been too long that you learnt this module.	Count	5	7	9	21
		% within Group_Department	21.7%	23.3%	60.0%	
	Not enough information in the revision materials.	Count	11	15	5	31
		% within Group_Department	47.8%	50.0%	33.3%	
	A content is difficult to understand.	Count	6	22	7	35
		% within Group_Department	26.1%	73.3%	46.7%	
	Structure of content is difficult to follow.	Count	5	13	5	23
		% within Group_Department	21.7%	43.3%	33.3%	
Total		Count	23	30	15	68

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.6: Results of chi-square (MMI) test calculated from Table 3.5.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	37.872
	df	12
	Sig.	.000

3.4.2 What resources are commonly used?

The next subject of enquiry was the resources that students commonly used during their revision. The questionnaire choices were drawn from the list of learning resources proposed in Section 2.4. The pattern of use of learning resources is presented in Figure 3.2.

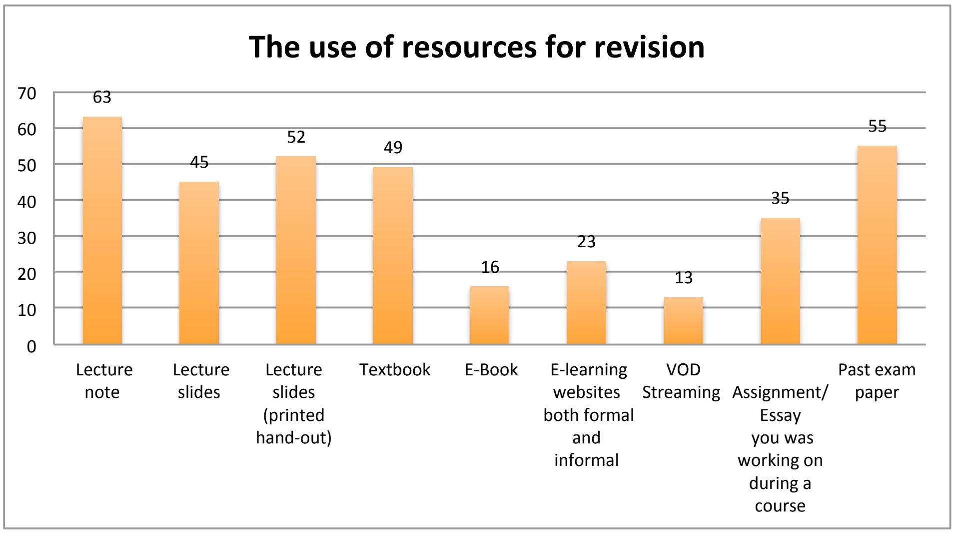


Figure 3.2: Number of students who have used each provided learning resource for revision.

Lecture notes were the most common resource for revision, selected by 63 students (92.5%). Students also frequently reviewed past exam papers (55/80%), printed lecture slides (52/76%) and textbooks (49/72%) as part of their revision. However, interestingly, there was very low usage of e-books (16/23%), VOD streaming (13/19%)

and e-learning websites (23/33%). In this regard, most universities provide relevant resources on their course websites. These results suggest that students typically used physical resources rather than online resources.

Relationship between use of resources and gender

To explore the relationship between use of each learning resource and gender, these variables were cross-tabulated, as presented in Table 3.7. The cross-tabulation shows that a higher percentage of male respondents used online resources (online lecture slides, e books, e-learning websites and VOD streaming) than females. Whilst there was no difference between male students' use of online and printed lecture slides, female students preferred printed slides. Although these results are significant at the 0.10 level, the hypothesis is accepted at the 0.05 significance level ($\chi^2_{MMI}(9, N = 68) = 15.922, p = 0.069$), as presented in Table 3.8. The results of a chi-square (MMI) test for independence indicate that gender was independent of use of learning resources.

Table 3.7: Cross-tabulation between common use of learning resources and gender.

			Gender		Total
			Male	Female	
The common resources that students usually used during the revision.[a]	Lecture note.	Count	26	37	63
		% within Gender	89.7%	94.9%	
	(Online) Lecture slides.	Count	22	23	45
		% within Gender	75.9%	59.0%	
	(Printed) Lecture slides.	Count	22	30	52
		% within Gender	75.9%	76.9%	
	Textbook.	Count	21	28	49
		% within Gender	72.4%	71.8%	
	E-book.	Count	8	8	16
		% within Gender	27.6%	20.5%	
	E-learning website.	Count	10	13	23
		% within Gender	34.5%	33.3%	
	VOD learing archieve.	Count	8	5	13
		% within Gender	27.6%	12.8%	
	Assignment or essay.	Count	15	20	35
		% within Gender	51.7%	51.3%	
	Pastexam paper.	Count	21	34	55
		% within Gender	72.4%	87.2%	
Total		Count	29	39	68

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.8: Results of chi-square (MMI) test calculated from Table 3.7.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	15.922
	df	9
	Sig.	.069

Relationship between use of resources and ethnicity

As shown in the cross-tabulation in Table 3.9, Asian students used printed lecture slides more frequently and online lecture slides less frequently than other ethnicities. Also, a higher percentage of Asian students used assignments and past exam papers for their revision than either European or African students. These results are significant at the 0.05 level ($\chi^2_{MMI}(18, N = 68) = 78.614, p < 0.001$), as shown in Table 3.10. The null hypothesis is rejected, indicating that common use of types of resource was related to ethnicity.

Relationship between use of resources and department

Table 3.11 shows the results of cross-tabulation between the use of learning resources and departments. A higher percentage of WBS students used past exam papers for revision than students from WMG and other departments, while the percentage use of other resources was approximately the same across other departments. These results are significant at the 0.05 level ($\chi^2_{MMI}(18, N = 68) = 39.547, p = 0.002$), as shown in Table 3.12. The null hypothesis is rejected, indicating that department was related to the use of learning resources.

Table 3.9: Cross-tabulation illustrating relationship between use of learning resources and ethnicity.

			The ethnic groups			
			European	Asian	African	Total
The common resources that students usually used during the revision.[a]	Lecture note.	Count	17	43	3	63
		% within Group_of_Nationality	94.4%	93.5%	75.0%	
	(Online) Lecture slides.	Count	16	26	3	45
		% within Group_of_Nationality	88.9%	56.5%	75.0%	
	(Printed) Lecture slides.	Count	9	41	2	52
		% within Group_of_Nationality	50.0%	89.1%	50.0%	
	Textbook.	Count	12	35	2	49
		% within Group_of_Nationality	66.7%	76.1%	50.0%	
	E-book.	Count	3	9	4	16
		% within Group_of_Nationality	16.7%	19.6%	100.0%	
	E-learning website.	Count	4	18	1	23
		% within Group_of_Nationality	22.2%	39.1%	25.0%	
	VOD learing archieve.	Count	2	11	0	13
		% within Group_of_Nationality	11.1%	23.9%	0.0%	
	Assignment or essay.	Count	7	26	2	35
		% within Group_of_Nationality	38.9%	56.5%	50.0%	
	Pastexam paper.	Count	12	41	2	55
		% within Group_of_Nationality	66.7%	89.1%	50.0%	
Total		Count	18	46	4	68

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.10: Results of chi-square (MMI) test calculated from Table 3.9.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	78.614
	df	18
	Sig.	.000

Table 3.11: Cross-tabulation illustrating relationship between use of learning resources and department.

			Group_Department			Total
			WMG	WBS	Other	
The common resources that students usually used during the revision.[a]	Lecture note.	Count	20	29	14	63
		% within Group_Department	87.0%	96.7%	93.3%	
	(Online) Lecture slides.	Count	13	21	11	45
		% within Group_Department	56.5%	70.0%	73.3%	
	(Printed) Lecture slides.	Count	16	23	13	52
		% within Group_Department	69.6%	76.7%	86.7%	
	Textbook.	Count	14	22	13	49
		% within Group_Department	60.9%	73.3%	86.7%	
	E-book.	Count	9	4	3	16
		% within Group_Department	39.1%	13.3%	20.0%	
	E-learning website.	Count	8	11	4	23
		% within Group_Department	34.8%	36.7%	26.7%	
	VOD learing archieve.	Count	5	3	5	13
		% within Group_Department	21.7%	10.0%	33.3%	
	Assignment or essay.	Count	13	12	10	35
		% within Group_Department	56.5%	40.0%	66.7%	
	Pastexam paper.	Count	17	28	10	55
		% within Group_Department	73.9%	93.3%	66.7%	
Total		Count	23	30	15	68

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.12: Results of chi-square (MMI) test calculated from Table 3.11.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	39.547
	df	18
	Sig.	.002

3.4.3 Which resources do students prefer to use first when starting to revise?

The students were also asked about the resource they preferred to use first for their revision, and why. The results shown in Figure 3.3 reveal that the majority of students (40/59%) used lecture slides as the initial material for their revision.

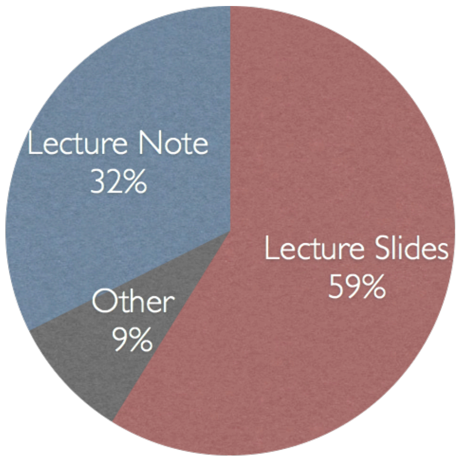


Figure 3.3: Percentage of students using each learning resource as a first resource when starting revision.

Most students who started their revision using lecture slides gave the reason that they could gain an overview of the course easily through lecture slides. The following statements were made by some of the 26 students who gave this reason.

> Student 21: Help me start remembering the material, understand the basic things.
>
> Student 25: They contain general knowledge and concept [sic] you need to understand before exams.
>
> Student 27: Most useful and can recall memory most efficiently.

> Student 29: It is the fastest and easiest way to start recapturing all knowledge from class.
>
> Student 30: To get the main idea and overall picture of each lecture first.

Other students who preferred to start with their own lecture notes commented that they had more trust in their own notes. The following statements were made by some of the 10 students who gave this reason.

> Student 5: It gives the entirety of the course — I like to work through it and know I'm not missing anything out.
>
> Student 7: Lecture notes are made by me based on my understanding which helps me to remember it easily.
>
> Student 22: The material is adjusted to the way I prefer.
>
> Student 45: It can recall my memory of what I have learnt from the beginning.
>
> Student 68: Lecture notes are created by myself which is the easiest way to get a flashback of what I have studied. After filling with some ideas, other resources will be used to prepare for the exam.

Only a few students preferred to start their revision with other materials such as textbooks, past exam papers or online websites. The following statements were made by these students.

> Student 24: I want to know the format and major content of the exam first. It will help me to catch the major point when I review the PowerPoint lecture. [Past exam paper]

> Student 35: Wikipedia can often provide a quick recap, allowing me to remember the overview of the topic before using other resources to go into detail. [Online-website]

> Student 54: Text book is like the general idea, that's why it's easier for me to get to the whole point first then move on to the lecture slides to get the main points. [Textbook]

Relationship between first resource used and gender

This section explores the relationship between the first resource that students used for their revision and gender. Table 3.13 shows that 47.8 per cent of female students preferred printed lecture slides. Only 5.1 per cent of female students preferred online lecture slides, compared with 34.5 per cent of male students. The percentage preferring to use other learning materials as a first material was approximately the same across genders. These results are statistically significant at the 0.05 level ($\chi^2(6, N = 68) = 13.359, p = 0.038$), as presented in Table 3.14. The null hypothesis is rejected, indicating that gender was related to the first resource used by students for their revision.

Relationship between first resource used and ethnicity

Table 3.15 cross-tabulates the first resource that students preferred to use and their ethnicity, showing that half of Asian students preferred to use printed lecture slides as a first material rather than other learning materials. However, the results in Table 3.16 illustrate that the null hypothesis is accepted at the 0.05 significance level ($\chi^2(12, N = 68) = 16.582, p = 0.166$). This chi-square result indicates that the first resource that students preferred was independent of ethnicity.

Table 3.13: Cross-tabulation between preferred first resource when starting revision and gender.

			Gender		
			Male	Female	Total
First resource that you normally use for revision	Lecture Note	Count	8	14	22
		% within Gender	27.6%	35.9%	32.4%
	Lecture Slides (online)	Count	10	2	12
		% within Gender	34.5%	5.1%	17.6%
	Lecture Slides (printed)	Count	9	19	28
		% within Gender	31.0%	48.7%	41.2%
	Textbook	Count	0	1	1
		% within Gender	0.0%	2.6%	1.5%
	E-book	Count	1	0	1
		% within Gender	3.4%	0.0%	1.5%
	E-learning website	Count	1	1	2
		% within Gender	3.4%	2.6%	2.9%
	PastExam paper	Count	0	2	2
		% within Gender	0.0%	5.1%	2.9%
Total		Count	29	39	68
		% within Gender	100.0%	100.0%	100.0%

Table 3.14: Results of chi-square test calculated from Table 3.13.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	13.359[a]	6	.038
Likelihood Ratio	15.200	6	.019
Linear-by-Linear Association	.840	1	.360
N of Valid Cases	68		

a. 8 cells (57.1%) have expected count less than 5. The minimum expected count is .43.

Table 3.15: Cross-tabulation between preferred first resource when starting revision and ethnicity.

			Ethnics			
			European	Asian	African	Total
First resource that you normally use for revision	Lecture Note	Count	7	13	2	22
		% within What is you nationality?	38.9%	28.3%	50.0%	32.4%
	Lecture Slides (online)	Count	5	6	1	12
		% within What is you nationality?	27.8%	13.0%	25.0%	17.6%
	Lecture Slides (printed)	Count	3	24	1	28
		% within What is you nationality?	16.7%	52.2%	25.0%	41.2%
	Textbook	Count	0	1	0	1
		% within What is you nationality?	0.0%	2.2%	0.0%	1.5%
	E-book	Count	1	0	0	1
		% within What is you nationality?	5.6%	0.0%	0.0%	1.5%
	E-learning website	Count	2	0	0	2
		% within What is you nationality?	11.1%	0.0%	0.0%	2.9%
	PastExam paper	Count	0	2	0	2
		% within What is you nationality?	0.0%	4.3%	0.0%	2.9%
Total		Count	18	46	4	68
		% within What is you nationality?	100.0%	100.0%	100.0%	100.0%

Table 3.16: Results of chi-square test calculated from Table 3.15.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	16.582[a]	12	.166
Likelihood Ratio	17.665	12	.126
Linear-by-Linear Association	.029	1	.865
N of Valid Cases	68		

a. 16 cells (76.2%) have expected count less than 5. The minimum expected count is .06.

Relationship between first resource used and department

This section explores whether the first resource that students preferred was related to their department. Table 3.17 illustrates that 34.8 per cent of WMG and 60 per cent of WBS students used printed lecture slides as the first resource, whereas only 6.7 per cent of WBS students preferred the online version. However, the percentage using online lecture slides was greater than for printed lecture slides for students from other departments. These results are statistically significant at the 0.1 level but are not significant at the 0.05 level ($\chi^2(12, N = 68) = 19.805, p = 0.071$), as shown in the results of the chi-square test presented in Table 3.18.

Table 3.17: Cross-tabulation between preferred first resource when starting revision and department.

			Departments			Total
			WMG	WBS	Other	
First resource that you normally use for revision	Lecture Note	Count	7	8	7	22
		% within Group_Department	30.4%	26.7%	46.7%	32.4%
	Lecture Slides (online)	Count	5	2	5	12
		% within Group_Department	21.7%	6.7%	33.3%	17.6%
	Lecture Slides (printed)	Count	8	18	2	28
		% within Group_Department	34.8%	60.0%	13.3%	41.2%
	Textbook	Count	0	1	0	1
		% within Group_Department	0.0%	3.3%	0.0%	1.5%
	E-book	Count	1	0	0	1
		% within Group_Department	4.3%	0.0%	0.0%	1.5%
	E-learning website	Count	2	0	0	2
		% within Group_Department	8.7%	0.0%	0.0%	2.9%
	PastExam paper	Count	0	1	1	2
		% within Group_Department	0.0%	3.3%	6.7%	2.9%
Total		Count	23	30	15	68
		% within Group_Department	100.0%	100.0%	100.0%	100.0%

Table 3.18: Results of chi-square test calculated from Table 3.17.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	19.805[a]	12	.071
Likelihood Ratio	22.102	12	.036
Linear-by-Linear Association	.382	1	.536
N of Valid Cases	68		

a. 15 cells (71.4%) have expected count less than 5. The minimum expected count is .22.

3.4.4 What actions do students take?

During the revision period, the main revision activities that students undertook were organising all their learning resources (50/73%) and doing exercises from past exam papers (47/69%), as indicated in Figure 3.4. Other activities were also popular for some students, as noted by the high numbers of responses.

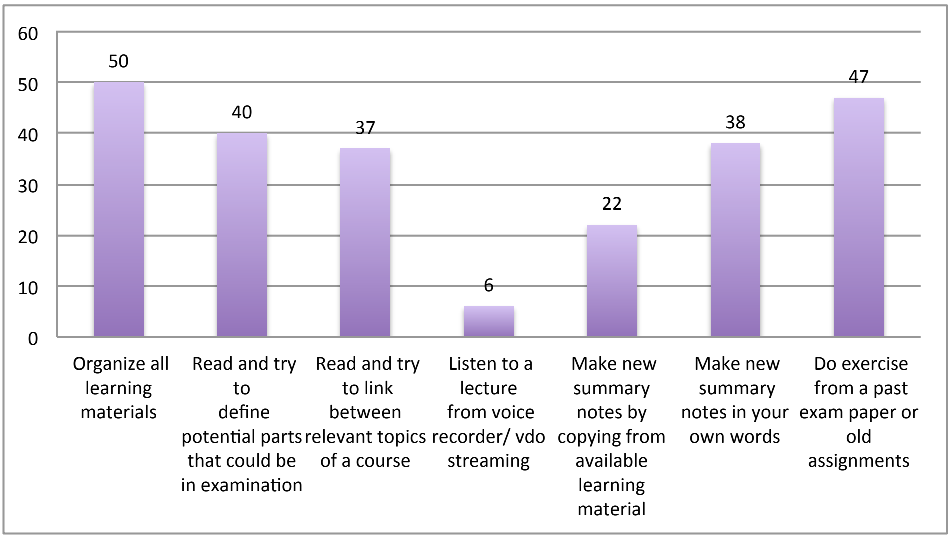


Figure 3.4: Number of students using each strategy during revision.

However, there was a very low response for listening to a lecture from a voice recorder or VOD lecture streaming (6/8%). This is confirmed by the results illustrated in Figure 3.2, which suggest that students made relatively little use of VOD streaming resources. Since such resources were not provided for all modules, it cannot be concluded that students preferred not to use them. To overcome this limitation, the university might provide VOD streaming resources for all lecture modules, which would provide students with alternative materials for revision.

Relationship between revision strategies and gender

The cross tabulation in Table 3.19 shows that a greater percentage of female respondents than male respondents used the revision strategies of linking between relevant topics, listening to a lecture from a voice recording, making new summary notes in their own words and working on past exam papers. For the other revision strategies, the percentage of male students was slightly higher than for female students. These results are significant at the 0.05 level ($\chi^2_{MMI}(7, N = 68) = 21.867, p = 0.003$), as shown in Table 3.20, rejecting the null hypothesis and indicating that gender was related to revision strategies.

Relationship between revision strategies and ethnicity

The cross-tabulation in Table 3.21 shows that for European students, the highest percentages with regard to revision strategies, with 61.1 per cent for each, were for organising all learning materials, reading and trying to link between relevant topics, and doing exercises from past exam papers. The strategy most commonly used by Asian students and other ethnicities was organising all learning materials. However, the relationship between revision strategies and ethnicity is not statistically significant at the 0.05 level ($\chi^2_{MMI}(14, N = 68) = 14.574, p = 0.408$), as indicated by the results of chi-square (MMI) test shown in Table 3.22.

Table 3.19: Cross-tabulation between revision strategies and gender.

			Gender		Total
			Male	Female	
The activity that students perform during the revision.[a]	Organize all learning materials.	Count	22	28	50
		% within Gender	78.6%	71.8%	
	Read and try to define potential part that could be in the exam paper.	Count	19	21	40
		% within Gender	67.9%	53.8%	
	Read and try to link between relevant topics.	Count	14	23	37
		% within Gender	50.0%	59.0%	
	Listen lecture from voice recorder or VOD lecture online.	Count	1	5	6
		% within Gender	3.6%	12.8%	
	Make a new summary note by copying from all avaliable materials.	Count	10	12	22
		% within Gender	35.7%	30.8%	
	Make a new summary note in your own words.	Count	11	27	38
		% within Gender	39.3%	69.2%	
	Do excercise from the pastexam paper.	Count	18	29	47
		% within Gender	64.3%	74.4%	
Total		Count	28	39	67

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.20: Results of chi-square (MMI) test calculated from Table 3.19.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	21.867
	df	7
	Sig.	.003

Table 3.21: Cross-tabulation between revision strategies and ethnicity.

			The ethnic groups			
			European	Asian	African	Total
The activity that students perform during the revision.[a]	Organize all learning materials.	Count	11	37	2	50
		% within Group_of_Nationality	61.1%	80.4%	66.7%	
	Read and try to define potential part that could be in the exam paper.	Count	10	28	2	40
		% within Group_of_Nationality	55.6%	60.9%	66.7%	
	Read and try to link between relevant topics.	Count	11	25	1	37
		% within Group_of_Nationality	61.1%	54.3%	33.3%	
	Listen lecture from voice recorder or VOD lecture online.	Count	1	5	0	6
		% within Group_of_Nationality	5.6%	10.9%	0.0%	
	Make a new summary note by copying from all avaliable materials.	Count	8	13	1	22
		% within Group_of_Nationality	44.4%	28.3%	33.3%	
	Make a new summary note in your own words.	Count	9	27	2	38
		% within Group_of_Nationality	50.0%	58.7%	66.7%	
	Do excercise from the pastexam paper.	Count	11	33	3	47
		% within Group_of_Nationality	61.1%	71.7%	100.0%	
Total		Count	18	46	3	67

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.22: Results of chi-square (MMI) test calculated from Table 3.21.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	14.574
	df	14
	Sig.	.408

Relationship between revision strategies and department

The results of cross-tabulation between revision strategies and department are presented in Table 3.23. Whilst a lower percentage of students from other departments organised all learning materials than from WBS and WMG, they had the highest percentage of respondents for the strategies of defining parts of materials that might be used in the exam and linking between relevant learning materials. These results are significant at the 0.05 level ($\chi^2_{MMI}(14, N = 68) = 27.062, p = 0.019$), indicating that department was somewhat related to revision strategies.

Table 3.23: Cross-tabulation between revision strategies and department.

			Group_Department			Total
			WMG	WBS	Other	
The activity that students perform during the revision.[a]	Organize all learning materials.	Count	16	24	10	50
		% within Group_Department	72.7%	80.0%	66.7%	
	Read and try to define potential part that could be in the exam paper.	Count	14	14	12	40
		% within Group_Department	63.6%	46.7%	80.0%	
	Read and try to link between relevant topics.	Count	11	14	12	37
		% within Group_Department	50.0%	46.7%	80.0%	
	Listen lecture from voice recorder or VOD lecture online.	Count	1	5	0	6
		% within Group_Department	4.5%	16.7%	0.0%	
	Make a new summary note by copying from all avaliable materials.	Count	6	11	5	22
		% within Group_Department	27.3%	36.7%	33.3%	
	Make a new summary note in your own words.	Count	12	19	7	38
		% within Group_Department	54.5%	63.3%	46.7%	
	Do excercise from the pastexam paper.	Count	15	23	9	47
		% within Group_Department	68.2%	76.7%	60.0%	
Total		Count	22	30	15	67

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.24: Results of chi-square (MMI) test calculated from Table 3.23.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	27.062
	df	14
	Sig.	.019

3.4.5 What do students do when they do not understand?

Having understood which resources students commonly used, as well as their common strategies for revision, the activities and resources that individual students used when they did not understand content during revision were also of interest. Figure 3.5 shows the activities undertaken by students when they did not understand a lecture or the content of learning resources.

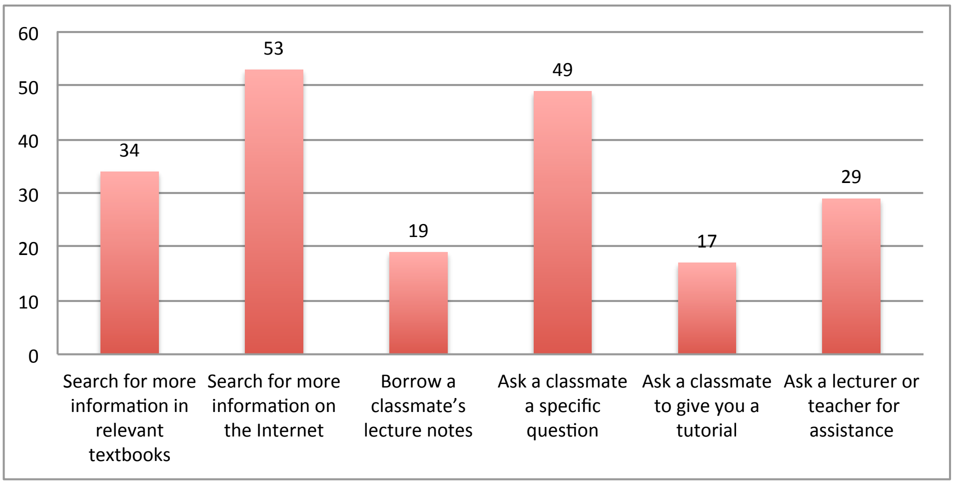


Figure 3.5: Number of students who adopted each strategy when they did not understand the content.

The results reveal that the three most common activities of students when they did not understand were searching for more information on the internet (53/77%), asking a classmate a specific question (49/72%) and searching for more information in relevant textbooks (34/50%). These ways in which students tried to understand difficult content by themselves corresponds with previous studies which have found that students commonly search for specific information they need [110, 112, 162]. Students tended to ask a classmate only with regard to a specific question, rather than asking for a tutorial. Moreover, internet technology seemed to be useful when students did not understand the content of learning resources.

Relationship between strategy when students did not understand and gender

The cross-tabulation between revision strategy when students did not understand and gender presented in Table 3.25 shows that, apart from the technique of searching for more information in textbooks, other revision strategies were adopted by approximately the same percentage of respondents across genders.

In addition, the percentage of female students who used the technique of searching for more information in textbooks was approximately 25.8 per cent, higher than for male students. These results are statistically significant at the 0.05 level ($\chi^2_{MMI}(6, N = 68) = 13.229, p = 0.040$), as presented in Table 3.26. The null hypothesis is rejected, indicating that gender was related to the strategies used by students when they did not understand.

Relationship between strategy when students did not understand and ethnicity

The cross-tabulation in Table 3.27 illustrates that a higher percentage of European students than Asian and African students used the strategy of searching for information in a textbook. This result is statistically significant at the 0.05 level ($\chi^2_{MMI}(12, N = 68) = 22.931, p = 0.028$), as presented in Table 3.28. The null hypothesis is rejected, indicating that ethnicity was related to the strategies that students used when they did not understand.

Table 3.25: Cross-tabulation between revision strategies when students did not understand and gender.

			Gender		
			Male	Female	Total
The activity that students perform when they do not understand content of materials.[a]	Search for more information on relevant textbooks.	Count	10	24	34
		% within Gender	35.7%	61.5%	
	Search for more information on the Internet.	Count	22	31	53
		% within Gender	78.6%	79.5%	
	Do you borrow a classmate's lecture notes? (don't understand)	Count	8	11	19
		% within Gender	28.6%	28.2%	
	Ask a classmate for a specific question.	Count	22	27	49
		% within Gender	78.6%	69.2%	
	Ask a classmate to give you a tutorial.	Count	9	8	17
		% within Gender	32.1%	20.5%	
	Ask a lecturer or teacher for assistance.	Count	11	18	29
		% within Gender	39.3%	46.2%	
Total		Count	28	39	67

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.26: Results of chi-square (MMI) test calculated from Table 3.25.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	13.229
	df	6
	Sig.	.040

Relationship between strategy when students did not understand and department

The cross-tabulation between the revision strategies adopted when students did not understand and their departments, shown in Table 3.29, indicates that only 26 per cent of WMG students searched for more information in a textbook, which was lower than students from WBS (69%) and other departments (53.3%). Interestingly, 93.3 per cent of students from other departments preferred to ask a classmate a specific question, while only 56.5 per cent of WMG and 75.9 per cent of WBS students responded on this strategy. These results are statistically significant at the 0.05

Table 3.27: Cross-tabulation between revision strategies when students did not understand and ethnicity.

			The ethnic groups			
			European	Asian	African	Total
The activity that students perform when they do not understand content of materials.[a]	Search for more information on relevant textbooks.	Count	11	22	1	34
		% within Group_of_Nationality	64.7%	47.8%	25.0%	
	Search for more information on the Internet.	Count	13	38	2	53
		% within Group_of_Nationality	76.5%	82.6%	50.0%	
	Do you borrow a classmate's lecture notes? (don't understand)	Count	6	13	0	19
		% within Group_of_Nationality	35.3%	28.3%	0.0%	
	Ask a classmate for a specific question.	Count	12	36	1	49
		% within Group_of_Nationality	70.6%	78.3%	25.0%	
	Ask a classmate to give you a tutorial.	Count	3	13	1	17
		% within Group_of_Nationality	17.6%	28.3%	25.0%	
	Ask a lecturer or teacher for assistance.	Count	7	22	0	29
		% within Group_of_Nationality	41.2%	47.8%	0.0%	
Total		Count	17	46	4	67

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.28: Results of chi-square (MMI) test calculated from Table 3.27.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	22.931
	df	12
	Sig.	.028

level $(\chi^2_{MMI}(12, N = 68) = 33.058, p = 0.001)$, as presented in Table 3.30. The null hypothesis is rejected, indicating that department of study was related to the strategies that students used when they did not understand.

Table 3.29: Cross-tabulation between revision strategies when students did not understand and department.

			Group_Department			
			WMG	WBS	Other	Total
The activity that students perform when they do not understand content of materials.[a]	Search for more information on relevant textbooks.	Count	6	20	8	34
		% within Group_Department	26.1%	69.0%	53.3%	
	Search for more information on the Internet.	Count	18	23	12	53
		% within Group_Department	78.3%	79.3%	80.0%	
	Do you borrow a classmate's lecture notes? (don't understand)	Count	5	7	7	19
		% within Group_Department	21.7%	24.1%	46.7%	
	Ask a classmate for a specific question.	Count	13	22	14	49
		% within Group_Department	56.5%	75.9%	93.3%	
	Ask a classmate to give you a tutorial.	Count	8	6	3	17
		% within Group_Department	34.8%	20.7%	20.0%	
	Ask a lecturer or teacher for assistance.	Count	8	13	8	29
		% within Group_Department	34.8%	44.8%	53.3%	
Total		Count	23	29	15	67

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.30: Results of chi-square (MMI) test calculated from Table 3.29.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	33.058
	df	12
	Sig.	.001

3.4.6 What do students need?

Students were also asked in the survey to specify what they needed for their revision, in order to understand to what extent they needed tools to support them in revision tasks. Figure 3.6 shows that the two highest responses were a function to extract an overview of key information from learning materials (45/66%) and a function to help them organise the content of all available resources in their own way (42/61%). The third-ranked item also received a reasonably high number of responses, which was a function for sharing an answer or idea in e-material during the revision period (37/54%).

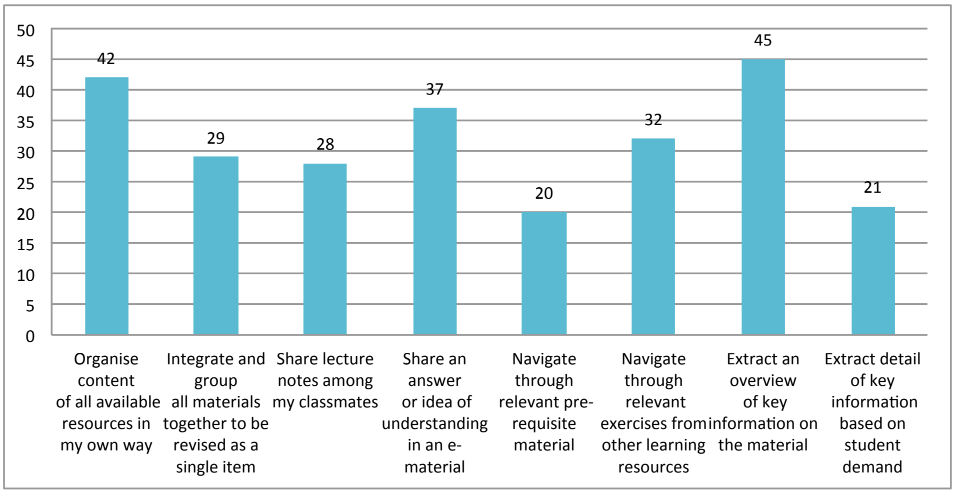


Figure 3.6: Number of students who preferred to use each tool or function to support their revision.

Relationship between students' needs and gender

The cross-tabulation shown in Table 3.31 indicates that a higher percentage of female than male students responded that they needed tools for sharing answers or ideas of understanding and for extracting key information from learning materials. However, this result is not statistically significant at the 0.05 level ($\chi^2_{MMI}(8, N = 68) = 7.008, p = 0.536$), as presented in Table 3.32. The null hypothesis is accepted, indicating that gender was not related to students' need for tools.

Table 3.31: Cross-tabulation between the need of tools to support revision and gender.

			Gender		Total
			Male	Female	
the tools that students need to support their revision.[a]	Organise content of all available resources in my own way.	Count	20	22	42
		% within Gender	69.0%	57.9%	
	Integrate and group all materials together to be revised as a single item.	Count	13	16	29
		% within Gender	44.8%	42.1%	
	Share lecture notes among my classmates.	Count	12	16	28
		% within Gender	41.4%	42.1%	
	Share an answer or idea of understanding in an e-material.	Count	15	22	37
		% within Gender	51.7%	57.9%	
	Support you to navigate through relevant pre-requisite material.	Count	11	9	20
		% within Gender	37.9%	23.7%	
	Support you to navigate through relevant exercises from other learning resources.	Count	15	17	32
		% within Gender	51.7%	44.7%	
	Support you to extract an overview of key information on the material.	Count	20	25	45
		% within Gender	69.0%	65.8%	
	Support you to extract detail of key information based on student demand.	Count	8	13	21
		% within Gender	27.6%	34.2%	
Total		Count	29	38	67

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.32: Results of chi-square (MMI) test calculated from Table 3.31.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	7.008
	df	8
	Sig.	.536

Relationship between students' needs and ethnicity

The cross-tabulation shown in Table 3.33 indicates that 77.8 per cent of European students responded that they needed tools to support their navigation through relevant exercises from other learning resources, compared with 31.6 per cent of Asian students and 25.0 per cent of African students. However, a higher percentage of Asian respondents (77.8%) said that they needed tools to support them in extracting an overview of key information from the materials than other tools, which was also higher than for other ethnicities. These results are statistically significant at the 0.05 level ($\chi^2_{MMI}(16, N = 68) = 42.254, p < 0.001$), as presented in Table 3.34. The null hypothesis is rejected, indicating that ethnicity was related to students' need for tools.

Table 3.33: Cross-tabulation between students' need for tools to support revision and ethnicity.

			The ethnic groups			
			European	Asian	African	Total
the tools that students need to support their revision.[a]	Organise content of all available resources in my own way.	Count	12	29	1	42
		% within Group_of_Nationality	66.7%	64.4%	25.0%	
	Integrate and group all materials together to be revised as a single item.	Count	5	22	2	29
		% within Group_of_Nationality	27.8%	48.9%	50.0%	
	Share lecture notes among my classmates.	Count	7	20	1	28
		% within Group_of_Nationality	38.9%	44.4%	25.0%	
	Share an answer or idea of understanding in an e-material.	Count	8	27	2	37
		% within Group_of_Nationality	44.4%	60.0%	50.0%	
	Support you to navigate through relevant pre-requisite material.	Count	6	13	1	20
		% within Group_of_Nationality	33.3%	28.9%	25.0%	
	Support you to navigate through relevant exercises from other learning resources.	Count	14	17	1	32
		% within Group_of_Nationality	77.8%	37.8%	25.0%	
	Support you to extract an overview of key information on the material.	Count	8	35	2	45
		% within Group_of_Nationality	44.4%	77.8%	50.0%	
	Support you to extract detail of key information based on student demand.	Count	6	15	0	21
		% within Group_of_Nationality	33.3%	33.3%	0.0%	
Total		Count	18	45	4	67

Percentages and totals are based on respondents.
a. Dichotomy group tabulated at value 1.

Table 3.34: Results of chi-square (MMI) test calculated from Table 3.33.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	42.245
	df	16
	Sig.	.000

Relationship between students' needs and department

The cross-tabulation shown in Table 3.35 indicates that most WMG students needed tools to support them in integrating all learning materials and in extracting an overview of key information, whereas 82.8 per cent of WBS students needed a tool to help them organise their learning materials, which was a higher percentage than for students from other departments. More students from other departments preferred a tool to extract an overview of key information than students from WMG and WBS. These results are statistically significant at the 0.05 level ($\chi^2_{MMI}(16, N = 68) = 44.869, p < 0.001$), as presented in Table 3.36. The null hypothesis is rejected, indicating that department of study was related to students' need for tools.

Table 3.35: Cross-tabulation between the need for tools to support revision and department.

			Group_Department			Total
			WMG	WBS	Other	
the tools that students need to support their revision.[a]	Organise content of all available resources in my own way.	Count	10	24	8	42
		% within Group_Department	43.5%	82.8%	53.3%	
	Integrate and group all materials together to be revised as a single item.	Count	14	9	6	29
		% within Group_Department	60.9%	31.0%	40.0%	
	Share lecture notes among my classmates.	Count	12	11	5	28
		% within Group_Department	52.2%	37.9%	33.3%	
	Share an answer or idea of understanding in an e-material.	Count	13	14	10	37
		% within Group_Department	56.5%	48.3%	66.7%	
	Support you to navigate through relevant pre-requisite material.	Count	11	7	2	20
		% within Group_Department	47.8%	24.1%	13.3%	
	Support you to navigate through relevant exercises from other learning resources.	Count	10	13	9	32
		% within Group_Department	43.5%	44.8%	60.0%	
	Support you to extract an overview of key information on the material.	Count	14	19	12	45
		% within Group_Department	60.9%	65.5%	80.0%	
	Support you to extract detail of key information based on student demand.	Count	4	10	7	21
		% within Group_Department	17.4%	34.5%	46.7%	
Total		Count	23	29	15	67

Percentages and totals are based on respondents.

a. Dichotomy group tabulated at value 1.

Table 3.36: Results of chi-square (MMI) test calculated from Table 3.35.

Approximate Chi-Square Tests

		Gender
Difficulties	Chi-square	44.869
	df	16
	Sig.	.000

3.4.7 Do you normally prefer to revise independently or with peer groups?

During revision, most students need private time for independent study. Sometimes group revision is preferred in order to discuss and share knowledge before an examination. In this survey, students were asked which approach they preferred. The results shown in Figure 3.7 illustrate that 67 per cent of students preferred self-study compared with 33 per cent who preferred peer group revision.

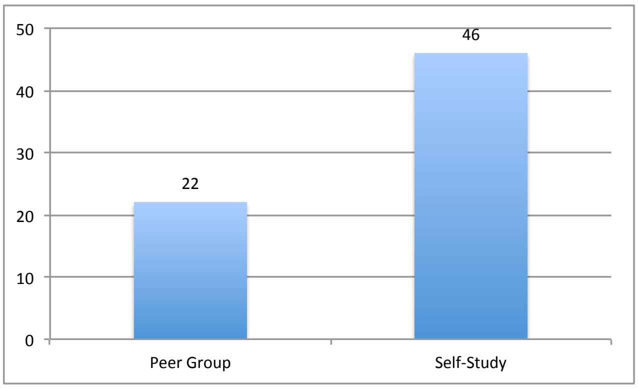


Figure 3.7: Numbers of tudents' preference for self-study or peer group revision.

Relationship between study mode preference and gender

Table 3.37 shows that approximately the same percentage of respondents of each gender preferred either self-study or peer group revision. In addition, Table 3.38 illustrates that gender was not related to study mode preference, with statistical significance at the 0.05 level ($\chi^2(1, N = 68) = 0.791, p = 0.397$). The null hypothesis is accepted.

Table 3.37: Cross-tabulation of preference for self-study or peer group revision and gender.

			Gender		Total
			Male	Female	
What type of revision do you prefer?	Self-Study Revision	Count	18	28	46
		% within Gender	62.1%	71.8%	67.6%
	Peer Group Revision	Count	11	11	22
		% within Gender	37.9%	28.2%	32.4%
Total		Count	29	39	68
		% within Gender	100.0%	100.0%	100.0%

Table 3.38: Results of chi-square test calculated from Table 3.37.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.719[a]	1	.397		
Continuity Correction[b]	.343	1	.558		
Likelihood Ratio	.715	1	.398		
Fisher's Exact Test				.440	.278
Linear-by-Linear Association	.708	1	.400		
N of Valid Cases	68				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 9.38.

b. Computed only for a 2x2 table

Relationship between study mode preference and ethnicity

This section explores whether a preference for either self-study or peer group revision was related to ethnicity, as presented in Table 3.39. It is clear that a higher percentage of all ethnic groups preferred the self-study approach to peer group revision. The percentage of Asian students who preferred group revision was higher than for European and African students. However, these results are not statistically significant at the 0.05 level (0.05, $\chi^2(2, N = 68) = 1.388, p = 0.499$), as illustrated in Table 3.40. The null hypothesis is accepted, indicating that ethnicity was independent of a preference for self-study or peer group revision.

Table 3.39: Cross-tabulation of preference for self-study or peer group revision and ethnicity.

			Ethnics			Total
			European	Asian	African	
What type of revision do you prefer?	Self-Study Revision	Count	14	29	3	46
		% within What is you nationality?	77.8%	63.0%	75.0%	67.6%
	Peer Group Revision	Count	4	17	1	22
		% within What is you nationality?	22.2%	37.0%	25.0%	32.4%
Total		Count	18	46	4	68
		% within What is you nationality?	100.0%	100.0%	100.0%	100.0%

Table 3.40: Results of chi-square test calculated from Table 3.39.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	1.388[a]	2	.499
Likelihood Ratio	1.441	2	.486
Linear-by-Linear Association	.551	1	.458
N of Valid Cases	68		

a. 2 cells (33.3%) have expected count less than 5. The minimum expected count is 1.29.

Relationship between study mode preference and department

This section explores whether a preference for either self-study or peer group revision was related to department of study, as presented in Table 3.41. It is clear that most WBS students preferred self-study revision (83.3%) to peer group revision (16.7%). Some students from WMG and other departments were evenly split between the two approaches. These results are statistically significant at the 0.05 level ($\chi^2(2, N = 68) = 6.078, p = 0.048$), as illustrated in Table 3.42. The null hypothesis is rejected, indicating that department was related to a preference for either self-study or peer group revision.

Table 3.41: Cross-tabulation of preference for self-study or peer group revision and department.

			Departments			Total
			WMG	WBS	Other	
What type of revision do you prefer?	Self-Study Revision	Count	13	25	8	46
		% within Group_Department	56.5%	83.3%	53.3%	67.6%
	Peer Group Revision	Count	10	5	7	22
		% within Group_Department	43.5%	16.7%	46.7%	32.4%
Total		Count	23	30	15	68
		% within Group_Department	100.0%	100.0%	100.0%	100.0%

Table 3.42: Results of chi-square test calculated from Table 3.41.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	6.078[a]	2	.048
Likelihood Ratio	6.358	2	.042
Linear-by-Linear Association	.021	1	.886
N of Valid Cases	68		

a. 1 cells (16.7%) have expected count less than 5. The minimum expected count is 4.85.

3.4.8 Would you be happy to share your notes with friends?

Sharing learning materials is a common activity during university study. The results of the survey shown in Figure 3.8 indicate that 98 per cent of students were willing to share their own notes with their friends. Only one student did not want to because:

> *I am afraid that they might lose them. I am the one who managed to have clear written lecture notes and I want to use them in the most efficient way. Hence, I am not going to risk giving them to someone untrustworthy. Additionally, I find it a bit unfair that someone who hasn't made any effort to have my notes for which I tried hard to have. Of course, to really close friends that I trust there would be no problem.*

Since only one student responded "no", a cross-tabulation is not required.

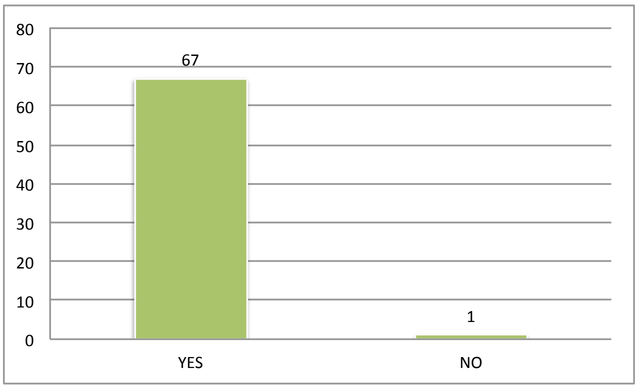


Figure 3.8: Students' willingness to share their own notes with friends.

3.5 Cross-Tabulation Analysis and Discussion

Also of interest to this study was whether the difficulties that students faced during revision, what they could remember before revising, and the length of time before they started their revision affected their strategies, the number of tools and techniques they used and their need for support tools. Hence, a cross-tabulation or chi-square test of independence was used to examine relationships between paired variables. In this study, seven pairs of observed data were considered: (i) the number of difficulties and the tools required for support, (ii) the number of difficulties and the techniques used for revision, (iii) memory of the subject before revising and the number of learning resources used for revision, (iv) memory of the subject before revising and the number of techniques used for revision, (v) memory of the subject before revising and the time before starting revision, (vi) the time before starting revision and the number of techniques used for revision and (vii) the time before starting revision and the number of learning resources used for revision. The results of the cross-tabulation analysis are discussed below.

3.5.1 Relationship between number of difficulties and number of support tools required

This section considers the number of difficulties faced by each student, as shown in Figure 3.1, compared with the number of tools or functions that they needed to support their revision, as shown in Figure 3.6. The data were prepared for a chi-square test by grouping the number of difficulties into three categories by frequency distribution: (i) less than three, (ii) equal to three, and (iii) greater than three. The number of tools that students needed for support was grouped into two categories: (i) less than four tools, and (ii) four or more tools. These two variables were cross-tabulated, as presented in Table 3.43.

Table 3.43: Cross-tabulation for chi-square test of independent variables. The observed count and expected count of the number of difficulties faced by each student and the number of tools or functions that students needed to support their revision are presented, with percentages for the independent variable.

Crosstab

			Number of tools that students required for support.		
			< 4	>= 4	Total
Number of difficulties that students had during revision.	< 3	Count	14	9	23
		Expected Count	11.5	11.5	23.0
		% within Number of tools that students required for support.	41.2%	26.5%	33.8%
	= 3	Count	17	8	25
		Expected Count	12.5	12.5	25.0
		% within Number of tools that students required for support.	50.0%	23.5%	36.8%
	> 3	Count	3	17	20
		Expected Count	10.0	10.0	20.0
		% within Number of tools that students required for support.	8.8%	50.0%	29.4%
Total		Count	34	34	68
		Expected Count	34.0	34.0	68.0
		% within Number of tools that students required for support.	100.0%	100.0%	100.0%

A chi-square test was performed using SPSS and the results are presented in Table 3.44. These indicate that the null hypothesis is rejected because the relationship between the two variables is statistically significant at the 0.05 level ($\chi^2(2, N = 68) = 14.127, p = 0.001$). In other words, the number of difficulties that students faced was related to the number of preferred tools. Since the chi-square is significant, the column percentages for the values of the independent variable in Table 3.43 can be considered. These variables are plotted in bar chart format in Figure 3.9, which shows that students who faced more than three difficulties were likely to require four or more supporting tools for their revision, while students who faced three or fewer difficulties tended to require fewer than four supporting tools.

Table 3.44: Results of chi-square test calculated from Table 3.43.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	14.127[a]	2	.001
Likelihood Ratio	15.227	2	.000
Linear-by-Linear Association	8.297	1	.004
N of Valid Cases	68		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 10.00.

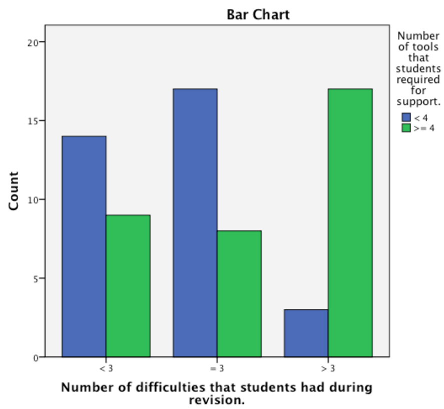


Figure 3.9: Number of difficulties faced by each student during revision compared with number of tools or functions they needed to support their revision.

3.5.2 Relationship between number of difficulties encountered and number of techniques used for revision

The relationship between the number of techniques that students used for revision and the number of difficulties they faced was also considered. For the chi-square test, the number of techniques (presented in Figure 3.4) was divided into two groups: (i) less than or equal to three techniques, and (ii) more than three techniques. The number of difficulties was categorised into three groups, as in Section 3.5.1. These raw data are presented as a cross-tabulation in Table 3.45.

Table 3.45: Cross-tabulation for chi-square test of independent variables. The observed count and expected count of the number of difficulties faced by each student and the number of techniques they used for revision are presented, including percentages for the independent variable.

Crosstab

			Number of revision techniques that students use.		
			use <= 3 techniques	use > 3 techniques	Total
Number of difficulties that students had during revision.	< 3	Count	16	7	23
		Expected Count	11.8	11.2	23.0
		% within Number of revision techniques that students use?	45.7%	21.2%	33.8%
	= 3	Count	13	12	25
		Expected Count	12.9	12.1	25.0
		% within Number of revision techniques that students use?	37.1%	36.4%	36.8%
	> 3	Count	6	14	20
		Expected Count	10.3	9.7	20.0
		% within Number of revision techniques that students use?	17.1%	42.4%	29.4%
Total		Count	35	33	68
		Expected Count	35.0	33.0	68.0
		% within Number of revision techniques that students use?	100.0%	100.0%	100.0%

The chi square results shown in Table 3.46 illustrate that the null hypothesis is rejected, with statistical significance at the 0.05 level ($\chi^2(2, N = 68) = 6.709, p = 0.035$). This result indicates that the number of difficulties that students faced during revision related to the number of revision techniques used. A bar chart of this trend is presented in Figure 3.10.

Table 3.46: Results of chi-square test calculated from Table 3.45.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	6.709[a]	2	.035
Likelihood Ratio	6.890	2	.032
Linear-by-Linear Association	6.579	1	.010
N of Valid Cases	68		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.71.

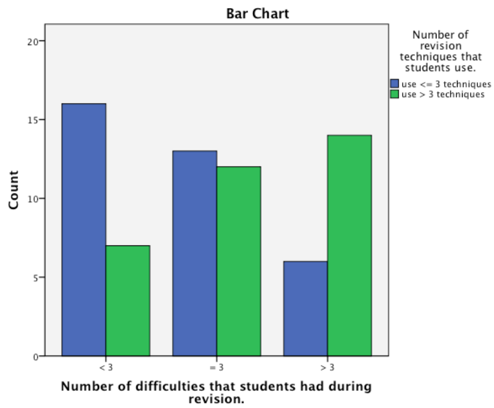


Figure 3.10: Number of difficulties faced by each student during revision compared with number of techniques used for revision.

3.5.3 Relationship between memory of the subject before revising and number of learning resources used for revision

This study sought to elicit whether there was any relationship between students' memory of a subject before their revision and the number of resources they used. Their memory before revising was divided into three groups based on the raw data: (i) 1-20%, (ii) 21-40% and (iii) 41-64%. The number of resources (presented in Figure 3.3)) was also divided into three groups based on number of resources: (i) less than or equal to four resources, (ii) five resources, and (iii) more than or equal to six resources. These raw data are presented as a cross tabulation in Table 3.47.

Table 3.47: Cross-tabulation for chi-square test of independent variables. The observed count and expected count of students' memory before revising and the number of learning resources they used for revision is presented, including percentages for the independent variable.

Crosstab

			How many resources do you use?			Total
			<=4	= 5	>=6	
How much memory do you have before revision?	1% - 20%	Count	8	5	6	19
		Expected Count	5.6	5.9	7.5	19.0
		% within How many resources do you use?	40.0%	23.8%	22.2%	27.9%
	21% - 40%	Count	7	9	8	24
		Expected Count	7.1	7.4	9.5	24.0
		% within How many resources do you use?	35.0%	42.9%	29.6%	35.3%
	41% - 64%	Count	5	7	13	25
		Expected Count	7.4	7.7	9.9	25.0
		% within How many resources do you use?	25.0%	33.3%	48.1%	36.8%
Total		Count	20	21	27	68
		Expected Count	20.0	21.0	27.0	68.0
		% within How many resources do you use?	100.0%	100.0%	100.0%	100.0%

The chi square results shown in Table 3.48 illustrate that the null hypothesis is accepted at the statistically significant 0.05 level ($\chi^2(2, N = 68) = 3.843, p = 0.428$). This indicates that students' memory of the subject before revising and number of resources used were unrelated and independent.

Table 3.48: Results of chi-square test calculated from Table 3.47.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	3.843[a]	4	.428
Likelihood Ratio	3.756	4	.440
Linear-by-Linear Association	2.932	1	.087
N of Valid Cases	68		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 5.59.

3.5.4 Relationship between memory of subject before revising and number of techniques used for revision

The survey also sought to establish whether there was any relationship between students' memory of a subject before revising and the number of techniques they used for their revision. Students' memory was divided into three groups as in Section 3.5.3, and the number of techniques used (presented in Figure 3.4) was divided into two groups as in Section 3.5.2. These raw data are presented as a cross-tabulation in Table 3.49.

Table 3.49: Cross-tabulation for chi-square test of independent variables.The observed count and expected count of students' memory before revising and the number of techniques they used for revision is presented, including percentages for the independent variable.

Crosstab

			How many revision techniques do student used?		
			use <= 3 techniques	use > 3 techniques	Total
How much memory do you have before revision?	1% - 20%	Count	13	6	19
		Expected Count	9.8	9.2	19.0
		% within How many revision techniques do student used?	37.1%	18.2%	27.9%
	21% - 40%	Count	12	12	24
		Expected Count	12.4	11.6	24.0
		% within How many revision techniques do student used?	34.3%	36.4%	35.3%
	41% - 64%	Count	10	15	25
		Expected Count	12.9	12.1	25.0
		% within How many revision techniques do student used?	28.6%	45.5%	36.8%
Total		Count	35	33	68
		Expected Count	35.0	33.0	68.0
		% within How many revision techniques do student used?	100.0%	100.0%	100.0%

The chi square results in Table 3.50 illustrate that the null hypothesis is accepted at the statistically significant 0.05 level ($\chi^2(2, N = 68) = 3.523, p = 0.172$). This indicates that students' memory of a subject before revising and the number of techniques used for revision were unrelated and independent.

Table 3.50: Results of chi-square test calculated from Table 3.49.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	3.523[a]	2	.172
Likelihood Ratio	3.589	2	.166
Linear-by-Linear Association	3.363	1	.067
N of Valid Cases	68		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.22.

3.5.5 Relationship between memory of a subject before revising and time before starting revision

The survey also examined whether there was any relationship between students' memory of a subject before revising and the time that had elapsed before they started their revision. The students' memory was divided into three groups as in Section 3.5.3, and the time before students started to revise was divided into two categories: (i) less than three weeks and (ii) more than or equal to three weeks. These raw data are presented as a cross-tabulation in Table 3.51.

The chi square results in Table 3.52 illustrate that the null hypothesis is accepted at the statistically significant 0.05 level ($\chi^2(2, N = 68) = 2.440, p = 0.295$). This indicates that students' memory of a subject before revising and the time before they started their revision were unrelated and independent.

3.5.6 Relationship between time before starting to revise and number of techniques used for revision

This section explores whether the time before students started their revision might have affected the number of techniques they used. The elapsed time was divided into two categories as in Section 3.5.5, and the number of techniques used was divided into two groups as in Section 3.5.2. The raw data are presented as a cross-tabulation

Table 3.51: Cross-tabulation for chi-square test of independent variables. The observed count and expected count of students' memory of a subject before revising and the time before they started their revision are presented, including percentages for the independent variable.

Crosstab

			How long before you start revision?		
			< 3 weeks	>= 3 weeks	Total
How much memory do you have before revision?	1% - 20%	Count	9	10	19
		Expected Count	11.5	7.5	19.0
		% within How long before you start revision?	22.0%	37.0%	27.9%
	21% - 40%	Count	17	7	24
		Expected Count	14.5	9.5	24.0
		% within How long before you start revision?	41.5%	25.9%	35.3%
	41% - 64%	Count	15	10	25
		Expected Count	15.1	9.9	25.0
		% within How long before you start revision?	36.6%	37.0%	36.8%
Total		Count	41	27	68
		Expected Count	41.0	27.0	68.0
		% within How long before you start revision?	100.0%	100.0%	100.0%

Table 3.52: Results of chi-square test calculated from Table 3.51.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	2.440[a]	2	.295
Likelihood Ratio	2.453	2	.293
Linear-by-Linear Association	.537	1	.464
N of Valid Cases	68		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 7.54.

in Table 3.53.

The chi square results in Table 3.54 illustrate that the null hypothesis is accepted at the statistically significant 0.05 level ($\chi^2(1, N = 68) = 0.003, p = 0.959$). This indicates that the time before students started their revision and the number of techniques they used were unrelated and independent.

Table 3.53: Cross-tabulation for chi-square test of independent variables. The observed count and expected count of the time before students started revising and the number of techniques used for revision are presented, including percentages for the independent variable.

crosstab

			How many revision techniques do student used? use <= 3 techniques	use > 3 techniques	Total
How long before you start revision?	< 3 weeks	Count	21	20	41
		Expected Count	21.1	19.9	41.0
		% within How many revision techniques do student used?	60.0%	60.6%	60.3%
	>= 3 weeks	Count	14	13	27
		Expected Count	13.9	13.1	27.0
		% within How many revision techniques do student used?	40.0%	39.4%	39.7%
Total		Count	35	33	68
		Expected Count	35.0	33.0	68.0
		% within How many revision techniques do student used?	100.0%	100.0%	100.0%

Table 3.54: Results of chi-square test calculated from Table 3.53.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.003[a]	1	.959		
Continuity Correction[b]	.000	1	1.000		
Likelihood Ratio	.003	1	.959		
Fisher's Exact Test				1.000	.578
Linear-by-Linear Association	.003	1	.960		
N of Valid Cases	68				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 13.10.

b. Computed only for a 2x2 table

3.5.7 Relationship between time before starting to revise and number of learning resources used for revision

The survey also explored whether the time before students started to revise affected the number of learning resources they used for revision. The elapsed time was divided into two categories as in Section 3.5.5, and the number of techniques used was divided into two groups as in Section 3.5.3. The raw data are presented as a cross-tabulation in Table 3.55.

Table 3.55: Cross-tabulation for chi-square test of independent variables. The observed count and expected count of the time before students started revising and the number of learning resources they used for revision is presented, including percentages for the independent variable.

crosstab

			How many resources do you use?			
			<=4	= 5	>=6	Total
How long before you start revision?	< 3 weeks	Count	15	13	13	41
		Expected Count	12.1	12.7	16.3	41.0
		% within How many resources do you use?	75.0%	61.9%	48.1%	60.3%
	>= 3 weeks	Count	5	8	14	27
		Expected Count	7.9	8.3	10.7	27.0
		% within How many resources do you use?	25.0%	38.1%	51.9%	39.7%
Total		Count	20	21	27	68
		Expected Count	20.0	21.0	27.0	68.0
		% within How many resources do you use?	100.0%	100.0%	100.0%	100.0%

The chi square results in Table 3.56 illustrate that the null hypothesis is accepted at the statistically significant 0.05 level ($\chi^2(2, N = 68) = 3.493, p = 0.174$). This indicates that the time before students started their revision and the number of learning resources they used for revision were unrelated and independent.

Table 3.56: Results of chi-square test calculated from Table 3.55.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	3.493[a]	2	.174
Likelihood Ratio	3.568	2	.168
Linear-by-Linear Association	3.441	1	.064
N of Valid Cases	68		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 7.94.

3.6 Conceptual Framework of the Use of E-Resources for Revision

The descriptive results in Section 3.4 reveal common patterns with regard to the use of learning resources by students at the University of Warwick. These patterns were combined with the types of cognitive tools proposed in Section 2.5 to generate a revision framework, as presented in Figure 3.11.

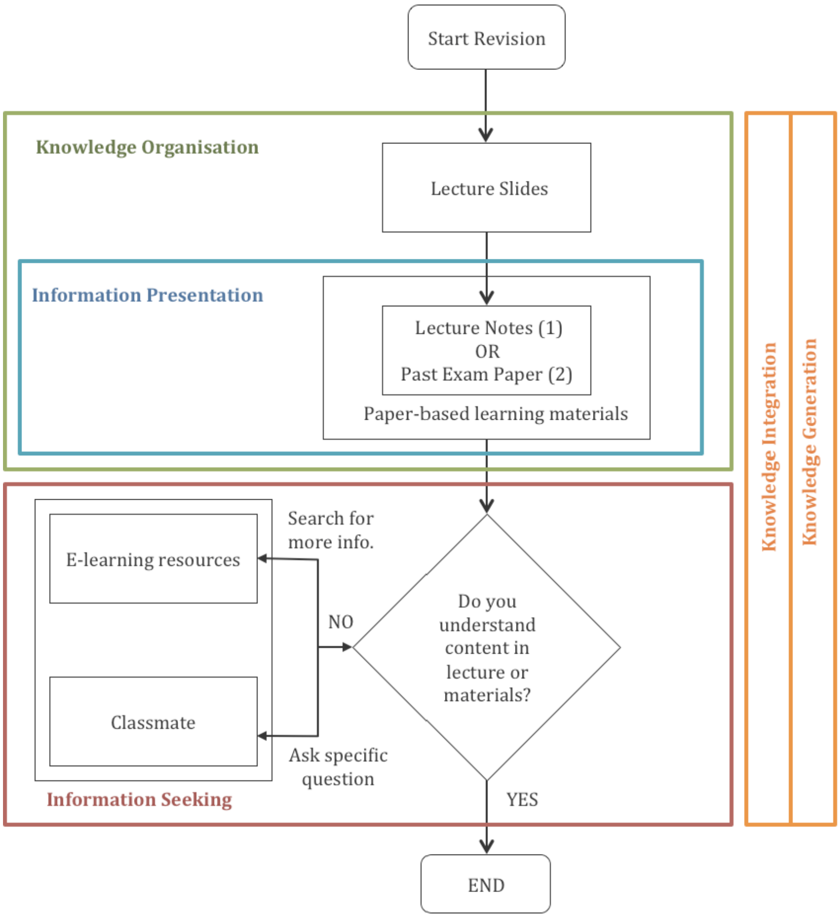


Figure 3.11: Conceptual revision framework.

The framework depicts a common process for revision pertaining to the use of learning resources by postgraduate students. The revision process starts with lecture slides, a common resource that students prefer to use first, as discussed in Section 3.4.3. The second process is then about gaining further detailed information. Two common resources that students are more likely to use in this process are lecture notes and past exam papers (see Section 3.4.2). Some students are more likely to use paper-based rather than online resources. The results from Section 3.4.5, regarding the strategy and learning resources that students use when they do not understand the content, form the next process in the revision framework. At this stage, students may have an issue relating to the content. When they do not understand the content, they commonly seek more information on the Internet first, and will then ask their friends a specific question rather than asking for a tutorial.

The definitions pertaining to the types of cognitive tool described in Section 2.5.1 show how current technologies may support students at the revision stage. Many universities suggest that students start their revision by organising and planning how to cope with the learning materials. The survey results presented in Sections 3.4.4 and 3.4.6 also confirm that organising all of the learning materials is a major activity undertaken by students, as well as a required tool for revision. Therefore, a knowledge organisation tool might be applied at this stage, covering the first and second process, as illustrated in Figure 3.11. Tools such as online note-taking and spreadsheets might support students in dealing with organising online course materials. In the second process, with regard to gaining further detailed information, a presentation tool might be applied, such as a graphic organiser or visualisation tool to support students in representing data from a different perspective and in a manner tailored to themselves. Obviously, an information seeking tool, such as a search engine, might be applied to support students in the third process, when they do not understand the content of the materials. Since the process of knowledge integration and generation may occur at any stage of learning, the mapping tool and the collaborative tool, which are two types of cognitive tool, might be applied at any stage of the framework.

This framework can be used not only as a guideline to design applications to support student revision, but also to reveal potential gaps that might be improved on in current revision strategies when considered in conjunction with the results relating to common difficulties and student requirements. For instance, Section 3.4 described how students are faced with a lot of learning materials in a short period of time, as well as poor learning resources. This issue might be approached in many ways, for example by designing a knowledge-organisation tool to allow students simply to rearrange their learning materials for revision in their own way, or by introducing note-taking, organising and archiving software, such as Evernote, to support students' summarisation of course materials. An information presentation tool might also be designed or applied to allow students to represent data in different forms, such as file organiser software like Tagspaces[1] to support students in generating tags or highlighting key information for quick access and review. An information-seeking tool such as Yahoo or Google might be used to support students in searching for further information quickly. A knowledge-integration tool, such as FreeMind, might be used to generate mind maps by integrating and linking ideas which might help students to organise and develop their understanding quickly. A knowledge-generation tool, such as Google Docs, might be supplied to allow students to share and brainstorm their ideas. These potential gaps led to the development of a software framework to support student revision, described in Chapter 4.

3.7 Summary

The main aims of this chapter were to gain an understanding of the pattern of student participation in the use of learning resources, and to construct a revision framework for use by both lecturers and developers as a guideline to apply or develop

[1] https://www.tagspaces.org

cognitive tools to support student revision. The findings contribute to achieving these aims, and also reveal students' preferences that may be used to design a system for the revision process.

The analysis shows that master's degree students at the University of Warwick commonly use all the resources provided in their study. However, the low response to the use of e-books and e-learning websites indicates that most students review the course materials provided by the lecturer rather than external materials. Furthermore, the results indicating higher usage of printed lecture slides than online lecture slides implies that students are more comfortable with physical than online resources. The survey results also show the diversity of students. For instance, European students have a stronger preference for online lecture slides than Asian and African students. Gender does not have a significant effect on the use of learning resources. These results suggest that there is still room to improve online resources to satisfy most students' needs.

The most common issue faced by students during the revision period is the large quantity of learning materials to be reviewed. This difficulty was mentioned by the highest percentages of respondents across gender, ethnicity and department. These results are consistent with the results presented in Section 3.4.4 regarding the most common revision strategies, indicating that students attempt to organise all their learning resources before revising. Furthermore, many students responded to the need for a system to support them that would provide an overview of key information from the learning resources provided by the lecturer and help them organise the content of all available resources in their own way. Again, these two types of tools were chosen by the first- and second-highest percentages of respondents from all backgrounds. This suggests that extracting an overview of key information from a large amount of learning resources is an important issue for students. In addition, the results shown in Figure 3.5 reveal that students prefer to search for more information when faced with difficult content. This result reveals an important issue concerning improved access to e-learning repositories, such as searching ability and navigation systems.

There is a significant dependent relationship between the number of difficulties faced by students during revision and the number of tools they require to support their revision. The results only reveal dependencies between the number of difficulties in using learning resources, the number of tools used and the number of revision techniques used. These results imply that difficulties with revision may affect students' selection of tools and techniques for their revision. However, the results described in Sections 3.5.3 to 3.5.7 are not statistically significant. This implies that students' memory of a subject and the time before starting revision are both independent of the number of resources and revision strategies used. The time before starting to revise is also unrelated to students' memory of the subject after the class has finished.

This study also indicates that, although individual students use learning resources in different ways, many select learning resources for revision in a similar order. This enables the construction of a revision framework from the analysed results discussed in Section 3.4, which demonstrates a common pattern of student participation in the use of learning resources. Five types of cognitive tools are mapped onto each process in the framework based on their definition. According to the survey results, knowledge organisation tools and information presentation tools should be seriously considered for use in the revision process. Information-seeking tools, such as Google and Yahoo search engines, also seem to be significant for supporting students.

Chapter 4

Designing a Framework for Self-Revision E-Course Materials (SRECMATs)

4.1 Introduction

The literature review provided in Chapter 2 and the survey findings of Chapter 3 outlined major issues preventing students from undertaking effective revision, as well as revealing students' needs for revision support. Although most universities provide online course materials to support students' revision, these tend to be simply uploaded by lecturers in a static format, such as PDF, with no consideration of their effectiveness. In fact, some lecturers may lack the programming skills, motivation and time necessary to rebuild course materials to support students' revision.

In this chapter, a software framework called "SRECMATs" is proposed for independent revision of e-course materials. The SRECMATs framework was designed according to the survey results and the proposed revision framework described in Chapter 3. Details of the concepts and techniques behind the construction of the

SRECMATs framework are explained in this chapter. Some sections of this chapter have previously been published [132, 133].

4.2 Software Framework for Revision

Chapter 2 discussed nine learning resources commonly available to students (see Section 2.4): lecture notes, lecture slides, lecture slide hand-outs, textbooks, e-books, both formal and informal e-learning websites, VOD streaming, assignments/essays and past exam papers.

At this preliminary stage, the focus was on improving the learning materials commonly provided by the lecturer and available for students to download from the course website. As mentioned in Section 3.4.2, the survey results revealed that the most common materials used by students were lecture notes, past exam papers and lecture slides. Of these three, lecture slides were preferred by most students in the sample when starting their revision. The research described in this chapter thus focused principally on enhancing lecture slides and past exam paper materials.

The review of literature on cognitive tools (Section 2.5.2) discussed how they support learning approaches but did not identify effective ways of designing an appropriate tool for students' revision. The challenge was thus to design a software framework for online revision tools that would support students' exploration of e-materials during the revision period. In the remainder of this thesis, the term "SRECMATs framework" is used to refer to the proposed software framework for student revision. The next section begins with a discussion of the characteristics of lecture slides and past exam papers used in the later research. This is followed by a discussion of the design of the software framework, including a literature review of the components and techniques chosen to develop the framework.

4.3 Understanding Characteristics of E-Materials

The syntactic structure of sentences used by each e-material may differ, depending on the design purpose. In this research, the first consideration was to improve the provision of lecture slides and past exam papers. In order to design a software framework for this purpose, it was necessary to understand their syntactic structure and how they might be used to support revision. Identifying the syntactic structures of these e-materials was a challenging issue. The next section explores lecture slides and the structure of examination papers, as well as identifying potential common features.

4.3.1 E-lecture slides

Lecture slides are a basic material commonly provided on course websites and used in class. In the classroom, students sometimes print slides (or "handouts") for notetaking purposes. Frey and Birnbaum [56] state that instructors do not want lecture slides to be a substitute for lecturing; their aim is to present only the main ideas, not a summary of the lecture. Holmes [64] also states that a slide presentation may serve as a guide for listeners or readers, but it will never be capable of replacing a good teacher. Instead, it may be used to conceal poor-quality teaching by providing validity, but with no real gains in terms of learning results [124]. Susskind [145] demonstrates that bullet points serve only to remind the recipient of the general context of a presentation. These findings imply that lecture slides may give an overview of the content, but lack detailed information.

The format of lecture slides usually comprises two major parts, the title and the content, as presented in Figure 4.1. The former offers an overview of the content in the body, while the latter contains key information relating to the title. The content is usually presented as a bullet list, allowing students to obtain information quickly.

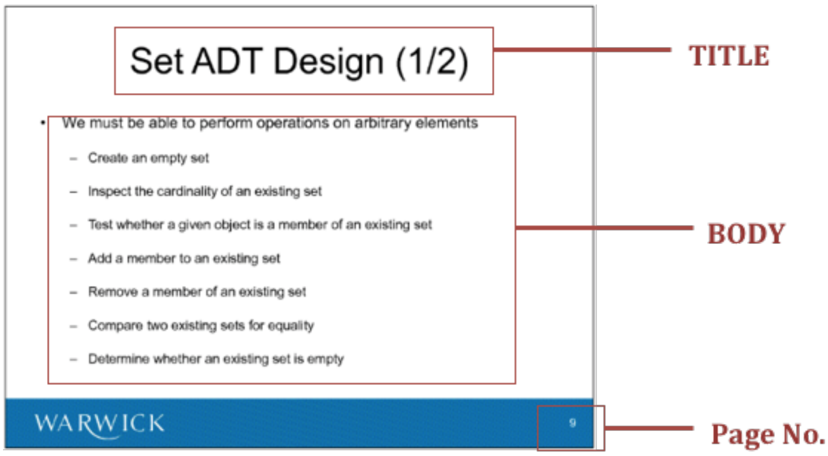


Figure 4.1: Example of lecture slide structure taken from course CS126 Design of Information Structure.

The format of lecture slides can be altered to suit the style of the author. Media selection and media format are the two major styles normally chosen by the author. Media selection is a process concerned with the media to be used in the lecture slide, such as figures, tables or text information. Media format is a process of selecting the properties of the media to be presented on the slide. For example, text information can be adjusted in terms of font size, colour or location.

4.3.2 Electronic past exam papers

Past exam papers are papers from a previous year used as a practice resource before a real assessment. Many universities provide this type of material as a guideline for students on exam themes and styles of exam questions, as well as developing students' time management skills. Although the format of exam papers is designed differently depending on the university template, they share some common structures.

Generally, exam papers comprise two major parts, cover pages and question pages. The former, as presented in Figure 4.2, consist of general information with regard to course information, date and time, exam time and length, as well as instructional information. The cover page does not usually contain any course content information.

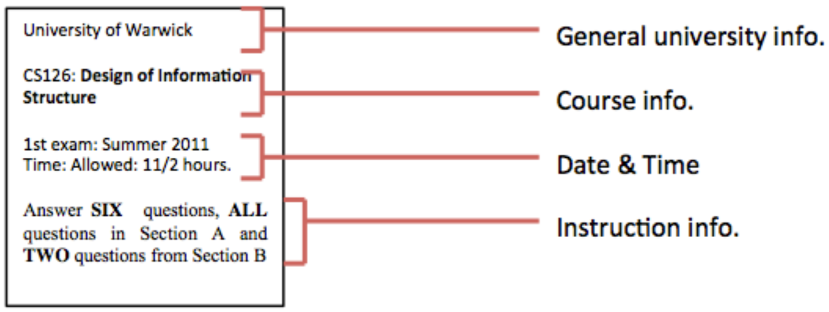


Figure 4.2: Example of an exam paper cover page from course CS126 Design of Information Structure.

The question pages, as presented in Figure 4.3, consist of a set of main questions and sub-questions. Sub-questions may be defined not only in the form of an interrogative sentence, but sometimes in the form of an affirmative sentence or equation following a core question to measure students' ability to explain and discuss. Each sub-question is scored or marked separately to assess students' performance.

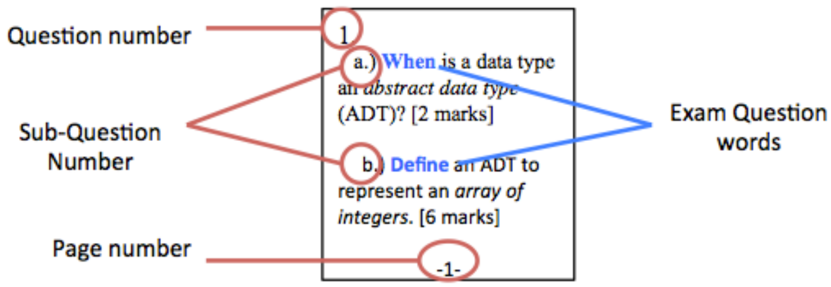


Figure 4.3: Example of a question page of an exam paper from course CS126 Design of Information Structure.

The format of exam papers may also differ based on the style of the authors and managers of educational organisations. Exam papers contain only text and static pictures, whereas lecture slides sometimes contain animation and sound. The content structure of exam papers may also vary, depending on the wishes of the author. For example, different letters may be used to indicate the question and sub-question number (e.g. Question 1, 1., a., A, i.), and the marks/scores for each question may be located differently, either in the middle or at the end of the question.

4.4 SRECMATs Framework

The revision framework described in Chapter 3 indicated the types of cognitive tools that might be applied to support student revision. Furthermore, there is a plethora of existing tools that may benefit students at different stages in their revision of online course materials. Note-taking tools (e.g. Evernote, OneNote) allow students to summarise, organise and archive learning materials in a digital format which is simple to search and review. Memorisation tools (e.g. flashcards or revision cards) allow students to remember or recall previous knowledge by establishing an environment for the repetition of information. Collaborative tools (e.g. Dropbox, Skype, WebBoard) allow students to work together and communicate with their friends by sharing learning materials or discussions on an assignment. Information-seeking tools (e.g. Google, Yahoo) allow students to search for more information on the Internet. However, these tools are intended to cover general tasks and general users, especially information-seeking tools such as Google or Yahoo which focus on searching for external resources. Although specific tools are designed for university education purposes, such as course management systems (CMS) commonly used by many universities, the features provided with regard to course content delivery in CMS do not consider the enhancement of online course materials to support student revision, as discussed in Section 2.3. Therefore, the aim here was to design a software framework to explore potential features that would maximise the use of online course materials to support student revision.

The SRECMATs framework was designed to support three cognitive load tasks of students (see Section 2.5) regarding knowledge organisation, information presentation, and particularly information seeking, by re-organising ways of presenting course materials, as well as enhancing the search capability for quick and simple accessing. These correspond with the benefits offered by cognitive tools, as stated in Shim and Li [140], which spread students' cognitive load by providing support for lower-level cognitive skills, leaving students to concentrate on higher-order thinking skills. Moreover, support for these cognitive tasks also relates to the survey results regarding major issues of revision (Section 3.4.1) and students' need for support (Section 3.4.6). These results indicate that students require systems that can support them simply by navigating and reading through organised online materials.

SRECMATs is a web-based tool that operates through a web browser. The software framework behind the tool can be divided into two main parts, front-end and back-end services, both presented in Figure 4.4. The front-end services work through a user interface for interaction with lecturers and students. The back-end services include underlying technology components that drive the system. The SRECMATs prototype was built from the proposed framework in order to evaluate the performance of the framework, as described in the next chapter. The user interfaces of the prototype were then used to illustrate the front-end services. The rest of this section will explain each component in detail.

4.5 Front-End Services

Front-end services concern the user interface and functionality of tools that are implemented, based on HTML language, the CSS bootstrap framework[1] and PDF viewer libraries[2]. SRECMATs provides a user interface for both lecturers and stu-

[1] `http://getbootstrap.com/css/`
[2] `http://view.samurajdata.se`

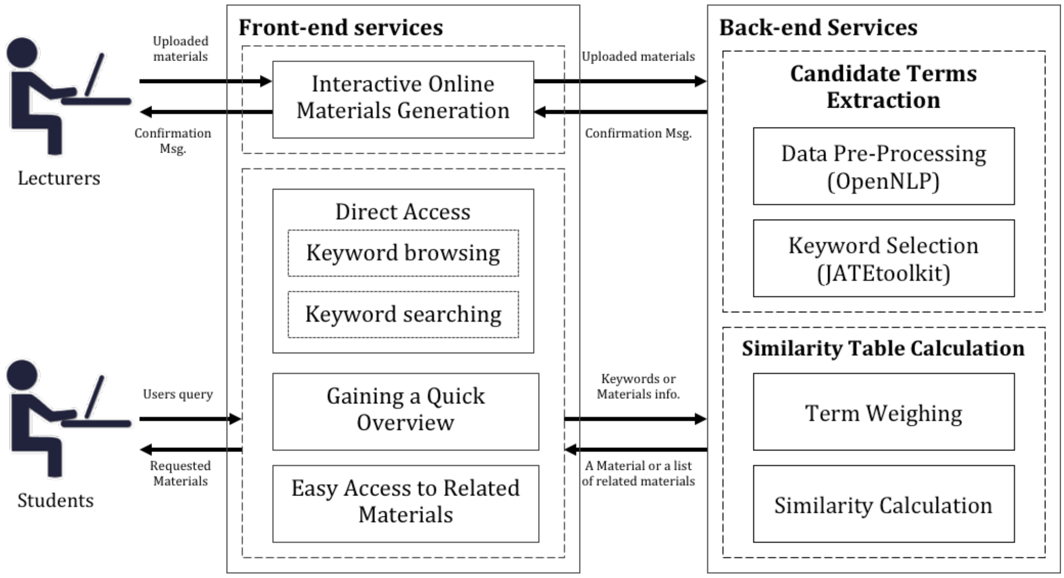


Figure 4.4: Software framework for designing self-revision e-course materials (SREC-MATs).

dents. Interactive online material generation is a component that supports lecturers in uploading e-materials to the system. For students, four interactive features are classified into three categories, based on the role of cognitive tools (Section 2.5.2) and the revision framework (Figure 3.11). These are: (i) direct access to e-materials using keyword browsing and keyword searching (information seeking); (ii) gaining quick overviews using keywords (information presentation); and (iii) easy access to related materials (information seeking and knowledge organisation).

Figure 4.5 illustrates the front-end processes of the SRECMATs system used by students. After choosing the type of material for revision, students can search or browse for specific information from the material. During revision, students can skim and scan quickly through a set of keywords to get a rough idea of the content of the material. Students may also switch easily to other types of learning materials or other related materials to gain more information and link knowledge.

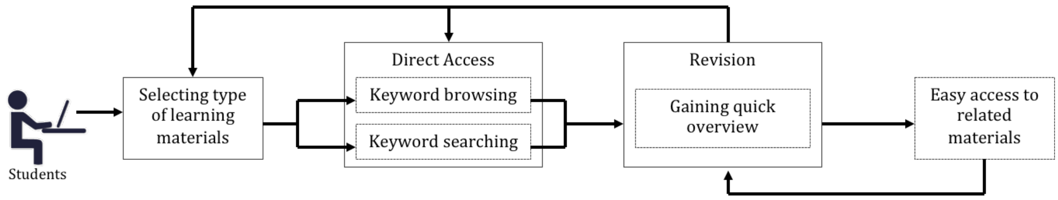


Figure 4.5: Overview of front-end processes for students.

The design of the user interface is based on the clean and flat concept proposed by Page [115] using the Bootstrap framework[3], including HTML and CSS languages. This ensures that students can use the system easily without training. Details of each feature are discussed in the following sub-sections.

4.5.1 Interactive online material generation

The interface of the interactive online material generation component is designed to support the creation and delivery of courses as a feature of CMSs [89]. It contains a template form for students to fill in with regard to the course information (see Figure 4.6). The interface also provides an upload button to generate folders and databases for storage of online materials (see Figure 4.7). Lecturers need only to fill in the course information and upload all the materials to the system. The system will automatically process all the materials and publish them for students in a "polished" form. Thus, lecturers are not involved in any coding.

Students can start their revision by choosing from the types of learning materials available from a list, as shown in Figure 4.8. Individual features for navigating within each material type are discussed in the next section.

4.5.2 Direct access

For recall purposes, students sometimes require quick access to a particular page of a set of lecture slides. On a traditional course website, students must access the

[3]http://getbootstrap.com

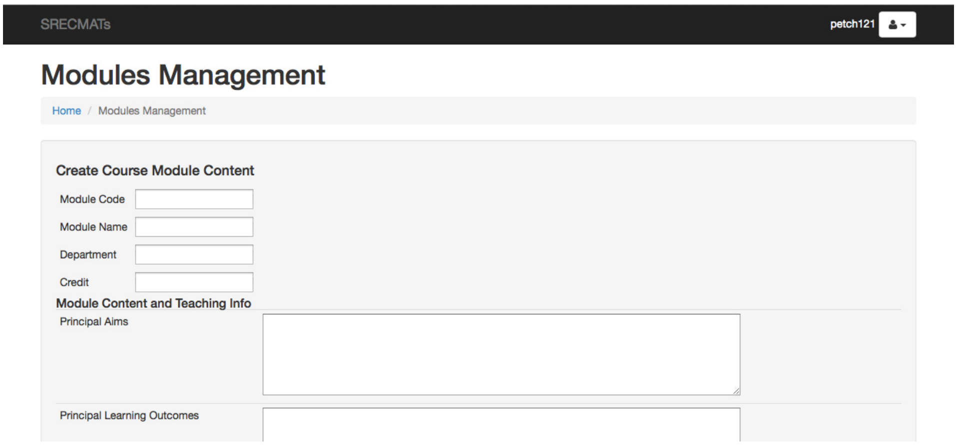


Figure 4.6: Module management page for lecturers to create new course materials.

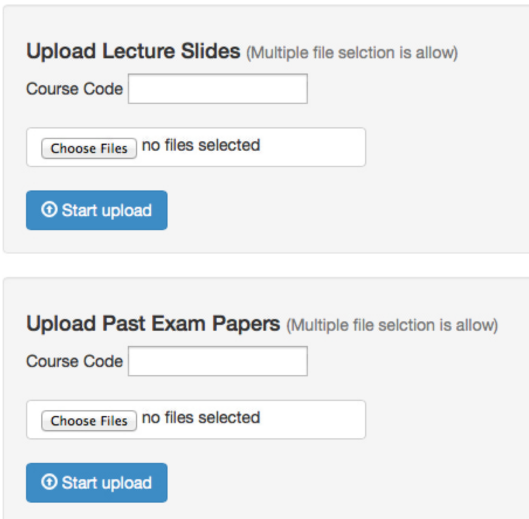


Figure 4.7: Form for uploading e-resources on the course website.

appropriate PDF file and scroll down the pages until they find the information they want. This relates to the survey results (Section 3.1) regarding the difficulty of reviewing a lot of learning materials in a short period of time.

One potential approach to addressing the issue of browsing a large amount of learning materials is to use content-based navigation, by constructing a list of topics structured from a collection of documents [125]. Mendes et al. [101] introduce a

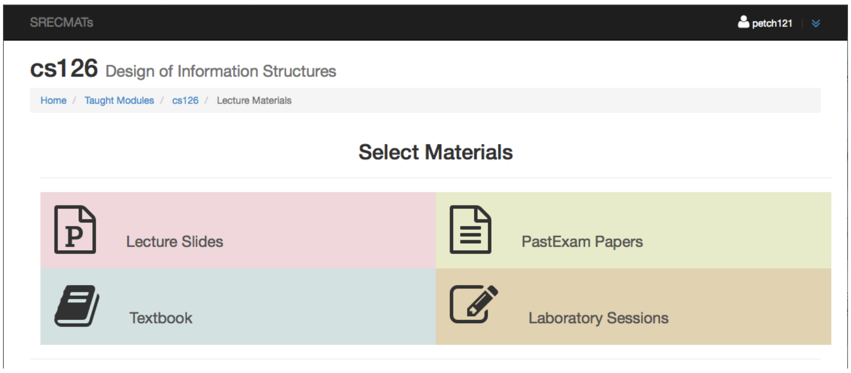


Figure 4.8: User interface for choosing learning materials to review.

similar approach using "knowledge navigation tools", which allow students to search and browse learning materials by keyword searching and topic browsing. They built a prototype system and validated it with a group of 25 telecommunications students. The average results for evaluation of the usefulness for keyword searching were 4.8 and for topic browsing 3.5, on a scale from 1 (not useful at all) to 5 (very useful). Therefore, SRECMATs applies this technique in providing two means of direct access to a specific page within a set of materials. The first is keyword browsing, as illustrated in Figure 4.9, where keywords from lecture slide material are drawn from content located in the slide headers extracted from a fixed region by iText [91], a Free Java-PDF library API. Keywords for other documents are extracted by filtering the content of document indexes at the backs of textbooks. In this framework, it is assumed that all index terms in the textbook contain keywords relevant to the subject of study. The second means of access is keyword searching, as illustrated in Figure 4.10, where all the materials are converted to plain text, allowing students to perform partial searches for terms inside the document. Search results show lists of relevant search documents with the title, type of material and eighty characters of content for a quick overview.

With direct access to e-materials, using keyword browsing and keyword searching, students can obtain a quick overview of e-material content through a set of keywords and easy access to related materials based on their subject of focus.

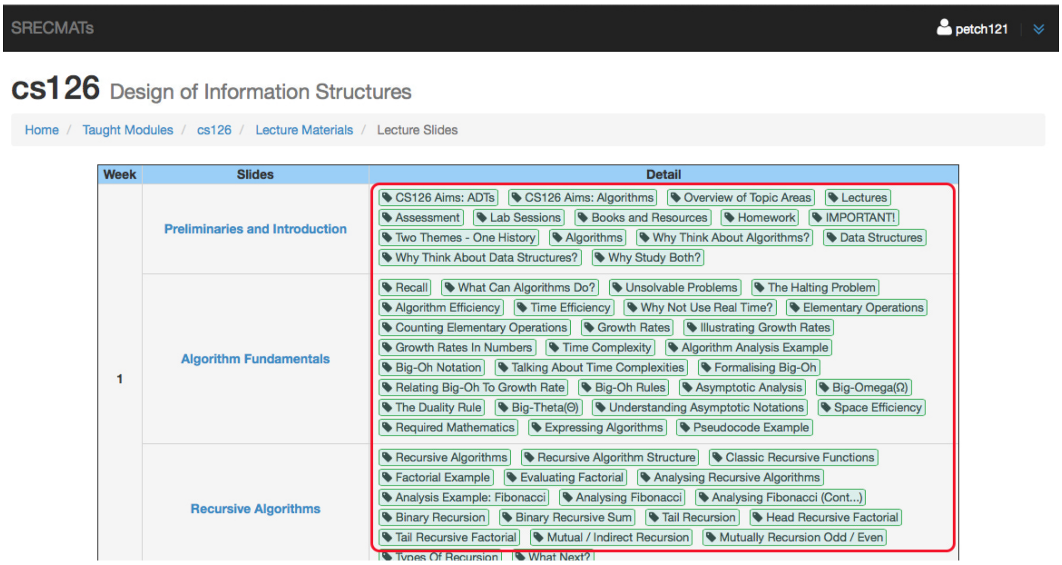


Figure 4.9: Direct access using keyword browsing.

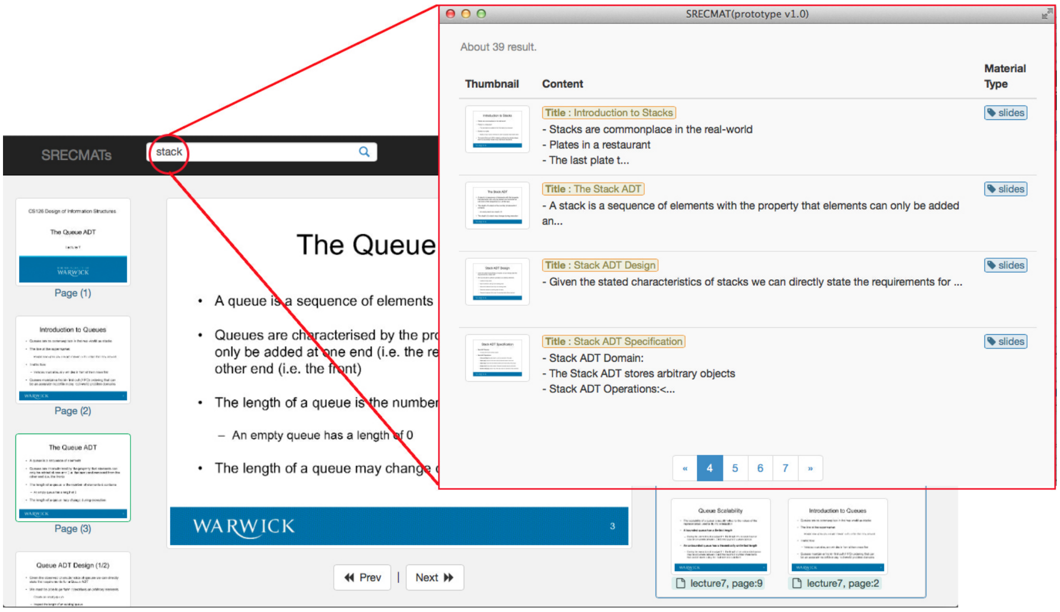


Figure 4.10: Direct access using keyword searching.

4.5.3 Gaining a quick overview

Skimming and scanning are two important strategies for speed reading [42, 109], whereas reading materials line by line to find key information may be time-consuming for some students. Keith [75] also states that readers can save 50 per cent of their reading time by using only keywords from the paragraph. He mentions that often 40 to 60 per cent of words in a document are unimportant. If these words are taken out, the content can still be understood. Moreover, the findings discussed in Section 3.4.6 illustrate that some students would prefer tools to support them in extracting an overview of key information from the learning materials. In order to allow students to grasp more quickly the main ideas in the material, a feature was proposed to automatically extract keywords from e-material content. As a student navigates through a set of materials, SRECMATs provides a list of keywords (see right-hand side of Figure 4.11). These keywords are presented in a "tag" format which allows students to obtain a quick overview.

4.5.4 Easy access to related materials

Sweller and Chandler [147] suggest that the difficulty of learning materials depends not only on the amount of content that must be learned but also the amount of content that students must learn simultaneously. Many research studies [27, 146] have demonstrated the negative effect of split attention, when learning materials are poorly designed in providing multiple sources of information on different pages. For example, lecture notes in which an image of triangle geometry and a statement about a calculation of the angle values are presented on different pages will increase the extraneous cognitive load on students, who have to mentally integrate the statement description with the image of triangle geometry. This thesis considers this learning effect, informed by multiple types of learning material, some of which have similar topics. During the revision period, students frequently switch between different materials to gain insights into a specific topic. When using a traditional website,

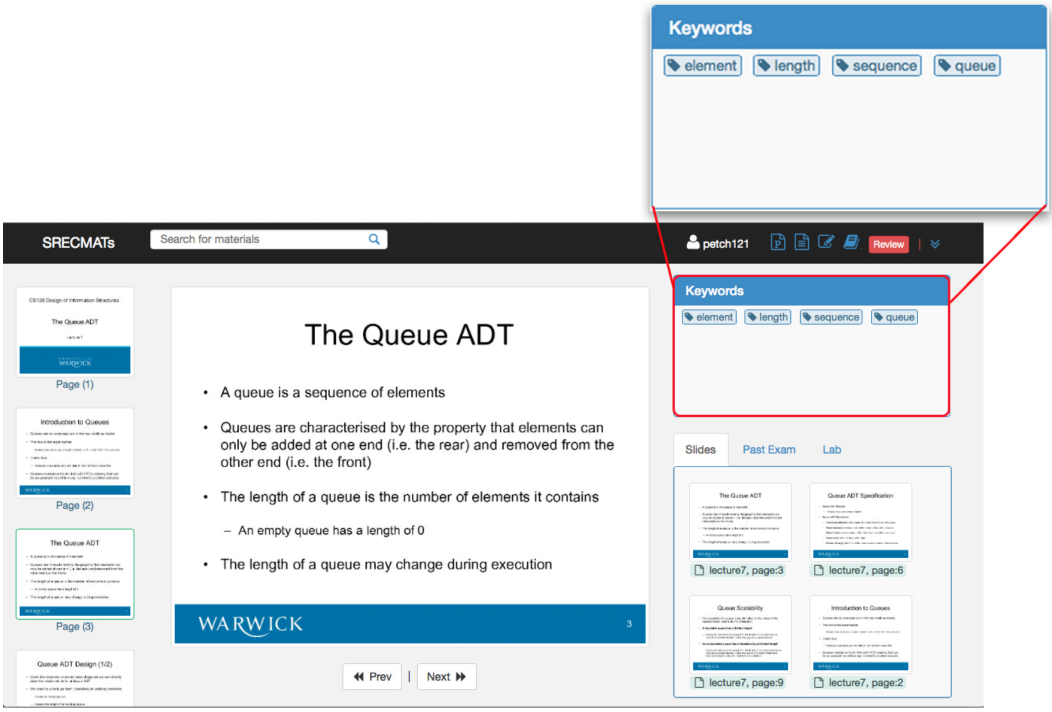


Figure 4.11: Quick overview of a set of keywords.

they must also spend time finding material as well as particular content, which also requires cognitive resources. To reduce the extraneous cognitive load, these results need to be integrated. Moreover, the results described in Section 3.4.6 reveal that some students would prefer to have tools that gather all the materials into one place and allow them to navigate through all relevant materials. By integrating all materials, SRECMATs allows students to switch between materials using an icon in the top-right corner (Figure 4.12).

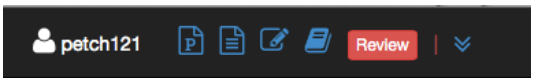


Figure 4.12: Icons for switching to other learning materials, including (from left to right) lecture slides, past exam papers, lecture notes and textbooks.

SRECMATs also provides recommendations on features which allow students to navigate through related material, based on their current focus. For example, this feature supports students when they are reading a past exam paper and need to find specific information in order to answer a question. The system also provides related materials in the form of lecture slides, other related past exam papers and lab sheets, as presented in Figure 4.13. These related materials are ranked based on a similarity score. Details of rankings are discussed in the next section, which deals with back-end services.

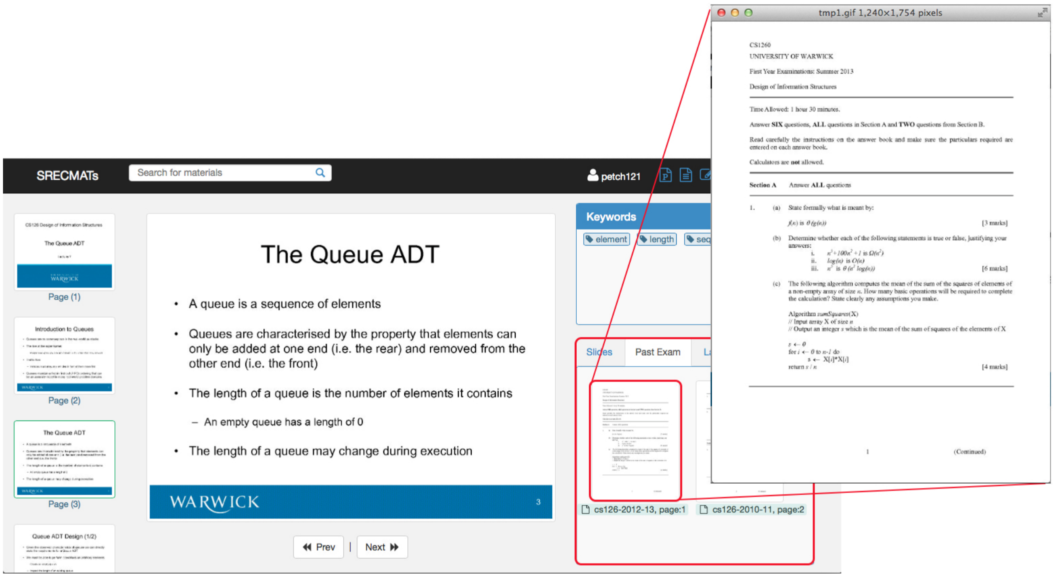


Figure 4.13: Accessing related materials through the recommendations feature.

4.6 Back-End Services

The back-end services comprise components used to process and deliver the front-end services. These were implemented based on the server-side script PHP, Shell script, Java and SQL. The architecture of the back-end services is presented in Figure 4.14. Two major components of the back-end services (candidate term extraction and similarity table calculation) were implemented using Java programming language.

Hence, after lecturers upload the materials, a PHP script executes a shell script to run the JAVA application on the web server. The results from the candidate term extraction and similarity table calculation processes are inserted into a MySQL database for later use by front-end services.

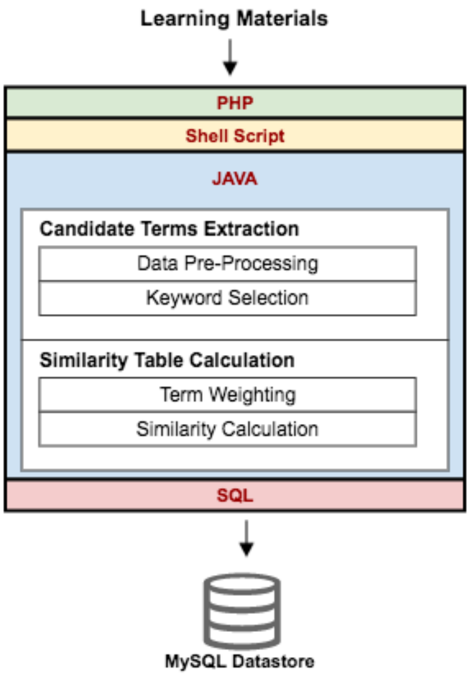


Figure 4.14: Architecture of back-end services.

In this study, natural language processing (NLP) techniques [9] were used to deal with the back-end service components. NLP techniques were chosen because most course materials uploaded onto course websites are provided in PDF format, which is simple to convert and process as plain text. Although other advanced techniques are promising, such as learning objects and semantic web, they require a system or an expert to convert e-materials (PDFs) into a rich format (e.g. XML or RDF). However, the current tools do not easily support such a process, while not all teachers prefer to do it manually. Other techniques regarding material recommendations, such as a folksonomy-based technique that relies on tags or keywords from learning materials generated by students, were not considered at this stage because it would be difficult to obtain sufficient data from students to make recommendations [12]. However, a folksonomy-based technique might be useful in future, once pre-defined sets of tags or keywords are available. The next sub-section outlines the literature reviewed and details of the techniques selected and used for the back-end services.

4.6.1 Candidate term extraction

Candidate term extraction is a process for extracting candidate technical terms from online materials. The results of this process are used mainly in three front-end features: direct access to material via keywords, gaining quick overviews and easy access to related materials. The candidate term-extraction process is thus composed of two sub-processes: data pre-processing and keyword selection.

Data Pre-processing

The data pre-processing stage involves a process of preparing materials to suit the requirements of the system. The pre-processing methods differ according to the input data required by term-extraction tools and techniques. Hence, transformation of raw data into specific input data is essential. The output needed from the pre-processing stage is a set of candidate terms presented in documents. Therefore, the common pre-processing tasks presented in Table 4.1. are used. These pre-processing tasks are performed using the iText and Apache OpenNLP toolkit[4], a Java machine-learning toolkit for NLP. Each task is briefly described in the next sub-sections.

Conversion of documents to plain text

Converting documents to plain text is a process of transforming a non-plain text document into a plain text document [54]. Examples of non-plain text documents

[4] `https://opennlp.apache.org`

Table 4.1: Common pre-processing tasks.

Conversion of Document to Plain Text
Sentence Segmentation
Tokenisation
Part-of-Speech Tagging
Stemming and Lemmatisation
Stop-words Filtering

are image files (JPEG, TIFF) and portable document format (PDF) files, including rich text formats such as PowerPoint (PPT), Microsoft Word (DOC) and HTML documents. The conversion process requires the machine to understand both the format of a document and the structure of its content. This study was concerned mainly with converting a PDF document to plain text because most learning materials provided for students are in PDF format. iText was used as a library for transforming PDF to TEXT. Two types of materials, lecture slides and past exam papers, were considered for the first prototype.

The process of converting documents to plain text not only converts from PDF to plain text but also automatically annotates the structure of lecture slides. Since the structure of lecture slides sometime depends on the authors, converting them to plain text may raise some issues. The two main issues in converting PDF lecture slides are document layout and typography.

- **The document layout issue** refers to the problem of extracting figure captions, page numbers and table data, including separating the title and body of the slide content. This study was concerned with converting the page number, title and body of slides (as presented in 4.15), while ignoring figure caption, image and table data issues. It was assumed that the title content is generally the first sentence in the slide and is usually located at the top of the slide, while page numbers are located at the bottom of the slide. In order to obtain this information automatically, the region was fixed to these specific sections during conversion, annotating the plain text output with the $< tag >$ format, as illustrated in Figure 4.16. Details of the $< tag >$ format are presented in Figure 4.17.

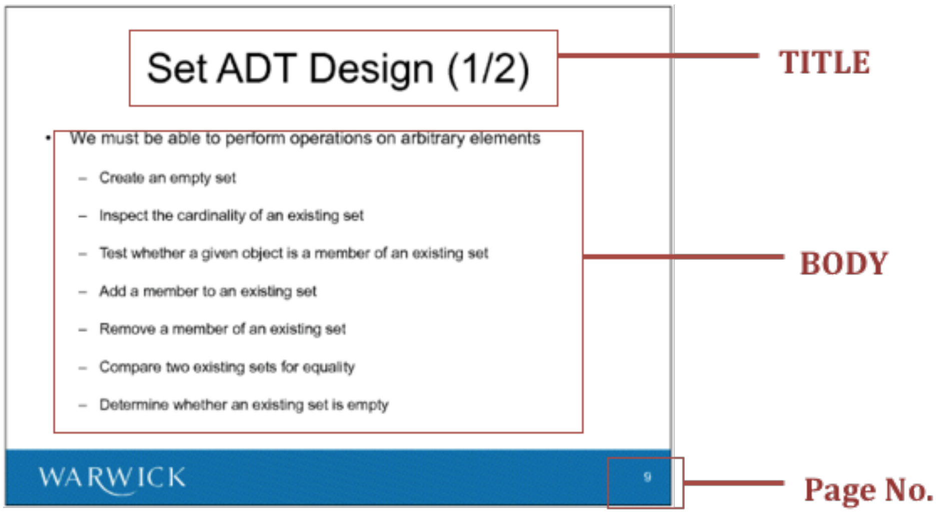


Figure 4.15: Example of a lecture slide layout.

```
<page>9</page>
<title> Set ADT Design (1/2)</title>
<body>
<i> We must be able to perform operations on arbitrary elements
<i> Create an empty set
<i> Inspect the cardinality of an existing set
<i> Test whether a given object is a member of an existing set
<i> Add a member to an existing set
<i> Remove a member of an existing set
<i> Compare two existing sets for equality
<i> Determine whether an existing set is empty
</body>
```

Figure 4.16: Example of lecture slide content in annotated plain text.

```
<page></page>   : a page number of a slide.
<title></title> : a title or topic of a slide.
<body></body>   : a body or content of a slide.
<i>             : an indent or a bullet point sentence.
```

Figure 4.17: List of annotations used in the SRECMATs framework.

- **The typography issue** is a problem relating to font style, such as subscript and superscript, italics, bold and underline. These features are not included in plain text, but an author may sometimes use these different font styles to represent different meanings in the document. However, this study did not address this issue, as it rarely affects the content of lecture slides.

With regard to past exam paper materials, converting and annotating their structure presents difficulties. This is because they contain many styles of question, such as questions about definitions, questions with many sub-questions, or questions with extra detail (e.g. algorithm, pseudocode). Therefore, this study considered each exam page, rather than each individual question, as a unit or document for processing. An example of an exam paper after conversion and annotation is presented in Figure 4.18.

Sentence segmentation

Sentence segmentation breaks up the sentences of a paragraph in a document. This process helps differentiate between the topic sentence, paragraph sentences and page number sections. It later allows a weighting score to be assigned to each candidate term, based on its occurrence in different sections. With regard to lecture slide material, the current approach to sentence segmentation is to break up sentences based on the annotated $<tag>$, as presented in Figure 4.16. For past exam paper material, carriage returns (CR) or line breaks are used to break up sentences.

```
cs126-2010-11.pdf
<page>1</page>
UNIVERSITY OF WARWICK
First Year Examinations: Summer 2011
Design of Information Structures

Time Allowed: 1:30 hours.

Answer SIX questions, ALL questions in Section A and TWO questions
from Section B

Read carefully the instructions on the answer book and make sure
the particulars required are entered on each answer book.

Section A Answer ALL questions

1. (a) State formally what is meant by:

f(n) is O(g(n)) [2 marks]

(b) Determine whether each of the following statements
is true or false, justifying your answers:

i. 2^n is O(3^n)
ii. n is  (n^-1)
iii. n(logn) is (n^2) [4 marks]

2. (a) When is a data type an abstract data type (ADT)?    [2 marks]
(b) Define an ADT to represent an array of integers.    [6 marks]
(c) State two reasons why an array which is part of a language such as
Java may not faithfully implement your answer to (b).  [2 marks]
(Continued)
```

Figure 4.18: Example of past exam paper content in annotated plain text.

Tokenisation

Tokenisation is a process of breaking up sentences into units (words or phrases) for processing in term-extraction methods, typically by looking at the white-space characters separating single words.

Part-of-speech tagging

Part-of-speech (POS) tagging is a process of assigning a part-of-speech to tokenised words. POS tagging is different from parsing as it does not consider resolving grammatical structure. In this study, the Open NLP POS Tagger[5] was used, which employs the Maxent probability model to predict the POS results based on the Penn Treebank standard[6].

Stemming and lemmatisation

Stemming and lemmatisation are both processes used to normalise words into a standard form. They are used to reduce the issue of inflection form; for example, data structure and data structures should be considered to be the same. The difference between stemming and normalisation is that stemming is only concerned with normalising a word based on specific rules (e.g. rule of SSES → SS; caresses → caress), while lemmatisation also considers grammatical context and tries to return to the base form (dictionary form) of a word (e.g. cars → car → automobile). The lemmatisation module in the JATEtoolkit was used to implement the SRECMATs prototype.

Stop-words filtering

Stop-words filtering is a process of eliminating non-relevant candidate terms, based on a list of pre-defined words. Automatic term extraction (ATE) cannot be performed with 100 per cent accuracy. A list of common words which are not candidate terms significantly improves the precision of the ATE process. The 517 stop-word list, built by Salton [134] for the experimental SMART information retrieval system at Cornell University, was used in the pre-processing stage.

[5] `http://opennlp.apache.org/documentation/manual/opennlp.html`

[6] See the lists of POS tags used in the Penn Treebank format `https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html`

Keywords selection

Having obtained a set of candidate terms in the form of sentences annotated with POS, terms to be used as keywords in the system then need to be selected. Therefore, a keyword selection process was used. Keyword selection or terminology extraction is a process of finding terms or keywords that represent the main content of documents from unstructured content (e.g. text) [62]. Terms or keywords are groups of words that represent the main content of the document. A document here refers to a unit of content on which extraction is performed. For the purposes of this research, each page of a lecture slide or past exam paper was treated as a document. The research regarding information retrieval, recommendation systems and search techniques deals with a range of techniques to extract terminologies. In order to decide which techniques were appropriate for this research, it was useful to classify and understand the categories of extraction techniques, which can be classified into two main approaches [3, 118, 33]: linguistic approaches and statistical approaches. The former deal with the use of pure linguistic properties to extract terminology, such as part-of-speech patterns and words related to the stem. The latter apply statistics to rank candidate terms by assigning a score based on statistical measurement techniques, such as basic term frequencies. This determines whether the term is chosen as a keyword. The purpose of a statistical approach is to obtain terms with high scores, because higher scores amongst candidate terms imply that those candidates should be selected as terms that represent a document. A statistical approach may sometimes be used to assign a level of applicability for term selection, which linguistic approaches lack.

However, the statistical approach relies heavily on corpus frequency information [62], which does not work well with low-frequency materials. Since this research concerned lecture slide and past exam paper material which, by its very nature, contains fewer words than other learning resources, such as textbooks or journals, the statistical approach was unlikely to be appropriate. Thus, at this stage, only the linguistic approach was used. There is evidence that terms normally contain syntactic properties [13]. Most candidate terms can be identified with a noun phrase, usually containing nouns and adjectives [130], although sometimes also prepositions [73]. Based on this idea, SRECMATs uses an unsupervised technique which extracts tagged terms based on noun phrase patterns after the POS tagging process. In addition, keyword selection based on linguistic approaches can be performed using the data pre-processing techniques of sentence segmentation, tokenisation, part-of-speech tagging, stemming and lemmatisation, and stop-words filtering. Selection of output from whichever technique is used depends on the following features of front-end services.

- **Direct access**: By keyword browsing for lecture slide material, outputs of the sentence segmentation process are used to obtain all the topic sentences of lecture slides as tags for navigation. Past exam paper material uses outputs after tokenisation that appear in the index at the back of the textbook.

- **Gaining quick overview**: Keywords used in this process (for both lecture slides and past exam paper material) should be useful for students to gain a quick overview. To ensure that the selected keyword is useful, a supervised technique is used, in which outputs of the tokenisation process are filtered based on training data through matching techniques. In this case, training data are terms identified from the index at the back of the textbook.

- **Accessing related materials**: The process of accessing related materials involves a similarity calculation for all documents in the corpus, which requires all possible keywords in normal form. Therefore, the keywords used here should be obtained from outputs of the stop-words filtering process.

The first prototype of the SRECMATs system only considered analysing and extracting keywords at a linguistic level (syntax), but was not extended to a semantic level. This was because the learning materials under consideration were general PDF files. Hence, in order to analyse at the semantic level, structured data or more advanced techniques would have been required.

4.6.2 Similarity table calculation

Khairil Imran Bin and Nor Aniza [77] suggest that popular approaches to recommending related learning materials to students are collaborative filtering, content-based filtering and hybrid filtering. Collaborative filtering recommends learning materials based on similarity of students' preferences, while content-based filtering makes recommendations according to similar content of learning materials [52]. The hybrid filtering approach uses both approaches to make recommendations. The first prototype of the SRECMATs framework focused on finding an appropriate technique to automatically recommend related materials based on similar content (particularly slides and past exam papers). Therefore, a content-based filtering approach was considered, which would produce automatic recommendations with no participation by students.

To recommend learning materials, the degree of similarity or similarity score between each pair of materials was calculated and kept in a relational database, as presented in Figure 4.14. Calculating the degree of similarity between online materials was another challenge. In this research, two components – term weighting and similarity calculation – were used to calculate the similarity between each pair of documents.

Term Weighting

Term weighting is a process of identifying the features of a document, calculating their weight and representing them through the information retrieval (IR) model. Before identifying features and calculating their weight, it was necessary to consider which IR models should be used. In this thesis, the classical IR model was used as described below.

Beazy-Yates [9] states that the IR model consists of four main parts. It can be defined as a framework to represent user information needs (Q) and documents in the collection (D). The notation $R(Q, D)$ or $R(D_1, D_2)$ is used to calculate similarity between two documents. The three classical IR models considered in this research were:

- **Boolean Model**: A simple model for retrieving information based on set theory and boolean algebra [121]. It considers whether or not an index of terms is present in a document. Weightings of index terms are all presented in binary form, which can be computed as presented in equation (4.1). Let i be a term appearing in the document j; the weight of the term i is computed by

$$w_{(i,j)} = \begin{cases} 1 & \text{if } i \in j, \\ 0 & \text{if } i \notin j. \end{cases} \tag{4.1}$$

  The Boolean model has a major drawback, insofar as the retrieval techniques are based only on a binary decision on whether a document is related or unrelated. Hence, it does not deal with a partial matching between documents.

- **Vector Model**: This is an algebraic model that represents a querying of documents in the form of a vector containing the weightings of features, allowing partial matching of documents [9]. Weightings of terms in the document are assigned as non-binary data to compute the degree of similarity between documents. For example, using term frequency as a feature for representing documents, the weight of term i in a document j ($w_{(i,j)}$) is a frequency of term i which appeared in the document j, as presented in equation (4.2).

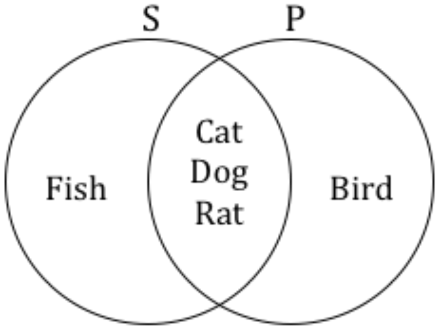
$$w_{(i,j)} = \mathit{freq}(i, j). \tag{4.2}$$

The vector model of document j can therefore be represented as:

$$\vec{j} = w_{(i,j)} = (w_{(1,j)}, w_{(2,j)}, \ldots, w_{(n,j)}). \tag{4.3}$$

- **Probabilistic Model**: This is a retrieval model based on a probabilistic framework. Similarity between document and query is calculated by the probability that the document appears in the answer set, divided by the probability that the document does not appear in the answer set. The answer set can initially be guessed and then adjusted later. The common ranking for a probabilistic model is a BM25 score. Major disadvantages include the need to guess whether the documents are related or unrelated, and lack of matching the frequency of candidate terms occurring in documents.

In this research, the vector model was chosen to represent documents, since most content-based recommenders use relatively simple but effective retrieval models [76, 78, 79, 90]. The vector model is a promising technique for retrieving relevant e-materials based on their degree of similarity. It requires features with weightings to characterise each document. For example, in Figure 4.19, sets S and P represent a lecture slide and a past exam paper, and the table below shows terms that appear in both documents, as well as their frequency.



	Cat	Dog	Rat	Fish	Bird
S	5	1	1	3	-
P	2	1	5	-	7

Figure 4.19: Example of terms in lecture slide document S and past exam paper P for similarity calculation

Assume that a raw term frequency is used as a feature to represent the documents. the $\overrightarrow{S}$ and $\overrightarrow{P}$ can be written as:

$$\overrightarrow{S} = (w_{(Cat,S)}, w_{(Dog,S)}, w_{(Rat,S),w_{(Fish,S)}}) = (5, 1, 1, 3).$$

$$\overrightarrow{P} = (w_{(Cat,P)}, w_{(Dog,S)}, w_{(Rat,S)}, w_{(Bird,P)}) = (2, 1, 5, 7).$$

The first version of the SRECMATs prototype used a classical term weighting, which was the term frequency with inverse document frequency (TF-IDF) provided by the open-source JATEtoolkit[7] [169], as a feature of each document. TF-IDF is a measure of the frequency of a candidate term appearing in the target document (TF), with the number of documents that contain the candidate term (IDF). The following equations show how TF-IDF is computed.

For the candidate term i in the document j, the normalised term frequency $TF(i,j)$ is derived by dividing the raw frequency $freq(i,j)$ by the maximum of raw frequency

[7] `https://code.google.com/p/jatetoolkit/`

of all terms in document j as $\max_l \mathit{freq}(l,j)$.

$$TF(i,j) = \frac{\mathit{freq}(i,j)}{\max_l \mathit{freq}(l,j)}. \tag{4.4}$$

From Figure 4.19, the use of the normalised term frequency of $TF(i,S)$ and $TF(i,P)$ as weightings of terms for $\overrightarrow{S}$ and $\overrightarrow{P}$ can be computed as follows:

$$\overrightarrow{S} = (\frac{5}{5}, \frac{1}{5}, \frac{1}{5}, \frac{3}{5}) = (1, 0.2, 0.2, 0.6).$$

$$\overrightarrow{P} = (\frac{2}{7}, \frac{1}{7}, \frac{5}{7}, \frac{7}{7}) = (0.28, 0.14, 0.71, 1).$$

Let N be the total number of documents and n_i the number of documents in which candidate term i appears. The inverse document frequency of term i, $IDF(i)$ [135] is computed by:

$$IDF(i) = \log \frac{N}{n_i}. \tag{4.5}$$

From Figure 4.19, the inverse document frequency $IDF(i)$ of both $\overrightarrow{S}$ and $\overrightarrow{P}$ can be computed as follow:

$$\overrightarrow{S} = \overrightarrow{P} = (\log \frac{2}{2}, \log \frac{2}{2}, \log \frac{2}{2}, \log \frac{2}{1}) = (0, 0, 0, 0.69).$$

The common term weighting score $\mathit{TF\text{-}IDF}(i,j)$ [135] is computed by:

$$\mathit{TF\text{-}IDF}(i,j) = TF(i,j) \cdot IDF(i). \tag{4.6}$$

From Figure 4.19, the final $\overrightarrow{S}$ and $\overrightarrow{P}$ based on *TF-IDF*(i, j) are computed as follow:

$$\overrightarrow{S} = (1 \times 0, 0.2 \times 0, 0.2 \times 0, 0.6 \times 0.69) = (0, 0, 0, 0.41).$$

$$\overrightarrow{P} = (0.28 \times 0, 0.14 \times 0, 0.71 \times 0, 0.1 \times 0.69) = (0, 0, 0, 0.69).$$

Similarity calculation

In order to calculate the degree of relevance between two learning materials (in the form of VSM), a commonly-used technique for content-based filtering known as cosine similarity was used [92]. Cosine similarity is a measure of the distance (cosine of the angle) between each two pairs of documents. Each document is considered as a vector, where each dimension corresponds with the weighting of a term appearing in a document. The classical term weighting scheme TF-IDF was used to weight terms in the first prototype, as shown in equation (4.6). For example, the degree of similarity between a lecture slide and a past exam paper, *Sim*(S, P), was calculated through a cosine similarity formula as follows:

$$\begin{aligned} Sim(S, P) &= \frac{\overrightarrow{S} \cdot \overrightarrow{P}}{|\overrightarrow{S}||\overrightarrow{P}|} \\ &= \frac{\sum_{i=1}^{n} w_{(i,S)} \times w_{(i,P)}}{\sqrt{\sum_{i=1}^{n} w_{(i,S)}^2} \times \sqrt{\sum_{i=1}^{n} w_{(i,P)}^2}}, \end{aligned} \tag{4.7}$$

where $w_{(i,j)}$ denotes a weight of term i in learning materials j and $\overrightarrow{j}$ is a weight of term vector $(w_{(1,j)}, w_{(2,j)}, \ldots, w_{(n,j)})$ with its magnitude $|\overrightarrow{j}|$. Details of the similarity calculations and term weighting components considered are discussed in Chapter 6.

From Figure 4.19 (using the raw frequency of terms), the cosine similarity between $\vec{S}$ and $\vec{P}$ can be calculated as follows:

$$\begin{aligned} Sim(S,P) &= \frac{(5\times 2)+(1\times 1)+(1\times 5)}{\sqrt{5^2+1^2+1^2+3^2}\times\sqrt{2^2+1^2+5^2+7^2}} \\ &\approx 0.3. \end{aligned}$$

4.7 Summary

The literature review presented in Chapter 2 and the survey results described in Chapter 3 enabled the development of a software framework to deliver online materials to students and support their revision by indexing and linking uploaded materials. Another reason for designing this framework was to reduce lecturer workloads, since it allows students greater flexibility in navigating through online materials during their revision. With the SRECMATs system, students can access materials anytime and anywhere, as well as browsing, searching and navigating through online materials for specific information in a single place. Thus, they can make maximum use of the online course materials, especially during the revision period.

The SRECMATs framework is composed of front-end and back-end services. The front-end services deal with the user interface and tool functionality, while the back-end services provide the technology that drives the system. The SRECMATs framework contains three main features that support students: direct access (keyword browsing and keyword searching), access to quick overviews and easy access to related materials.

Since the materials commonly available on University of Warwick course websites (Sitebuilder) are uploaded in PDF format and simply converted to plain text format, the back-end service then uses NLP as a technique to develop the front-end features of the SRECMATs framework. The back-end services comprise two major components: candidate term extraction and similarity table calculation. These two components were implemented based on open source iText library, Apache Open NLP tool and JATEtoolkit. iText contains a library for converting PDF documents to plain text. The Apache Open NLP tool contains a library with regard to data pre-processing for sentence segmentation, tokenisation, part-of-speech tagging, stemming and lemmatisation, and stop-words filtering. The JATEtoolkit contains a library for the statistical approach, including term frequency (TF) and inverse document frequency (IDF). In addition, information in the similarity table is calculated from cosine similarity, based on a vector space model.

This chapter has discussed background studies on components relating to the SRECMATs framework. The next chapter will evaluate the SRECMATs prototype built from the SRECMATs framework.

Chapter 5

Students' Experience of SRECMATs

5.1 Introduction

In order to develop effective features for a course website and instructional materials, a needs assessment was conducted through the questionnaire survey described in Chapter 3, and a rapid prototype of the SRECMATs framework was designed, as presented in Chapter 4. These processes were insufficient to ensure that the proposed software framework would be appropriate for students. A usefulness and usability evaluation of the system were essential processes to strengthen both the educational theory behind the framework and its benefits in supporting students' revision.

Assessment of online learning environments is somewhat challenging because they are difficult to evaluate without observing students' behaviour. Surveys and questionnaires are traditional methods of evaluation; however, in this study, these methods provided only limited information on the issues in question [11]. Therefore, log file analysis was introduced to overcome this issue, enabling an understanding of students' behaviour through their digital tracks [61]. This research thus made use of both questionnaires and log file analysis to evaluate the usefulness and usability of the proposed framework.

5.2 Evaluation of SRECMATs Framework

The SRECMATs framework was designed mainly to reduce the cognitive load of students in their use of course materials by enhancing the capability of these materials through four main features: direct access by keyword browsing, direct access by keyword searching, gaining a quick overview, and easy access to related materials. In order to evaluate usability, including students' satisfaction with and perceptions of these features, the SRECMATs system prototype was developed and launched in 2015 with a first-year undergraduate course, CS126 Design of Information Structures, delivered by the Department of Computer Science at the University of Warwick. It was made available for a 28-day period (30 April 2015 — 26 May 2015) prior to the final examination as an alternative means of providing course materials for student revision purposes. In an online learning environment, students are free to choose their own study pathway [11]. The SRECMATs system was introduced in a revision session, giving them an option to review materials online. The students also had access to the traditional course website, which did not provide interactive materials. The SRECMATs system was announced on the course website, in the revision session, and through emails to all students on the course.

It was hypothesised that the proposed features of the software would satisfy certain students and allow them to navigate easily and accurately through a substantial volume of online materials. The evaluation results were crucial to answering RQ2.1 and RQ2.2 regarding whether or not a traditional website would benefit from this framework, as well as whether the features provided would support the students' experience in using e learning material for self-revision.

This chapter begins with the methodology used to evaluate the SRECMATs framework, including the instruments and procedure, arguing that the features provided in the framework have the potential to support students' revision. The results of the evaluations are then presented. The results described in this chapter were important for improving the SRECMATs framework.

5.3 Methodology

This chapter seeks to answer research question RQ2.1, regarding whether the SRECMATs software framework would benefit a traditional course website in terms of supporting students' revision, and RQ2.2 as to whether or not the SRECMATs features would be useful for students' experience in terms of using e-learning material for self-revision (see Section 1.2). To answer the research questions, the evaluation focused on three issues: students' behaviour while using SRECMATs, students' perceptions of the tool, and the usability of the proposed features. The instruments and procedure for evaluation of these issues are described in the next sub-section.

5.3.1 Instruments

The University of Warwick's course websites are designed using Sitebuilder, a content management tool. Sitebuilder[1]. does record some student actions, but this information is limited to information provided by other LMS tools [66], such as log-in frequency and page visiting history, as presented in Figure 5.1.

In order to design effective online course materials and improve the proposed framework, more information was required, such as the pattern of students' use of online resources and how long they used the system [25, 102]. Therefore, both log files and questionnaires were used in this experiment. Details of the methods used to evaluate each issue are as follows.

[1] http://www2.warwick.ac.uk/services/its/servicessupport/web/sitebuilder2/

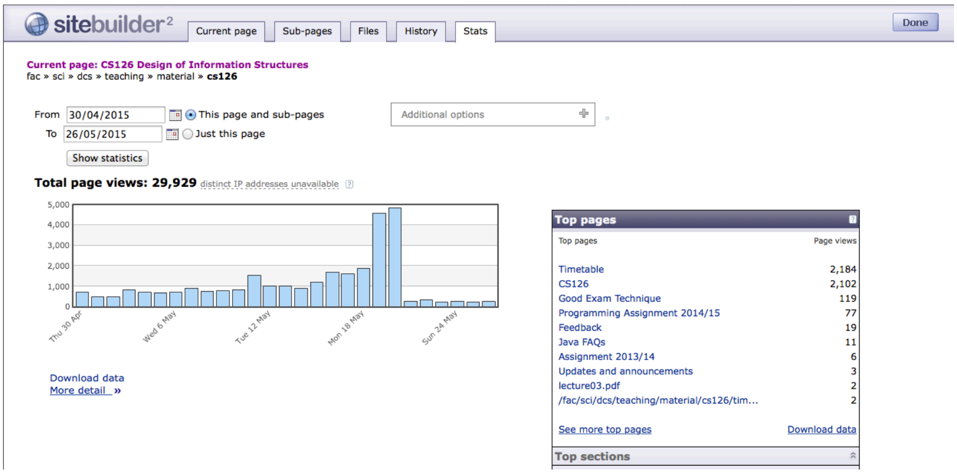


Figure 5.1: Example of transaction log information from CS126 Design of Information Structures course website obtained from Sitebuilder.

- **Student behaviour**: Students' behaviour was studied by analysing log files. The transaction log for the university course website was exported into Microsoft Excel format (XLS), and all logs of all activities or transactions that students performed on the SRECMATs system were recorded in a MySQL database[2] [71]. The log files from the SRECMATs system were later queried for specific information and exported into Microsoft Excel format for presentation in graphical form. The main question posed by this study was whether there were any differences in student behaviour between using the traditional course website and the SRECMATs system based on:
  - how often students used the system;
  - how long they spent on their revision online;
  - how they navigated through the online materials.

[2] https://www.mysql.com

The answers to these questions support the two research questions: RQ1.1 regarding the actual pattern of students' use of online resources; and RQ2.1 regarding whether students were willing to use the SRECMATs system rather than the traditional course website.

- **Student perceptions**: In order to gain a rough idea of how students felt about the SRECMATs system, a five-point Likert scale [15, 114] rating system was used to measure their overall satisfaction, which was simple to construct and easy for participants to read and complete. Students were also asked to provide comments or suggestions on how the system could be improved. In addition, volunteers who were interested in improving the project were asked to participate in interviews to provide in-depth data for analysis after their exam. Unfortunately, only one student was willing to be interviewed. Data from the interview are therefore not included in this thesis.

- **Usability**: Usability was based on the definition of ISO 9241-11 [70]: "the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use". Many experts have proposed methods of usability evaluation based on this definition [111, 113, 127, 139]. Most have used similar terms, but there is no full equivalence [7]. For example, Nielsen's [111] usability concept has five attributes — learnability, efficiency, memorability, errors and satisfaction — while Quesenbery's [127] five attributes are easy to learn, effective, efficient, error tolerant and engaging. The only major difference here is that Nielsen's concepts do not fully consider effectiveness. In this research, usability was measured through the questionnaire method, as this was less time-consuming than other methods and simpler for students to complete. The design of the questionnaire was based on Quesenbery's [127] 5Es scheme, which provides standard attributes for usability evaluation.

5.3.2 Procedure

Students on the CS126 Design of Information Structures course were introduced to the SRECMATs system during the revision class as an alternative for revision. A link to the SRECMATs system was sent to all students the day after the revision class. While they used the SRECMATs system, all the activities they performed after logging into the system, such as actions, navigated links and accessed objects, were recorded in a log file table in the SRECMATs database, as shown in Table 5.1. Details of each attribute are explained in Table 5.2.

Table 5.1: Attributes of a log file table in the SRECMATs database.

logID	username	action	object	serverDate	serverTime	target

Table 5.2: Description of attributes in a log file table in the SRECMATs database.

Attributes	Definition
logID	a running number of table logfiles which is a transaction table.
username	a username created by students.
action	students' activities in using the system, e.g. login, logout, browsing, searching.
object	name of objects triggered by action. For example, browsing → cs126_slides_lecture3_2.
serverDate	server date when action started.
serverTime	server time when action is started.
target	a url that is redirected by triggering action.

After they had used it for five minutes, the students were directed to a feedback survey, as presented in Figure 5.2. This allowed them to rate how useful the system was on a scale of 1 to 5 and asked them for comments. If they were not ready to rate the system, they could close the pop-up window and do it later. After submitting the survey, students were granted full functionality of the system without being disturbed by further surveys.

The experiment ended one day after the examination. Having finished the examination, an online evaluation questionnaire regarding usability was sent to all students by email. Ethical consent was obtained from the University's Biomedical & Scientific Research Ethics Committee (approval REGO–2013–413).

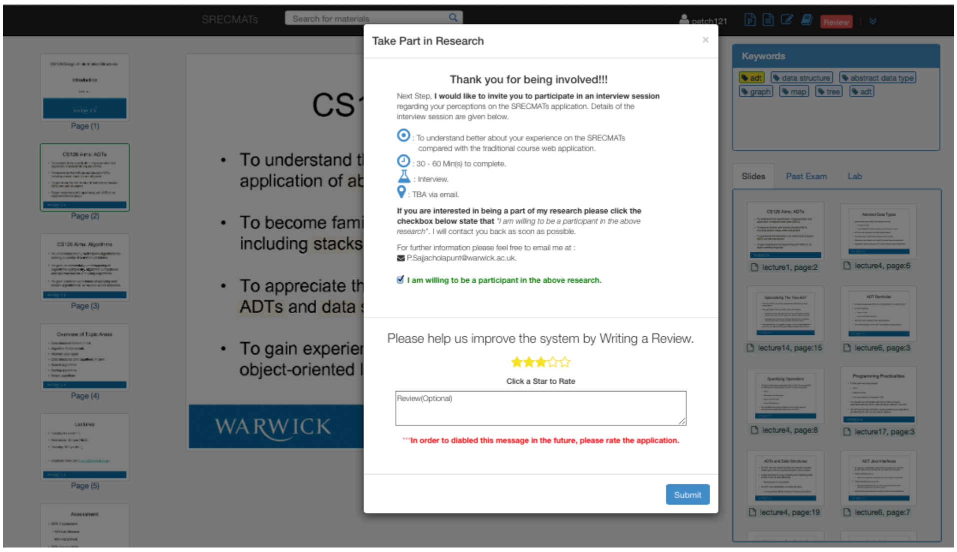


Figure 5.2: Pop-up of the feedback survey shown in the system after five minutes of use.

5.4 Results and Discussion

The results for each issue mentioned in Section 5.3 are discussed next.

5.4.1 Student behaviour during the use of the tool

This section discusses how students used the prototype system. From the log file, it was possible to track how often students used the system and how long they spent on their revision online, together with data on how they navigated through the e-materials. Although the log file alone could not fully support the claim that the system prototype was helpful to students, analysis of the results strengthens the results of the questionnaire survey on the system's usability and students' perceptions.

The results of the analysis are presented in the next sub-section based on three main questions: how often students used the system, how long they spent on their revision online, and how they navigated through the online materials.

How often did students use the system?

To answer RQ2.1, the number of students registered and logged onto the system was used to indicate the extent to which students were interested in revising online. In this experiment, a total of 132 students were registered on the CS126 course. After the system had been introduced to the students, 73 students (53% of the population) registered to use it, indicating that half the students were interested in testing the new online revision system. However, of more interest were the 63 students (47% of the population) who actually logged onto the system at least once during the experiment.

Figure 5.3 shows the number of students who accessed the traditional course website compared with the SRECMATs system. This indicates that the trend in the number of students accessing each website was similar, in that the number of users increased steadily from the start until reaching a peak the day before the examination. Most students reviewed the material just a few days prior to the examination. Only a few accessed online materials constantly after the introduction of the SRECMATs system.

It is also obvious that most students spent time on the traditional course website rather than using the SRECMATs system. This is unsurprising because the SRECMATs tool was introduced to provide an alternative way of revising but was not intended to replace the existing system. Students may have feared that the new system would require extra work, which would affect their revision routine. How-

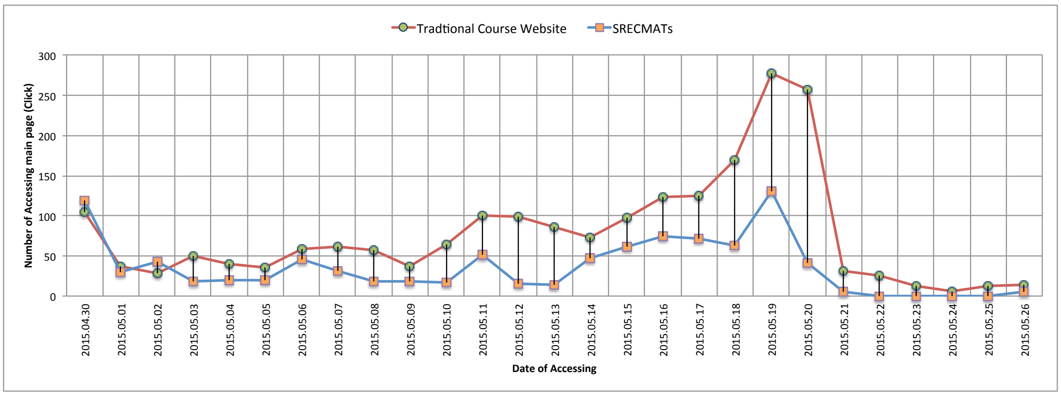


Figure 5.3: Number of students accessing the traditional course website (red) and the SRECMATs system (blue).

ever, the fact that some students continuously accessed SRECMATs indicates that features of this system were helpful to some of them.

How long did students spend on the system?

Actual time spent online has been used in previous studies as a factor to determine the level of students' engagement in an e-learning environment [10, 31]. Hence, this study also considered testing students' engagement and satisfaction through use of the SRECMATs system by measuring the time that students spent on it between logging in and logging out. In addition, several studies [24, 26, 36, 85] have explored whether increased time spent online has a positive effect on students' performance. Unfortunately, an experiment to support this finding could not be performed because of the difficulty in obtaining students' information due to university policy.

Figure 5.4 illustrates the student time spent on the SRECMATs system. Although 36 students (49%) spent only between zero and 10 minutes on the system, it cannot be concluded that they were not satisfied with SRECMATs, as they may only have used the system as a reference tool to recall or confirm their knowledge. One interesting result is that 25 students spent more than an hour revising materials on SRECMATs. This result is difficult to interpret, as they may either have been satisfied with the system, or have moved away from the keyboard.

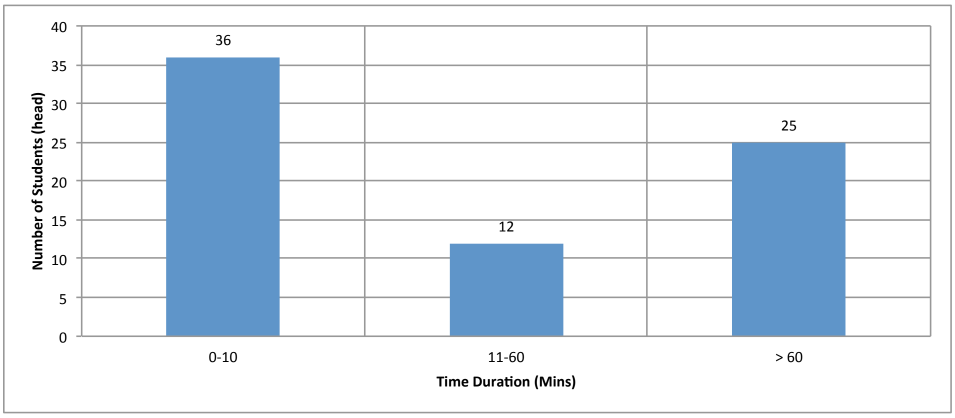


Figure 5.4: Time spent by students on the SRECMATs system, classified into 0-10 minutes, 11-60 minutes and more than 60 minutes.

How did students use the system?

The log file also captured the types of materials to which students navigated, for instance lecture slides, past exam papers, lab sheets and textbooks. In this experiment, the order of materials through which each student navigated from log-in until log-out was extracted, as well as the time they spent on reading materials. The data in the object attribute (see Table 5.2) regarding materials that students visited were grouped into four main types, as presented in Table 5.3, to understand their pattern of usage.

The types of revision strategy listed in Table 5.3 were used to ascertain the number of students making use of various strategies on the SRECMATs system, as shown in Figure 5.5. The results presented in Figure 5.5, ignoring students who did not intend to use the system (Type IV), show that most students used the SRECMATs as a tool for referencing (Type II) by revising past exam papers and lecture slides for a short period of time. The most common strategies that students adopted were

Table 5.3: Description of types of revision strategy. Each type was extracted from the log activity recorded in the database by grouping a similar pattern of students' navigation to materials and capturing the time they spent on each material.

Type I (Reading)	(1) Start revision on (all) lecture slides. (2) Go through past exam papers. (3) Go back to specific lecture slides.
Type II (Referencing)	(1) Start with past exam papers. (2) Go to related specific lecture slides. (Quick look for reference)
Type III (Subject reading)	(1) Start with past exam papers. (2) Go to a set of related lecture slides. (Spend Time Reading)
Type IV (Not using)	(1) Students who do not intend to use the system. (only login and navigate through few functions which do not show any revision patterns).

Types II and III, in which they started their revision with past exam papers before navigating to the lecture slides for detailed information. This result contradicts the previous survey (see Section 3.4.2), which found that students tended to start their revision with lecture slides before past exam papers. However, this may result from students having undertaken other activities outside the system, such as starting their revision with printed lecture slides, before practising on the past exam paper materials.

How students used the proposed features was also of interest. In this study, the number of accesses (per click) was recorded for the three proposed features, as presented in Figure 5.6. These features were: direct access through keyword browsing, direct access through keyword searching, and easy access to related material (browsing recommendations). However, the quick overview feature through keywords was

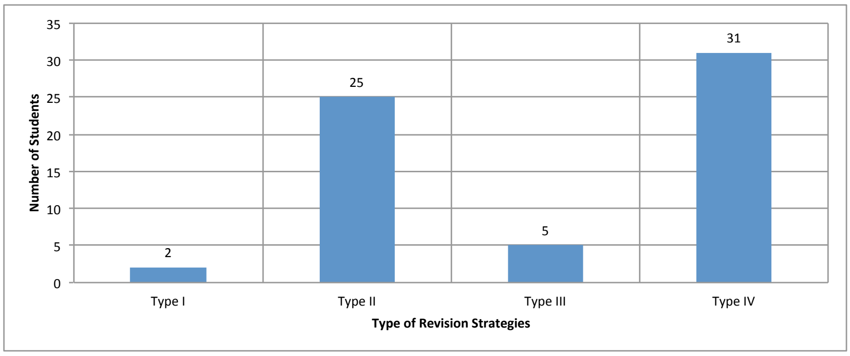


Figure 5.5: Number of students adopting each revision strategy on the SRECMATs system.

not considered because it did not require a physical action by the students which could be captured.

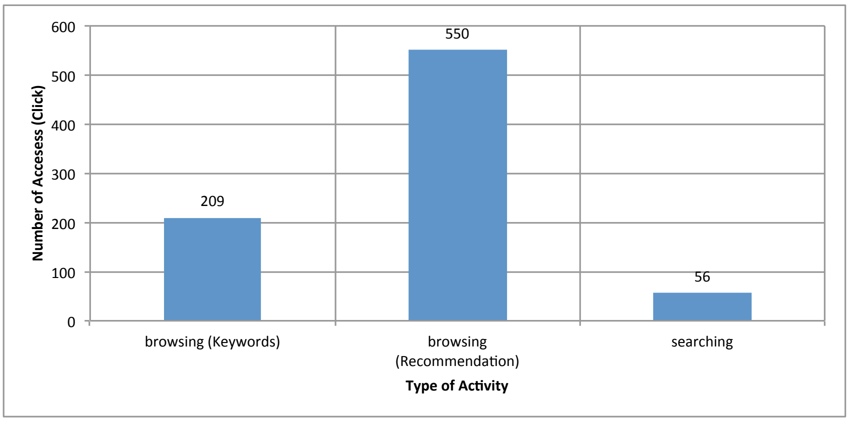


Figure 5.6: Number of uses of each navigation function in the SRECMATs system.

The results in Figure 5.6 show that most students accessed the related materials feature (browsing recommendations) more than the other two (browsing keywords and searching). The high number using the proposed features can be interpreted in two ways: either they may have preferred to use these features or, alternatively, these features may have provided inaccurate results and the students thus needed to use the feature many times to find what they were looking for. Therefore, a usability evaluation was later performed on these features.

5.4.2 Students' perceptions of the tools

The students' perceptions or attitudes with regard to the usefulness of the system were measured using a five-star rating method, in which one star meant that the system was not at all useful and five stars meant that the system was totally useful for revision. The students were also asked to comment on their feelings about or suggestions for the system. The evaluation form was presented to students after they had used the SRECMATs system for five minutes (as presented in Figure 5.2). Although the star rating may appear to be a "quick and dirty" technique, research has shown that the results may be useful in many businesses [106]. For example, Zhang et al. [168] claim that average star-rating techniques can predict the future better than other measurements. The major reason for using this technique was that it was simple but effective for students who did not want to spend time answering a long questionnaire.

Table 5.4 presents the rating scores of the 30 students who rated the system (the remaining 43 students did not participate in the rating exercise). Most students (mode) who rated the system gave the SRECMATs system four stars, meaning that it was a useful tool. Six students gave the system the full score of five stars, indicating that the SRECMATs system had considerable benefit for them. However, six students responded with three stars, indicating that they felt neutral about the system. The average rating score (mean) was 4, indicating that students were most likely to feel that the tool was useful.

With regard to the comments and suggestions text box, six students contributed their opinions. Their comments are presented below.

> **Student 1**: "It's nice that all the resources are gathered in one place, but this thing is a bit broken. When I'm looking at past papers or

Table 5.4: Average star rating of the SRECMATs system.

Rating Score	Number of students
not response	43
★	0
★★	0
★★★	6
★★★★	18
★★★★★	6

lecture slides, and I try to go into past exam papers or slides using the blue buttons on the top right, it never works on the first try. When it works after a couple of clicks, it goes to the right page but shows my name wrongly, and then again for some reason I have to try a couple of times before I get to the lecture/past paper I need."

Student 2: "A quick and easy way to look for the information you want in the lecture slides and the exam papers."

Student 3: "A search bar."

Student 4: "Useful for CS126, would be more interested if there were other options available too (CS136, CS137, CS140, etc...). A great idea!"

Student 5: "It's helpful to have everything in one place."

Student 6: "Clean design but the fact that the 'back' button (specifically in the Chrome browser) does not have any use may confuse people due to the fact that it's conventional that if you want to go back to the previous page, you want to use the back button. Otherwise, it's a good app!"

Most of these comments and suggestions indicated a positive attitude to the system. However, **Student 3's** comment provided no useful information, and the comments by Students 1 and 6 indicated some bugs in the system. These issues related to usability, which is discussed further in the next section.

5.4.3 Usability of the proposed features

After the examination, students who had used SRECMATs for more than one day (26 students, 42% of the sample) were asked to complete a questionnaire survey regarding usability and their perceptions of the tool. Seven students (26.92% of users) responded to the survey. The four previously-mentioned front-end services were assessed by the 5Es [127] in terms of the usability of the system. This approach considered how easy it was to learn the features, how effective the features were in terms of completeness and accuracy, how efficient the features were in terms of reducing time spent on the task, how error-tolerant the features were in terms of preventing errors that might affect the ability of users to navigate through the system, and the extent to which students liked engaging with these features. Five-point Likert scales were used to measure the level of 5Es in each question (from 1 = totally disagree to 5 = totally agree). This evaluation process answered research question RQ2 regarding the usability of the SRECMATs system. The questions and results are presented in Table 5.5.

Table 5.5 presents average scores for the four features provided in SRECMATs, based on five questions taken from the 5Es usability scheme. These data were also converted into a radar chart, as presented in Figure 5.7, allowing the strengths and weaknesses of each feature to be seen at a glance.

It can be seen that the average scores, in terms of the system being easy to learn, were higher than 4.0 for all features, especially for the browsing and searching

Table 5.5: Results of usability survey based on 5Es scheme.

Five E's	Question?	Browsing	Searching	Recommending	Keywords Tagging
Easy to Learn	I can start using this function without any tutorial.	4.42	4.42	4	4.14
Effective	This function allows me to navigate through e-materials easily and precisely.	3.85	3.71	3.14	3.57
Efficient	This function reduces time I spend on browsing e-materials.	3.57	3.85	3.28	3.28
Error Tolerant	I found that this function disturbs my ability to navigate through e-materials	1.85	1.71	2.14	2
Engaging	I prefer to have this function on the course website.	4	4	3.28	3.28

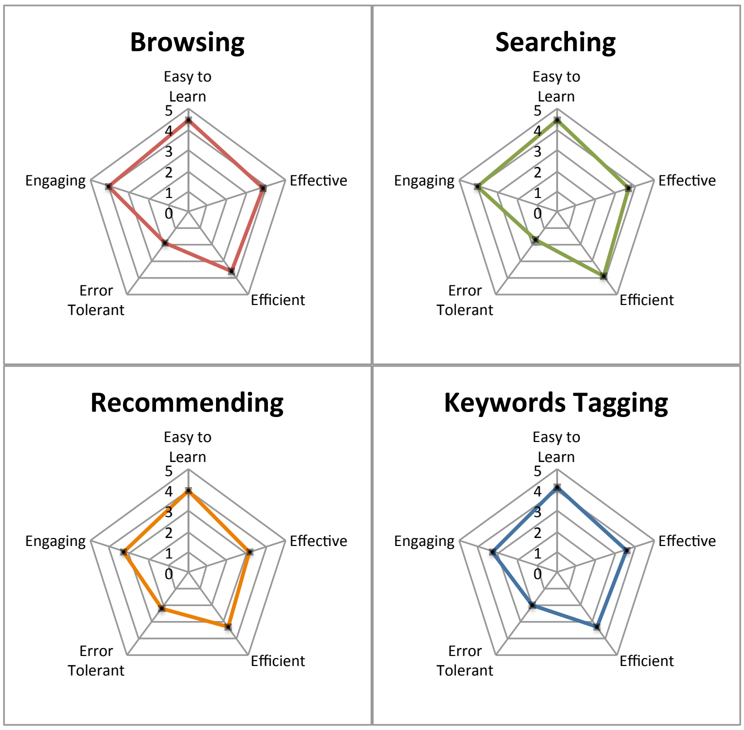


Figure 5.7: Results of 5Es usability survey presented in radar chart.

features. This suggests that all these features were easy to use with no need for extra tutorial support.

The average effectiveness scores for browsing, searching and keyword tagging were all above 3.5, suggesting that the students were satisfied with the accuracy and completeness of these features. However, the effective score for the recommendations system was 3.14, which was the lowest score, suggesting a need to improve the accuracy of this feature.

The average efficiency scores were similar to the effectiveness scores, with browsing and searching rated as more efficient than the recommendations system. The recommendations and keyword tagging features had the lowest average scores in terms of efficiency, implying that these two features were the least helpful in terms of reducing students' time spent on navigation.

With regard to error tolerance, a negatively worded question was used to prevent response bias from students when their answers did not reflect actual opinions [152]. The low score for error tolerance indicates that students encountered smooth, error-free navigation, without irrelevant results on the interface. All features had average error tolerance scores below 2.5, indicating that most students were not disturbed by errors in navigating through these features. The searching feature was the best technique with the least disturbance by errors during navigation, with a score of 1.71, followed by browsing, keyword tagging and recommendation techniques respectively.

The average score of 4.0 (Agree) for engagement shows that students were willing to use the system, and preferred to have keyword browsing and search features on the course website. However, they were only satisfied with the recommendations and keyword tagging features, with scores of 3.28. This may imply that these features still needed significant improvement to attract students.

5.5 Summary

This chapter has provided an evaluation of the SRECMATs framework proposed in Chapter 4 in order to answer RQ2.1 and RQ2.2. The methodology used to evaluate the framework focused on three issues: student behaviour while using SRECMATs, student perceptions of the tool, and the usability of the proposed features.

The first issue regarding student behaviour while using SRECMATs was evaluated using the log file, which captured students' activities. The results show that 47 per cent of all registered students used the system more than once. Although the transaction log information for students accessing the traditional course website (Figure 5.1) illustrates that most students spent time on the traditional course website rather than the SRECMATs system, the results of the SRECMATs log file show that some students used the SRECMATs system continuously during their revision period. Moreover, 39 per cent spent an average of more than an hour on online revision. This statistic indicates that some students preferred to revise online, and preferred to use the SRECMATs system.

To obtain information on students' perceptions of and attitudes to the SRECMATs system, a Likert scale (star rating) and comment text box were used for feedback. The average rating score was four out of five stars, including five positive comments from students indicating that they were satisfied with the SRECMATs system. Most other students' comments were also positive. A few students reported minor issues regarding bugs in the system. This result is consistent with the students' activities analysed from the log file.

Furthermore, a usability evaluation using the 5Es scheme was conducted to answer RQ2.2. The usability results show that all the proposed features were easy to use without additional training. For the browsing and searching features, the effectiveness, efficiency and engagement scores were above 3.5, indicating that most students were positive about the performance of these features and preferred to have them on the course website in order to find online materials. Most 5Es usability scheme scores for the recommendations and keyword tagging features were just above the borderline, indicating that they required improvement, especially in term of effectiveness and efficiency. The next chapter describes an experiment to improve the feature relating to the efficiency and effectiveness of access to related materials (browsing recommendations).

Finally, from the positive results in terms of instances of use, students' perceptions and usability evaluations, it can be concluded that the proposed revision framework was somewhat useful for designing a tool to support revision strategies. Although the features provided by the SRECMATs system were not used by all students, the positive responses from students who did use it indicate that these features may maximize the benefits of online materials, providing students with alternative ways of revising online materials that may be more appropriate in terms of their learning strategies than the traditional online materials version.

Chapter 6

Improving the Accuracy of the Related Materials Recommendation Feature through Classical Term-Weighting Schemes

6.1 Introduction

The survey results presented in Section 3.4.6 illustrate that some students (42%) preferred a tool to integrate all online materials together for revision and some (47%) preferred a tool to navigate through relevant exercises from other learning resources. A system for easy access to related materials, also known as a recommendations system, was therefore considered to be an important component of a revision system. The idea of the recommendations system was to reduce the time that students would otherwise spend on seeking related information from the current material. The challenge for such a system was to retrieve relevant documents quickly and precisely from a user query.

Chapter 5 detailed the launch of the SRECMATs prototype for students on the Design of Information Structure course (CS126) run by the Department of Computer Science, University of Warwick. The results relating to the recommendations feature show that most students accessed the recommendations system more than other features (see Figure 5.6). Users also made positive comments pertaining to the integration of all learning materials in one place (Section 5.4.2). However, the usability evaluation of the recommendations system (Section 5.4.3) revealed that it received the lowest average score for effectiveness (3.14 out of 5). This suggested that the accuracy of the recommendations system needed to be improved. Therefore, this chapter examines how the techniques used for the recommendations feature described in Chapter 4 might be improved in order to increase the accuracy of the system.

6.2 Problems with the classical term-weighting scheme

The classical technique used for the SRECMATs recommendations system was cosine similarity calculation with TF-IDF as a term weighting scheme, as discussed in Section 4.6.2. Since the degree of similarity was calculated by cosine similarity, as presented in Equation (4.7), the similarity score depended on two major factors: the number of matched terms between two documents, and the weighting of terms in each document. The former could not be controlled, while the latter could be changed based on features of the documents being considered. One major factor that may produce low accuracy in matching results is that university online course materials (with the exception of textbooks), and especially lecture slides and past exam papers, may contain only a few candidate terms with a low frequency in each document. Using only a term frequency to assign a weighting may not be effective because the frequencies of each term in each document do not differ significantly, so too many irrelevant documents are retrieved. This chapter therefore focuses on finding an appropriate method to adjust the classical term weighting that would work best with fewer text documents. This study only considered lecture slides and past exam paper materials.

6.3 Potential Approaches

To deal with problems regarding a low frequency of terms appearing in a document, and to improve the outcome of cosine similarity calculation, a technique to define term weighting in course materials based on the level of importance of terms rather than frequency was considered. In this first attempt, experiments were considered using two potential techniques that might improve the capability of current classical term-weighting schemes, especially in dealing with lecture slides and past exam paper materials.

6.3.1 Term location technique (TL)

Several areas of research have considered the concept of identifying the importance of terms in lecture slides based on location [116, 117, 159]. Pattanasri et al. [117] propose a method for searching inside lecture materials that makes full use of a textbook ontology constructed from a table of contents (TOC) and a textbook index. They assume that terms located in slide titles represent the main topics being discussed in the slides. These terms are therefore appropriate to build a mapping table from lecture slides to textbook segments. Pattanasri et al. use an XML-based format, known as OpenDocument (ODF), for lecture slides, whereby PPT documents are converted to ODF using OpenOffice Presentation[1]. This process is similar to the current study, except that this study extends the idea and focuses on mapping lecture slides with past exam paper materials rather than textbooks.

[1] `https://www.openoffice.org`

Wang and Sumiya [159] propose a method for searching for and retrieving lecture slides to meet users' requirements. In their research, the levels of terms appearing on a slide (e.g. title, body, indent level) were used to classify the presentation structure of lecture slides between generalised and detailed slides. Their method retrieves relevant slides by considering both conceptual relationships between slides (e.g. is-a-part-of) and the presentation structure. The terms and structure of the lecture slides (PPT) are extracted by a morphological analyser known as Mecab[2]. However, this tool has only been implemented for the Japanese language. Patil and Potey [116] introduce a holistic method for multi-modal lecture video retrieval. To perform video slide segmentation, they also deal with slide structure analysis to identify the title of a slide, enabling a search engine to give more accurate results. In summarising a slide, they also assume that the content of the slide title and subtitles are more important than the slide body text. Clearly, the location of terms appearing on lecture slides is important, and previous research illustrates different ways of applying this idea. In the current research, this idea was used to improve the capability of classical term weighting.

The key idea of the term location (TL) technique is to derive the level of importance for each term from its location. For example, terms that appear in the title of a lecture slide are more significant and are thus given more weight than terms that appear in the body. To apply this technique, the position of content in the learning materials must be defined. Owing to difficulties with annotating the past exam paper structure in the SRECMATs system (see Section 4.6.1), this technique was only considered for use with terms in lecture slide materials.

[2]MeCab is a Japanese morphological analyzer: `http://sourceforge.net/projects/mecab/files/mecab-ipadic/`

6.3.2 Term importance technique (TI)

The term “dictionary” means a reference book containing a list of words on a particular subject and their meaning in alphabetical order [100]. Terms in a dictionary are thus considered as keywords for a particular subject. The term importance (TI) technique increases the weight of terms in a document based on the number of dictionaries in which the terms appear. The importance of the term is defined by the number of overlapping dictionaries in which the term is found. In this experiment, three dictionaries relating to the Design and Information Structure (CS126) course were used: (D1) the index at the back of Data Structures and Algorithms in Java, 5th Edition [57], (D2) NIST's Dictionary of Algorithms and Data Structures[3], and (D3) Free Online Dictionary of Computing (FOLDOC)[4]. Figure 6.1 gives the example of three dictionaries, D1, D2, and D3, for identifying term importance (TI). For example, a term that appears in three dictionaries should be more significant than a term that appears in only one or two.

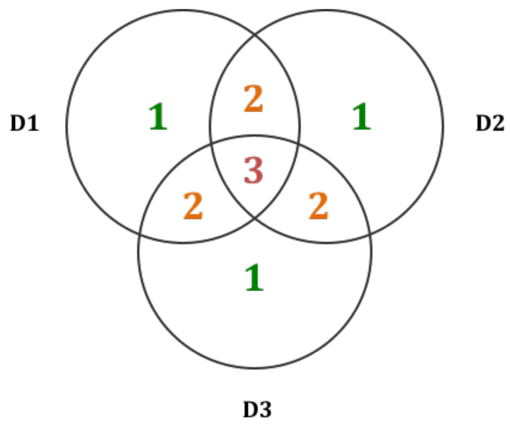


Figure 6.1: Example of three dictionaries, D1, D2, and D3, for identifying term importance (TI). Each circle represents a dictionary. The intersections between the circles represent duplicate terms in the dictionaries, where 1, 2 and 3 represent a number of overlapping dictionaries.

[3] https://xlinux.nist.gov/dads/
[4] http://foldoc.org

This technique ensures that important terms have high weightings. Therefore, applying this technique should result in an increase in the similarity scores of relevant materials and enhancement of the overall accuracy of the SRECMATs recommendations system.

6.4 Methodology

This section describes the methodology adopted to answer research question RQ3 set out in Chapter 1. It initially discusses basic information regarding the datasets that were used in the experiments and how the materials from the datasets were prepared. It then explains the term-weighting techniques used. Finally, it provides an overview of the methodology used for each experiment.

6.4.1 Datasets for evaluation

The datasets for testing the experiment were obtained from two courses: Design of Information Structures (CS126) and Database Systems (CS258). These were selected on the basis that tutors on these courses were willing to be involved in a process of defining the answer set in the experiment, and that lecture slides, past exam papers and textbook materials were provided for these courses, which were required for this study. Two different courses were used in the experiment in order to ensure that the proposed method would work effectively for both subject domains.

The datasets were collected from two sources: two internal modules, Design of Information Structure (CS126) and Database Systems (CS258), drawn from a body of undergraduate lecture slides at the Department of Computer Science, University of Warwick; and two external data structure modules (CS225 and CS2100) available from the online public-access websites of the computer science departments at the University of Illinois at Urbana-Champaign and The Chinese University of Hong Kong. Details of the documents used in this experiment are illustrated in Figure 6.2.

Course	Course code	Lecture slides		Past exam papers	
		Number of lectures	Total Number of slides in the lectures	Number of exam papers	Total Number of pages in the exam papers
Data Structure	CS126	30	797	3	12
	CS225	30	536	6	105
	CS2100	14	234	2	7
Database	CS258	11	260	3	18

Figure 6.2: Information pertaining to learning materials in the datasets for evaluation.

6.4.2 Dataset preparation

To answer research questions RQ3.1 and RQ3.2 referred to in Chapter 1, basic statistical analysis and comparative study were applied in the experiments. MATLAB was selected as the programming language with which to carry out these experiments because it contains a built-in function that is helpful for numerical analysis, including the ability to deal with matrix structures, allowing simple and fast calculations of the distance similarity between all documents. Before the datasets could be used for the experiments in MATLAB, they had be converted into matrix form. The process of preparing the datasets comprised three sub-processes: pre-processing, defining the answer set, and data conversion for MATLAB (Figure 6.3).

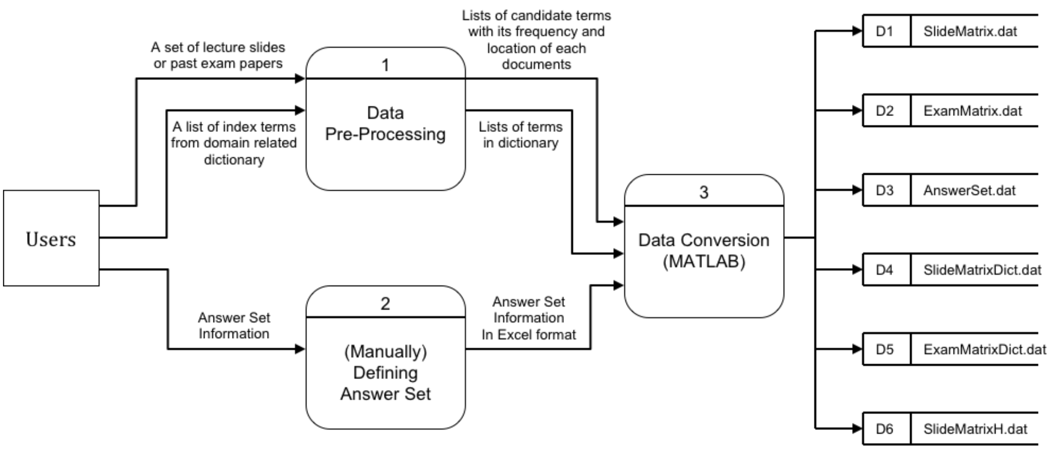


Figure 6.3: Data flow diagram of the data preparation process for the experiments.

Pre-processing comprises term extraction, as explained in Section 4.6.1. The input of this process is a raw PDF file of lecture slides or past exam papers. The output is all candidate terms extracted from the materials, including candidate terms' frequency and location. In addition, if an input is an index at the back of a textbook or index terms from a dictionary, the pre-processing will return output as a list of index terms. These outputs are later converted to matrix format through data conversion for the MATLAB component. The data conversion process was designed through Java programming to convert input data into a matrix format that could be processed by MATLAB. After the data conversion process, the outputs were stored in five files: SlideMatrix.dat, SlideMatrixDict.dat, SlideMattrixH.dat, ExamMatrix.dat, and ExamMatrixDict.dat.

To evaluate the accuracy of the proposed techniques, the answer set had to be defined. This process was done manually by tutors on the Design and Information Structure course (CS126). The mapping tables from slides to past exam papers were recorded in Excel spreadsheet (XLS) format. These Excel files were later converted to matrix format through the data conversion process. The output of conversion was stored in AnswerSet.dat. Details of all output generated by the data conversion are as follows.

- **SlideMatrix.dat**: a two-dimensional matrix representing the frequency with which terms appear in each lecture slide. Each column in the matrix represents the name of the lecture slide and rows represent a list of candidate terms.
- **SlideMatrixDict.dat**: a two-dimensional matrix representing the number of terms that appear in a lecture slide and the provided dictionary. Each column in the matrix represents the name of the lecture slide and rows represent a list of candidate terms.
- **SlideMatrixH.dat**:a two-dimensional matrix representing existing terms that

appear in the title of a lecture slide: 1 indicates its existence in the title and "0" otherwise. Each column represents the name of the lecture slide and rows represent a list of candidate terms.

- **ExamMatrix.dat**: a two-dimensional matrix representing the frequency with which terms appear in each past exam paper. Each column represents the name of a past exam paper and rows represent a list of candidate terms.
- **SlideMatrixDict.dat**: : a two-dimensional matrix representing the number of terms that appear in a past exam paper and the provided dictionary. Each column represents the name of a past exam paper and rows represents a list of candidate terms.
- **AnswerSet.dat**: a two-dimensional matrix representing the correct answer relationship between lecture slides and past exam paper: "1" is relevant and "0" is irrelevant. Each column represents the name of a past exam paper and rows represent a list of the lecture slides.

6.4.3 Term-weighting components

In this experiment, four components were considered in formulating term-weighting schemes. Term frequency (TF) and inverse document frequency (IDF) were two major components that needed adjustment. TL and TI were components proposed for adjusting the major components. Details of each component are as follows.

TF measures the frequency of a candidate term i that appears in target document j, denoted by

$$tf(i,j) = freq(i,j). \tag{6.1}$$

In this research, a normalised term frequency was used to reduce anomalies that might be caused by different lengths of documents (eliminating bias from longer or shorter documents). The following equations show how normalised TF was computed [135]. For candidate term i in the document j, the normalised term frequency, $\mathit{TF}(i,j)$ was derived by dividing the raw frequency, $\mathit{freq}(i,j)$ by the maximum of raw frequency, l, which was computed over all terms in document j as $\max_l \mathit{freq}(l,j)$

$$\mathit{TF}(i,j) = \frac{\mathit{freq}(i,j)}{\max_l \mathit{freq}(l,j)}. \tag{4.4 revisited}$$

Sometimes a high frequency of terms in the document may not represent the content of the document. This situation occurs when high frequencies of terms appear in many documents in the corpus. In this case, the IDF is considered. The IDF component considers a rare term as an important term, while considering common terms as general terms [135]. The IDF was computed by the following equation. Let N be the total number of documents and n_i the number of documents in which candidate term i appears. The inverse document frequency of term i was computed by

$$\mathit{IDF}(i) = \log \frac{N}{n_i}. \tag{4.5 revisited}$$

The common use of traditional term weighting is a combination of TF and IDF, known as TF-IDF. The term weighting score $\mathit{TF\text{-}IDF}(i,j)$ [135] was computed by.

$$\mathit{TF\text{-}IDF}(i,j) = \mathit{TF}(i,j) \cdot \mathit{IDF}(i). \tag{4.6 revisited}$$

The TL component was designed to increase the weighting of term frequency based on the location in which terms appeared in the document. Let W_{header} be a constant weighting for adjusting any term located in the title of a slide, and H_j a set of terms located in the title of document j. The adjusted term-frequency-based location of term i in document j was computed by:

$$tl(i,j) = freq_2(i,j), \tag{6.2}$$

where

$$freq_2(i,j) = \begin{cases} freq(i,j) & \text{if } i \notin H_j, \\ \\ freq(i,j) \cdot W_{header} & \text{if } i \in H_j. \end{cases}$$

For the normalised TL, we write

$$TL(i,j) = \frac{tl(i,j)}{\max_l \ tl(l,j)}. \tag{6.3}$$

The TI component was designed to determine a level of term importance based on the number of domain-related dictionaries in which a term was contained. Let k be the number of dictionaries that contain term i, and W_k a constant weighting to adjust the frequency of term i appearing in k dictionaries. The adjusted term frequency based on the importance of term i in document j was computed by:

$$ti(i,j) = freq_3(i,j), \tag{6.4}$$

where

$$freq_3(i,j) = \begin{cases} freq(i,j) \cdot W_k & \text{if } i \in k \ dictionaries, \\ freq(i,j) & \text{otherwise}. \end{cases}$$

For the normalised of TI, we write

$$TI(i,j) = \frac{ti(i,j)}{\max_l \ ti(l,j)}. \tag{6.5}$$

6.4.4 Methods for experiments

The research was divided into three experiments, as explained below.

- **Technical feasibility assessment**: The first experiment aimed to answer

RQ3.1 by testing the possibility of applying TL and TI to adjust the frequency of terms that appeared in the datasets. In order to do so, a simple statistical analysis considered the number of distinct candidate terms in the datasets, the number of distinct terms that appeared in a domain-related dictionary, and the number of terms located in the titles of lecture slides.

- **Performance evaluation**: This experiment was conducted after obtaining a positive result from the previous experiment. A comparative study of different term-weighting components was conducted and evaluated through the *f-measure* score in order to find the best term weighting for the SRECMATs recommendations system. This experiment also aimed to answer RQ3.2 by proving that adjusting the TF weighting scheme using the TL or TI components would increase the accuracy of the SRECMATs system's recommendations.

- **Performance evaluation II** (after manual dataset editing): The previous performance evaluation was conducted on the assumption that the dataset had been automatically converted correctly. This was not entirely accurate. For example, terms embedded in images and arithmetic operations were not automatically extracted; similarly, abbreviations could not be matched with full terms (e.g. BST, standing for binary search tree). This may have affected the f-measure results. This experiment was conducted to rectify these issues manually and re-evaluate the performance of the term weighting to obtain the actual performance of each term-weighting scheme. Extraction of terms from images, etc. is possible in principle, but was beyond the scope of the current work.

Details of these experiments are discussed in the next section.

6.5 Technical feasibility assessment

This section explains the details of the experiments, presents the results and discusses how to assess the technical feasibility of applying the TL and TI components to adjust TF. The results of this assessment were used to determine whether the proposed techniques could be used with the datasets.

6.5.1 Details of experiment

The technical feasibility assessment involved observing the frequency distribution of distinct candidate terms from all datasets based on three cases:

- **Case 1** (Slide/PastExam): the number of distinct candidate terms in each document. This revealed the average number of terms in slides and past exam papers.
- **Case 2** (SlideTL): the number of distinct candidate terms that appeared in the titles of the lecture slides. The higher the number of distinct candidate terms appearing in the slide title, the more confidence that applying the TL component would affect the weighting of candidate terms.
- **Case 3** (SlideTI/PastExamTI): the number of distinct candidate terms appearing in both documents and a dictionary. The higher the number of distinct candidate terms appearing in the dictionaries, the more confidence that applying the TI component would affect the weighting of candidate terms.

In order to demonstrate how candidate terms in each case were distributed across the datasets, the frequency distributions of candidate terms in each dataset were plotted, as shown in Figures 6.4 and 6.5. A frequency histogram displays the number of distinct candidate terms for each case.

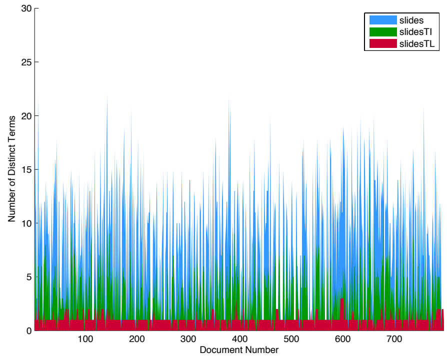
6.5.2 Results and discussion

Figures 6.4 and 6.5 present the results of the frequency distribution of candidate terms in the Design of Information Structures and Database Systems domains respectively. All four datasets demonstrated a similar pattern of area charts between the three cases (red, green and blue), The green area (SlideTI and PastExamTI) of all datasets covered almost 50 per cent as much as the blue area (Slide and PastExam), and the red area (SlideTL) appeared in almost every slide document. This result indicates that a significant number of distinct terms appeared in both document and dictionary, as well as in slide titles. The result also indicates that enough candidate terms met the criteria to apply the TI and TL components. Applying the TI and TL components might therefore affect the term-weighting score.

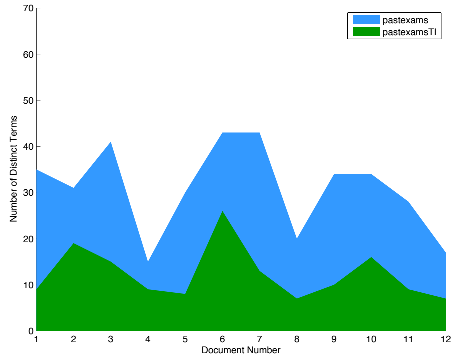
All basic statistical information: (minimum, maximum, mean and standard deviation) on the results from Figures 6.4 and 6.5 is presented in Table 6.1. This shows that the mean score of SlideTI for all datasets was similar, ranging between 2.9 and 3.3 words per lecture slide, while the average score of ExamTI for all datasets fluctuated between 5.2 and 25.4 words per exam paper. These results strengthen the previous observation of the green area in Figures 6.4 and 6.5 as follows.

The TI component has the potential to improve the classical term weighting. The mean scores of SlideTL for all datasets were also similar, but with a low range of between 0.7 and 1.1 words per lecture slide. The lower mean score for SlideTL compared with SlideTI suggests that applying the TL component may have less effect on the similarity score than the TI component.

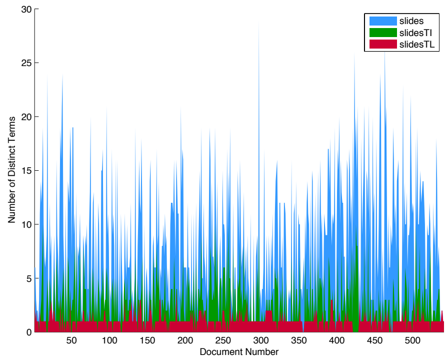
In addition, the TI technique based on a domain-related dictionary increases the importance of terms in all lecture slide and past exam paper documents of the datasets. Therefore, both TI and TL should be used to adjust the classical term weighting for performance evaluation in the next experiment.



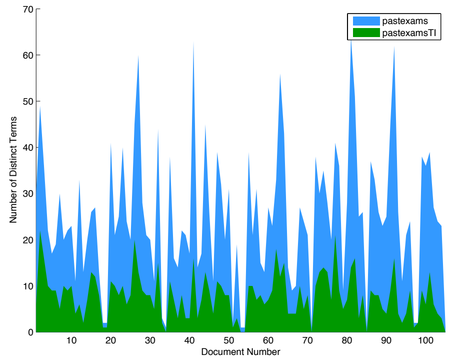
(a) CS126 (Slides)



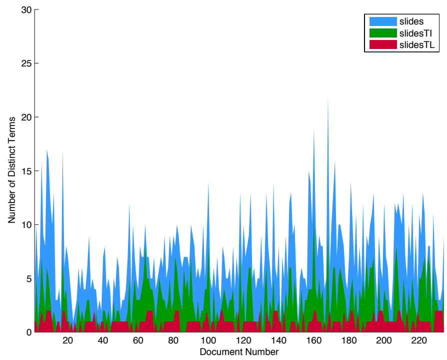
(b) CS126 (Past Exam Papers)



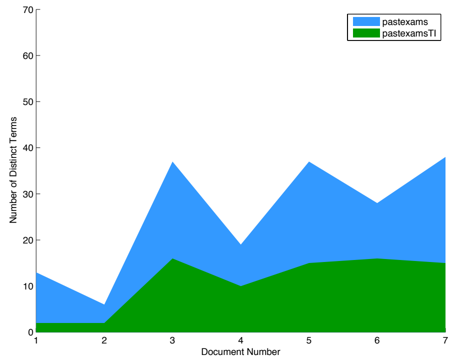
(c) CS225 (Slides)



(d) CS225 (Past Exam Papers)

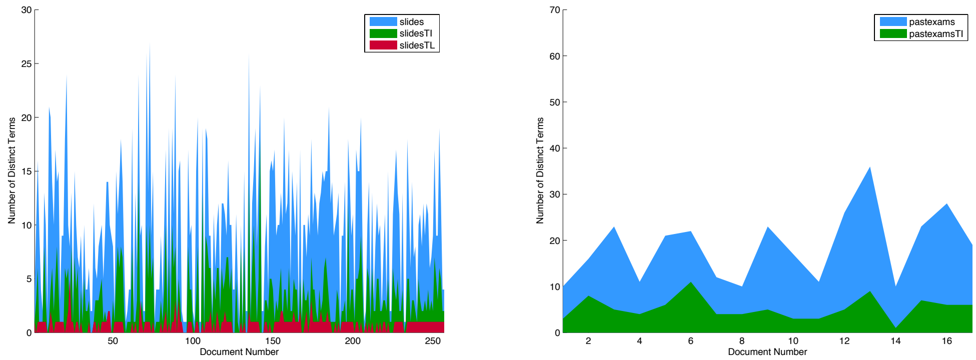


(e) CS2100 (Slides)



(f) CS2100 (Past Exam Papers)

Figure 6.4: Frequency distribution of candidate terms of all documents in the CS126, CS225 and CS2100 datasets. The x axis represents the number of documents in each dataset. The y axis represents the number of terms that appear in each document. ■ (slides and pastexams) represents the number of distinct candidate terms, ■ (slidesTI and pastexamsTI) represents the number of distinct candidate terms appearing in a dictionary, and ■ (slidesTL and pastexamsTL) represents the number of distinct candidate terms appearing in the titles of the lecture slides.



(a) CS258 (Slides) (b) CS258 (Past Exam Papers)

Figure 6.5: The frequency distribution of candidate terms of all documents in the CS258 dataset. The x axis represents the number of documents in each dataset. The y axis represents the number of terms that appear in each document. Each graph represents three cases of terms, as mentioned in Section 6.5.1, whereby ■ (slides and pastexams) represents the number of distinct candidate terms, ■ (slidesTI and pastexamsTI) represents the number of distinct candidate terms appearing in a dictionary, and ■ (slidesTL and pastexamsTL) represents the number of distinct candidate terms appearing in the titles of the lecture slides.

Table 6.1: Statistical description of datasets: minimum (min), maximum (max), mean and standard deviation (STD).

		Statistic Description (# of Terms)			
		Min	**Max**	**Mean**	**STD.**
CS126	**Slide**	1	22	8.4221	5.181
	SlideTI	0	16	3.3869	2.5616
	SlideTL	0	3	1.0716	0.5436
	PastExam	15	43	30.9167	9.558
	PastExamTI	7	26	12.3333	5.7735
CS225	**Slide**	1	29	8.8706	5.5526
	SlideTI	0	10	2.9279	2.2658
	SlideTL	0	4	1.1201	0.6342
	PastExam	1	64	25.0667	14.6006
	PastExamTI	0	22	7.8095	4.814
CS2100	**Slide**	1	22	7.2137	3.5214
	SlideTI	0	11	3.0128	2.0789
	SlideTL	0	2	0.9231	0.6764
	PastExam	6	38	25.4286	12.9468
	PastExamTI	2	16	10.8571	6.3882
CS258	**Slide**	1	27	9.8794	5.8781
	SlideTI	0	18	3.4981	2.9397
	SlideTL	0	5	0.786	0.6825
	PastExam	10	36	18.7059	7.5479
	PastExamTI	1	11	5.2941	2.4689

6.6 Performance evaluation

This section explains the details of the performance evaluation experiment, presents the results and discusses how to evaluate the performance of the TL and TI components. The results of this experiment revealed the effectiveness of the TL and TI components compared with pure traditional term weighting. Details of the experiment are discussed in the next sub-section.

6.6.1 Details of experiment

This experiment evaluated the overall effectiveness of classical term-weighting schemes, TF and IDF, with and without adjusting the weighting of terms with the TL and TI components. To evaluate the effectiveness of each term-weighting scheme, the *f-measure* (see Equation 6.12) was used to measure the accuracy of retrieving a pair of related documents based on a different similarity threshold. A similarity threshold is a value that must be exceeded in order to retrieve the related learning materials. Increasing the similarity threshold results in reducing the number of retrieved documents. It may be difficult to define what similarity threshold should be used in a system. It was anticipated that the classical term-weighting schemes, with some weighting adjustment using the TI and TL techniques, would perform more accurately than without any adjustment at any similarity threshold.

The output from the data conversion process described in Section 6.4.2 was used to calculate similarity scores between documents for all pairs of documents through MATLAB programming. The similarity scores for lecture slide S and past exam paper P, denoted by $Sim(S, P)$, was calculated using the cosine similarity formula 4.7:

$$Sim(S,P) = \frac{\overrightarrow{S} \cdot \overrightarrow{P}}{|\overrightarrow{S}||\overrightarrow{P}|} = \frac{\sum_{i=1}^{n} w_{S(i)} w_{P(i)}}{\sqrt{\sum_{i=1}^{n} w_{S(i)}^2}\sqrt{\sum_{i=1}^{n} w_{P(i)}^2}} \qquad \text{(4.7 revisited)}$$

The similarity score between lecture slide S and past exam paper P was calculated based on the weighting of terms $w_{S(i)}$ and $w_{P(i)}$, which were given by different term-weighting schemes depending on the type and content of the document. The next section discusses the term-weighting schemes used and evaluated in this experiment.

Term-weighting schemes

The term-weighting schemes considered for this experiment were derived from classical term-weighting schemes (TF and IDF), as well as a combination of classical term-weighting schemes with adjustments using TL and TI techniques, to formulate new term-weighting schemes as specified in Section 6.4.3. As a result, nine term-weighting schemes were generated for performance evaluation, as presented in Table 6.2.

In order to compare the performance of these term-weighting schemes, precision (6.10) and recall scores (6.11) were calculated. Precision is a measure of how many selected materials are relevant, while the recall score is a measure of how many relevant materials are selected. However, in order to measure the overall performance, the *f-measure* score (6.12) had be computed to balance the precision and recall scores.

$$\text{Precision} = \frac{|\text{answer set} \cap \text{retrieved document}|}{|\text{retrieved document}|} \qquad (6.10)$$

Table 6.2: List of term-weighting schemes used in this experiment, where $Method(i, j)$ denotes denotes weighting scheme method of term i in learning materials j. In this experiment, j refers to either lecture slide S or past exam paper P.

Case	Methods	Formula
1	$TF(i,j)$	$\dfrac{freq(i,j)}{\max_l freq(l,j)}$. (4.4 revisited)
2	$IDF(i)$	$\log \dfrac{N}{n_i}$. (4.5 revisited)
3	$TL(i,j)$	$\dfrac{tl(i,j)}{\max_l tl(l,j)}$. (6.3 revisited)
4	$TI(i,j)$	$\dfrac{ti(i,j)}{\max_l ti(l,j)}$. (6.5 revisited)
5	$TL\text{-}TI(i,j)$	$\dfrac{tl(i,j) \cdot ti(i,j)}{\max_l (tl(l,j) \cdot ti(l,j))}$. (6.6)
6	$TF\text{-}IDF(i,j)$	$TF(i,j) \cdot IDF(i,j)$. (4.6 revisited)
7	$TL\text{-}IDF(i,j)$	$TL(i,j) \cdot IDF(i,j)$. (6.7)
8	$TI\text{-}IDF(i,j)$	$TI(i,j) \cdot IDF(i,j)$. (6.8)
9	$TL\text{-}TI\text{-}IDF(i,j)$	$\dfrac{tl(i,j) \cdot ti(i,j)}{\max_l (tl(l,j) \cdot ti(l,j))} \cdot IDF(i,j)$. (6.9)

$$\text{Recall} = \frac{|\text{answer set} \cap \text{retrieved document}|}{|\text{answer set}|} \tag{6.11}$$

$$\text{F-Measure} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6.12}$$

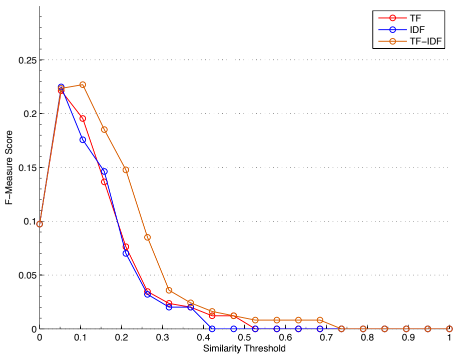
6.6.2 Results and discussion

This section compares the *f-measure* of all term-weighting schemes in Table 6.2 based on their performance for the provided datasets. The results of this experiment were divided into three phases: classical term-weighting scheme, adjusted TF scheme, and adjusted TF-IDF scheme. Each phase is described in the following sections.

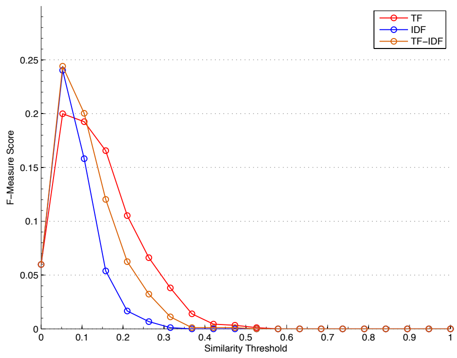
Phase I: Classical term-weighting schemes

The first phase observed the retrieval performance (*f-measure*) of the cosine similarity calculation, based on the three classical term-weighting schemes (TF, IDF and TF-IDF). This aimed to compare the classical term-weighting schemes for lecture slides and past exam papers in the domain of computer science. Line charts of the *f-measure* score and similarity threshold were plotted to analyse the pattern of each term-weighting scheme.

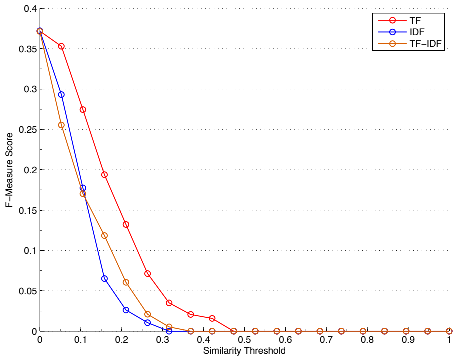
Figure 6.6 illustrates that a similarity threshold between 0 and 0.5 affected the *f-measure* score more, as increasing the similarity threshold led to an increase in the *f-measure* until it reached a peak before a steady decline. In similarity thresholds above 0.2, the TF scheme produced better results than IDF and TF-IDF for the CS225, CS2100 and CS258 datasets. In contrast, the TF-IDF scheme performed better than other schemes for the CS126 dataset. The plots indicate that the IDF seemed to eliminate relevant pairs of documents by reducing their cosine similarity score to lower than the similarity threshold. This caused the IDF and TF-IDF to perform less well than the TF. In addition, the fact that IDF was used to weight terms appearing frequently in many documents, while scaling up rare ones, means that the level of a term's importance depended on the number of appearances in all documents. Therefore, several of the same terms appeared in many documents.



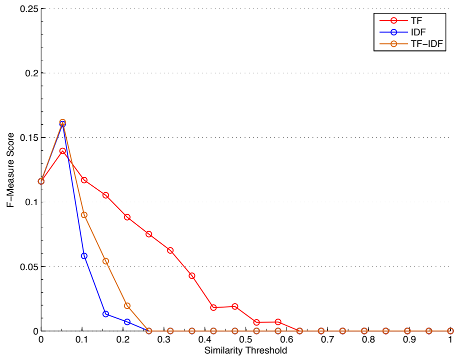
(a) CS126



(b) CS225



(c) CS2100



(d) CS258

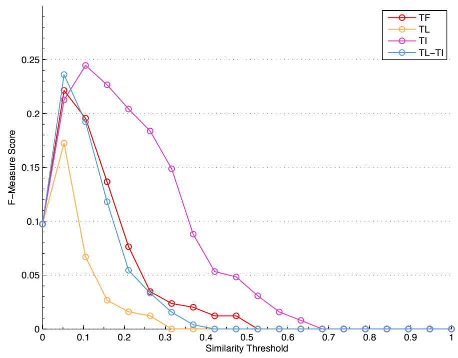
Figure 6.6: *F-measure* comparison of classical term-weighting schemes at different similarity thresholds for four provided datasets: (a) CS126, (b) CS225, (c) CS2100 and (d) CS258. The x axis represents the similarity threshold, while the y axis represents the *f-measure* score. Each plot contains three lines representing term-weighting schemes: : TF(——) , IDF (——), and TF-IDF (——).

Detailed analysis of the past exam papers for the CS225, CS2100 and CS258 courses reveals that the content of each past exam paper was similar and that the extracted terms were more or less the same. This issue meant that the terms appeared in many documents, (n_i) in Equation (4.5), which caused low performance when applying the IDF scheme. Furthermore, each classical term-weighting scheme exhibited its best *f-measure* at a low similarity threshold for all datasets. This indicates that the existing classical term-weighting schemes were ineffective for lecture slides and past exam papers. Although the TF scheme performed better than the others, the *f-measure* result still needed improvement. The issue in using the IDF scheme also emphasised that a new method was required in order to adjust the importance of terms in lecture slides and past exam paper materials.

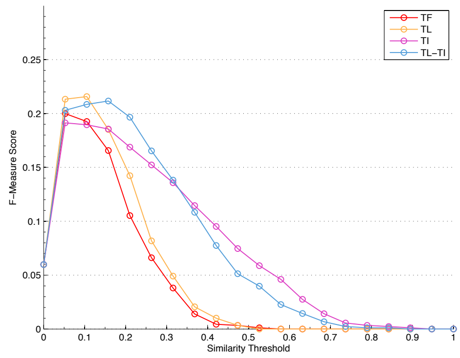
Phase II: Adjusted term-frequency scheme (TF)

This experiment studied how the weightings of terms induced by the TL and TI components altered the performance of the TF scheme, where TI and TL refer to the TF scheme with weightings adjusted by the TI and TL components respectively. The results of these term-weighting schemes are illustrated in Figure 6.7, which shows a higher *f-measure* for the TI (pink) scheme than for the pure TF (red) scheme for all datasets at a similarity threshold greater than 0.2, especially for the CS126 course. Moreover, at a similarity threshold above 0.35 for all datasets, the *f-measure* of the TI (pink) scheme also increased.

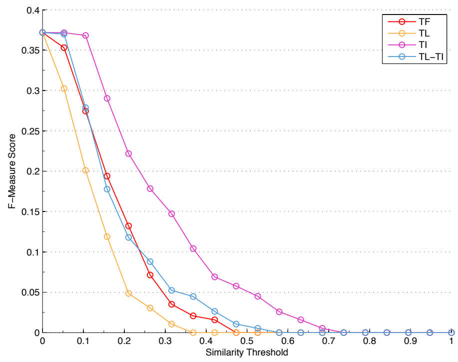
These results illustrate that applying the TI component may have improved the classical TF scheme by increasing the cosine similarity score of relevant documents. In contrast, the *f-measure* for the TL (orange) was better than for the pure TF (red) scheme only for the CS225 dataset (see Figure 6.7b). In addition, the TL component increased the weighting of terms when terms in the title position were matched; where they did not match, the *f-measure* score was reduced. This can be interpreted in two ways: either the lecture slides for datasets CS126, CS2100 and CS258 contained no key terms in their titles, or the terms in the titles were not extracted. These issues were re-analysed in the third experiment. Since the TL scheme did not deal very effectively with the provided datasets, the *f-measure* performance of the TL-TI (teal) scheme clearly did not improve.



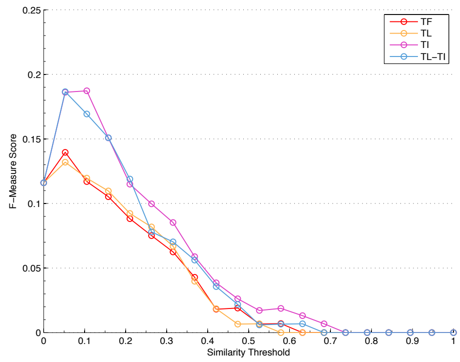
(a) CS126



(b) CS225



(c) CS2100

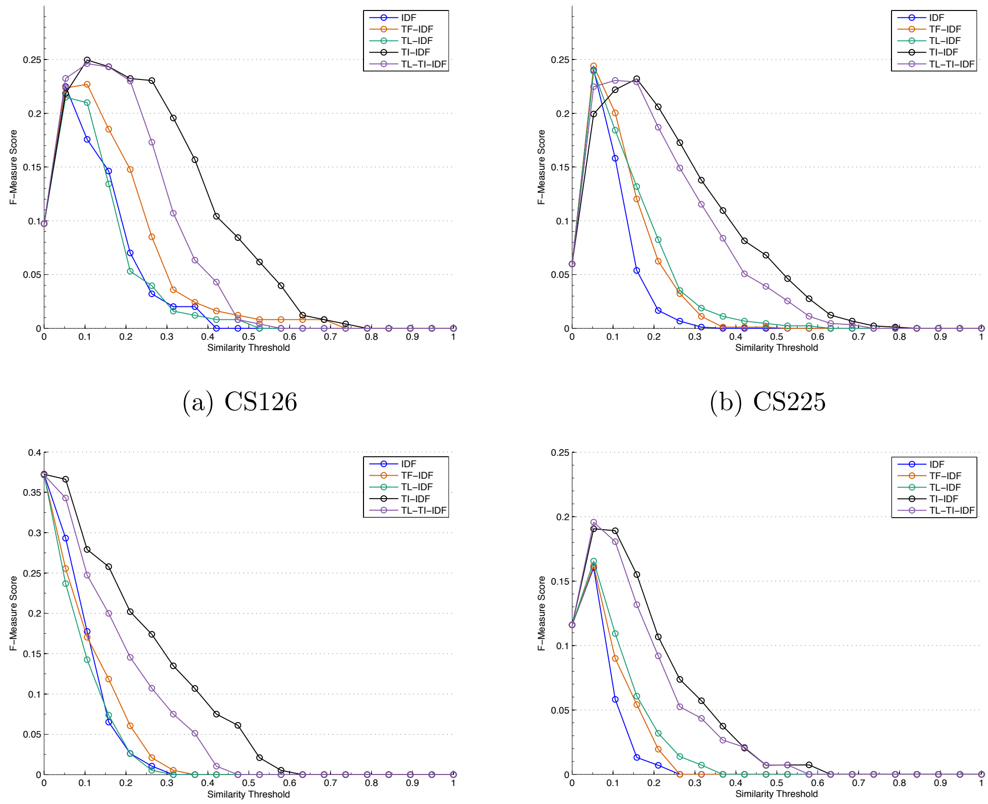


(d) CS258

Figure 6.7: *F-measure* comparison of the TF scheme, both with and without adjusting the weighting of the term with TL and TI components at different similarity thresholds for four provided datasets: (a) CS126, (b) CS225, (c) CS2100 and (d) CS258. The x axis represents the similarity threshold, while the y axis represents the *f-measure* score. Each plot contains four lines representing term-weighting schemes: TF(——), TL(——), TI(——), and TL-TI(——).

Phase III: Adjusted term-frequency and inverse document-frequency scheme (TF-IDF)

This study considered adjusting the TF-IDF scheme with the TL and TI components, in order to determine whether they might improve the *f-measure* result for the classical TF-IDF scheme. In this experiment, TI-IDF and TL-IDF refer to the TF-IDF scheme, with weightings adjusted by the TI and TL components respectively. The results of these term-weighting schemes are illustrated in Figure 6.8.



(a) CS126 (b) CS225

(c) CS2100 (d) CS258

Figure 6.8: *F-measure* comparison of the TF scheme, both with and without adjusting the weighting of the term with TL and TI components at different similarity thresholds for four provided datasets: (a) CS126, (b) CS225, (c) CS2100 and (d) CS258. The x axis represents the similarity threshold, while the y axis represents the *f-measure* score. Each plot contains five lines representing term-weighting schemes: IDF(——), TF-IDF(——), TL-IDF(——), TI-IDF(——), and TL-TI-IDF(——).

Figure 6.8 provides a comparison of the *f-measure* for the TF-IDF scheme, with and without weightings adjusted by the TL and TI components. At a high similarity threshold, the TI-IDF (black) scheme produced a better *f-measure* than the other term-weighting schemes for all datasets. The *f-measure* result also increased compared with the TI-IDF (black) at a high similarity threshold. However, when the TL component was added into the TI-IDF scheme, the TL-TI-IDF (purple) led to a decrease in the *f-measure*. In comparing the results of phase II, it is concluded that the TI component was appropriate for adjusting classical term-weighting schemes for lecture slides and past exam paper materials. The TL-IDF (green) schemes performed more effectively than classical IDF (blue) and TF-IDF (brown) for some datasets, including CS126 (see Figure 6.8a). There was no apparent improvement in the efficiency of the other two datasets. This is because the title terms of the lecture slides did not match terms in the past exam papers, which caused a low similarity score.

The performance evaluation illustrates that the proposed techniques, and especially the TI component, may have improved the f measure score. The most effective scheme in the experiment was the TI-IDF (black), which yielded the best *f-measure* for all datasets. However, the experiment was conducted on candidate terms that had been automatically extracted by pre-processing, as discussed in Section 4.6.1. The outputs from pre-processing were not always accurate, which may have resulted in poor performance. Therefore, in order to obtain the actual performance of the proposed term weighting, the extracted terms in datasets required manual editing.

6.7 Performance evaluation II (after manual dataset editing)

The previous experiment illustrated that the TI scheme might improve the classical term weighting (TF-IDF) and worked best for all datasets. However, the accuracy of results from the system was still low. This may have been affected by other factors relating to the term extraction process. Therefore, this experiment investigated possible factors in the term extraction process that might have affected the accuracy of the results from the system. Some of these factors were then fixed manually before re-evaluating the process to determine the true performance.

6.7.1 Details of experiment

As described in Section 4.6.1, the output of the term extraction process was derived from the pre-processing tasks, which were performed using two existing libraries, iText and JATEtoolkit, as shown in Table 6.3.

Table 6.3: Common pre-processing tasks with their libraries

Pre-Processing Tasks	**Libraries**
Converted Document to Plain Text	iText
Sentence Segmentation Tokenisation Part-of-Speech Tagging Stemming and Lemmatisation Stop-words Filtering	JATE toolkit

Based on the output generated by the existing libraries, factors that affected the accuracy of the system were divided into two stages: output after automatic conversion of a document to plain text; and output after noun phrase extraction.

The outputs from automatic conversion from a document to plain text were not always 100 per cent accurate due to differing document structures and character spacing, and faulty character recognition. Therefore, these issues were fixed manually line by line before passing output to the second stage. For the second stage, the output from the noun phrase extraction engine (JATEtoolkit) was analysed. Issues that affected the accuracy of the recommendations system were divided into two parts, term extraction and term matching, details of which are explained below.

- **Terms extraction**: The term extraction process was undertaken using the OpenNLP library under the JATEtoolkit library. Although OpenNLP is widely used in many applications, there are some cases that prevent it from extracting terms from documents.

– **Arithmetic Operation**: Mathematical operations such as superscript, subscript and omega sign (Ω), and especially Big-O notation, cannot be extracted by the OpenNLP library (see Figure 6.9). Slides relating to Big-O notation therefore cannot be linked by these terms.

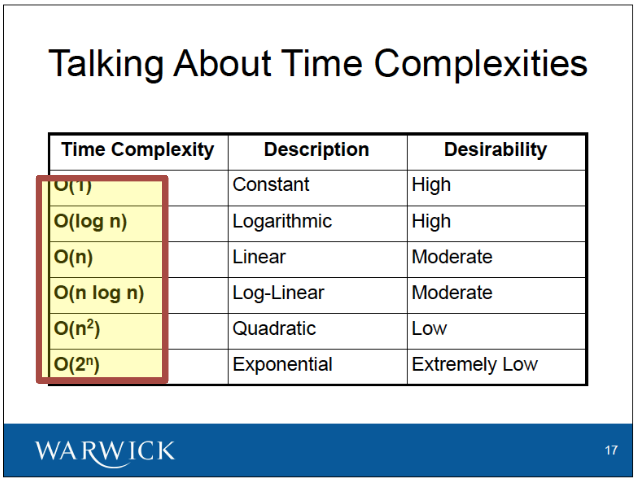


Figure 6.9: Example of arithmetic operations that were not extracted (Lecture 2, p.17).

– **Extraction Engine** (OpenNLP): Most keywords and technical terms were presented in the form of a noun phrase. In this case, the OpenNLP noun phrase extractor was used to extract candidate terms. However, the part-of-speech tagging was not 100 per cent accurate. This affected the noun phrase chunking as a result of failure to extract some candidate terms (see Figure 6.10).

– **Embedded terms in picture** In some instances, a lecture slide was captured from the screen and presented as a picture, such as a source code. This kind of information could not be extracted using OpenNLP library (see Figure 6.11).

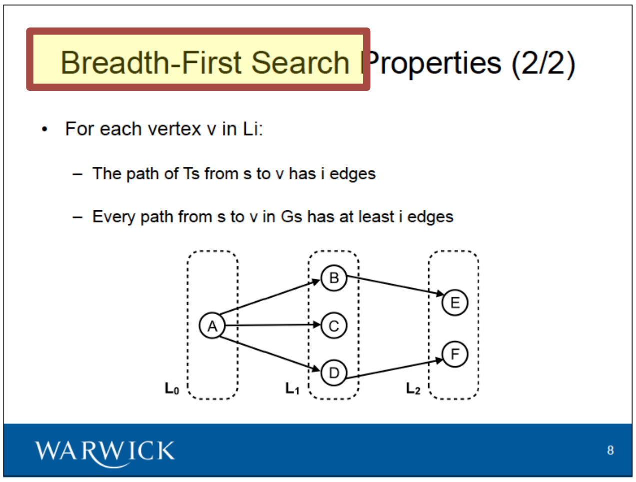


Figure 6.10: Example of part-of-speech tagging problem where the breadth-first term search was not extracted (Lecture 23, p.8).

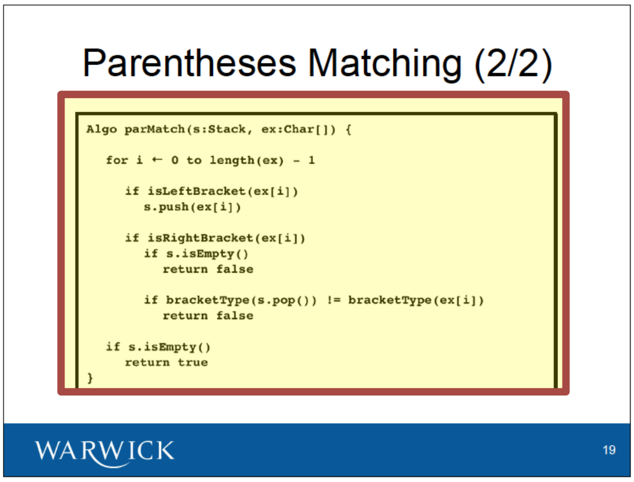


Figure 6.11: Example of terms embedded in picture, where terms in the box, which is a picture, were not extracted (Lecture 23, p.19).

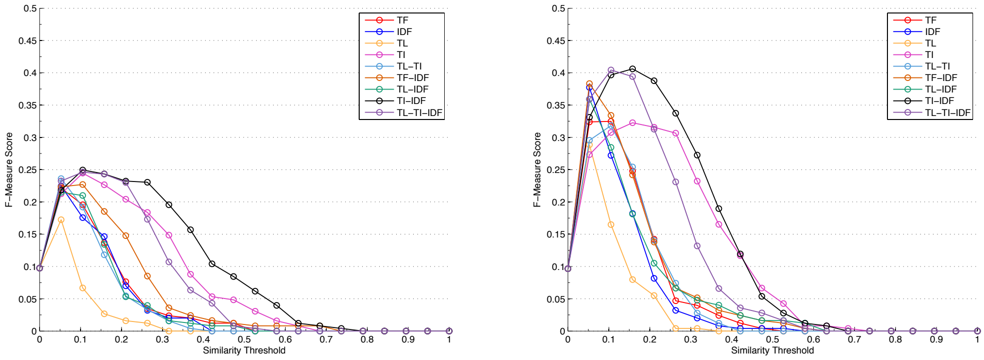
- **Term matching** In order to perform term matching, all candidate terms were listed in a vector space model (VSM). The similarity formula only performs an exact match; consequently, in some instances candidate terms could not be matched, such as the following.
    - **Abbreviation**: Shortened forms of candidate terms were not matched, for example ADT for abstract data type, and DFS for depth-first search.
    - **Synonym**: sSome candidate terms were written in a slightly different format, but still had the same meaning. For example, hash code function was sometimes mentioned as hash function.
    - **Partial Matching**: Some candidate terms formed parts of other candidate terms, such as queue and priority queue.
    - **Spacing**: Some candidate terms contained spaces while others did not, although they referred to the same thing, such as priority queue and PriorityQueue.

In this research, these issues were fixed manually slide-by-slide to obtain the least error output for term-weighting evaluation. This was a time-consuming process. As a result, and due to time limitations, a decision was made to perform this experiment only for the CS126 datasets. The comparison results of all term-weighting schemes after fixing the datasets are discussed in the next section.

6.7.2 Results and discussion

Figure 6.12 provides a comparison of the f-measure for all term-weighting schemes on the CS126 dataset, before and after fixing the data (Figures 6.12a and 6.12b).

Figure 6.12b shows that the overall *f-measure* scores increased after fixing the datasets, compared with the unfixed datasets in Figure 6.12a. In this experiment, the TI-IDF scheme still performed better than the other schemes, with an increase



(a) Overall (Original). (b) Overall (Manually Fixing).

Figure 6.12: Average *f-measure* score comparison of all term-weighting schemes both before and after manually fixing the CS126 dataset. The x axis represents the similarity threshold, while the y axis represents the *f-measure* score. Each plot contains nine lines representing term-weighting schemes: TF(——), IDF(——), TL(——), TI(——), TL-TI(——),TF-IDF(——), TL-IDF(——), TI-IDF(——), and TL-TI-IDF(——).

in the *f-measure* score from 0.25 to 0.41. This result not only confirmed that TI-IDF worked better than the other proposed term-weighting schemes, but also that issues regarding automatic term extraction had affected the previous poor *f-measures*. This presented a challenge to improve the capability of automatic term extraction features in future.

6.8 Summary

This chapter has described and discussed the results regarding potential components and techniques for improving classical term-weighting schemes (TF and IDF), and has assessed the proposed term-weighting schemes. This evaluation not only measured the accuracy performance (*f-measure*) of each term-weighting scheme, but also considered issues that might hinder their capability. Nine term-weighting schemes were compared and evaluated: TF, IDF, TL, TI, TL-TI, TF-IDF, TL-IDF, TI-IDF, and TL-TI-IDF.

The results indicate that the TI component may improve the classical TF scheme by increasing the cosine similarity score of relevant documents, while the TL component is less effective. The TI-IDF scheme performed better than the other schemes.

Although the TI-IDF scheme performed best for lecture slides and past exam paper materials, the *f-measure* result for this scheme was still poor. This was due to a number of issues regarding dirty output from the document to plain text conversion and from the noun phrase extraction process. However, these issues were fixed manually and the term weighting re-evaluated. Following this re-evaluation, the *f-measure* result increased by almost 50 per cent. The TI-IDF scheme continued to work most effectively after re-evaluation.

Chapter 7

Conclusions and Recommendations

7.1 Introduction

This study aimed to conduct research and propose a model to enhance the provision of online course materials for self-revision in higher education. The objectives of this study were to understand potential ways of enhancing online learning materials to support students, to determine the effectiveness of a proposed model to enhance the online material, and to identify whether the proposed model could be used in other courses and at other universities.

The first stage of primary research described in Chapter 3 was conducted to identify potential factors that might be used to enhance online learning materials for self-revision. A quantitative questionnaire survey was used to gather data on the experiences of students' use of online materials. The results of this research were used to construct a conceptual revision framework, described in Section 3.6.

In the second stage (Chapter 5), a log activity analysis and a questionnaire survey were conducted with computer science students at the University of Warwick registered on the Design and Information Structure course (CS126). The aim of this experiment was to establish the students' perceptions of and activities in the use of the SRECMATs tool compared with the traditional course website.

The final stage was to experiment further on how to improve the results of the recommendations feature (Chapter 6). Two proposed techniques were applied to actual course materials from the Design and Information Structure (CS126) and Database Design (CS255) courses, with the aim of evaluating the performance of the proposed techniques. The next sections discuss the main findings, summarise the contributions of this thesis, and consider the limitations and recommendations for future research.

7.2 Discussion of the findings

This section discusses four interesting issues which contribute to existing theories: use of the SRECMATs tool to reduce cognitive load; social learning with regard to online materials; improvements to search techniques for learning materials; and the limitations of using a specific group for the survey.

7.2.1 Use of the SRECMATs tool to reduce cognitive load

One aim in conducting this research on enhancing online learning materials was to reduce unnecessary cognitive load (intrinsic and extraneous) in the use of current learning materials, as discussed in Section 2.5. The results with regard to RQ1, presented in Section 3.4, show that the issue of content being difficult to understand was ranked third among six other difficulties, with 51 per cent of respondents, while 33.82 per cent of respondents mentioned difficulties with the structure of the content, which was the second lowest ranking of the issues. These results indicate that students in this sample considered that more difficulties arose from the intrinsic than from the extraneous cognitive load.

The opportunities to reduce the intrinsic cognitive load of a learning material are arguably limited. Therefore, in this thesis, the extraneous cognitive load regarding the structure of the content of online learning materials was viewed as a potential feature for enhancement. The SRECMATs framework was thus designed to reduce the extraneous cognitive load of existing online learning materials. The framework was designed to offer students simple navigation through relevant learning materials by integrating all learning resources together in one place and allowing a content search of all learning materials. This design complied with Mayer and Moreno's [99]. solution of integrating presentation to reduce extraneous cognitive loads.

The usability evaluation of the proposed features, described in Chapter 5, produced average scores from students of 3.85 out of 5.0 for effectiveness and 5.0 out of 5.0 for efficiency of the search features. These results might be interpreted as suggesting that the system made it easy for students to navigate through the existing learning materials, as well as saving their time in looking for relevant information. These results are also consistent with Mayer's [96] analysis, which found that students who studied through integrated presentations had better problem-solving skills than students who studied from separate presentations. In this thesis, only the usability of features was investigated. The students' feedback on effectiveness and efficiency showed a little reduction in the extraneous cognitive load on some students, but did not confirm that the search feature completely eliminated the extraneous cognitive load in existing learning materials. Further research is needed to confirm the results of the load-reducing methods used for learning materials. There is also a need for research on the measurement of cognitive loads, such as how to measure students' cognitive experiences.

7.2.2 Social learning through online materials

Although 67 per cent of respondents to the survey (Section 3.4.7) preferred self-study during revision, 33 per cent considered peer group revision. This result complies with Lau's [88] finding that most students indicated that peer group study helped them considerably in learning subject materials and that they also enjoyed this approach. These results indicate that social learning is an important approach for revision.

The results of the investigations in this thesis also show that department of study was related to types of revision. The results illustrate that similar proportions of students from WMG and other departments preferred self-study or peer group revision, while more WBS students preferred self-study (83.3%) to peer group revision (16.7%). Although the results of this survey show that gender and ethnicity were independent of the two types of revision, a survey of a larger sample is needed to strengthen the findings. A larger-scale survey might establish that ethnicity is related to types of study.

According to the results described in Section 3.4.5, when students did not understand the content of learning materials, 72 per cent would ask a classmate a specific question, which was the second most common of the six strategies. The lowest-ranked strategy (10%) was to ask a classmate for a whole tutorial. These results are consistent with Lau's [88] finding that students learn to ask for help when necessary, and imply that participants preferred to use social learning to solve particular problems, rather than seeking whole tutorials from friends. The results described in Section 3.4.8 also show that 99 per cent of participants were willing to share online materials.

In this study, only a few investigations were conducted on social learning methods. The results weakly indicate that social learning methods, such as sharing learning resources and sharing ideas about exercises, may be useful for peer group revision. Therefore, additional research on whether students prefer in-person or online social learning methods and how each social learning method affects revision need to be explored in order to strengthen the results of this thesis. Further research on these issues might enhance the provision of online learning materials.

7.2.3 Improvements to recommendation techniques for learning materials

There are two common approaches to recommendations for learning materials, a content-based approach and a folksonomy-based approach [69]. The content-based approach relies only on content in documents, while the folksonomy-based approach relies on tags or keywords from learning materials generated by students. In this thesis, the vector space model and the cosine similarity technique which underpin the content-based approach were used for recommendations for learning materials. The use of a technique to calculate similarity between lecture slides and past exam paper materials has not previously been considered in a recommendations system. This thesis investigated the use of cosine similarity techniques with lecture slides and past exam papers and how the results of these recommendation techniques might be improved.

The TL technique was introduced to improve the accuracy of the recommendations feature. The design of this technique was based on existing systems used to index lecture slide materials [117, 161]. The results are consistent with previous findings that using TL as a term-weighting method may improve the accuracy of the recommendations feature [117].

Although, this method produced slightly improved results, the idea of identifying term weighting based on TI was also investigated. The results show that the TI technique yielded better results than the TL technique.

Although the results of the investigation described in Chapter 6 show that the proposed TI technique may have improved the accuracy of the recommendations system for lecture slides and past exam papers, it was not tested with students. Further exploration is required to confirm this improvement to the recommendation techniques. Alternatively, other possible techniques, such as multinomial naive Bayes, K-nearest neighbour or Rocchio, should also be investigated to improve the results of recommendations. Furthermore, the investigation in this thesis was only performed on materials for two courses (CS126 and CS258); further investigation is required on other course materials.

7.2.4 Limitations of the survey sample

The survey results for the use of learning materials during revision, described in Chapter 3, were conducted with postgraduate students at the University of Warwick. In this study, only five departments – WBS, WMG, Economics, Computer Science and Mathematics – were involved because they had an examination and were willing to co-operate in the study. The results of this study are therefore applicable only to a specific context.

The major limitation of using such a specific group for a survey is the difficulty of generalising the findings to a larger scale, such as using these results to design tools to support students from other departments or universities. The reason for this limitation is that students from each department or university have specific characteristics and personalities, as suggested by Felder and Silverman [51] and Gosling [58]. Their approaches to teaching also differ, which may affect the ways in which students use learning materials. To overcome this limitation, a further survey should be conducted with all other departments that have examinations, and also with other universities. This would strengthen the results and ensure their generalisability.

7.3 Summary of Contributions

This thesis contributes to knowledge in the field of computer education, particularly with regard to the revision process in higher education. It provides evidence that extends existing research and theories and makes contributions in three key areas: (i) a contribution to understanding user behaviour; (ii) a contribution to the architecture and framework; and (iii) a contribution to term-weighting schemes.

7.3.1 Contribution to understanding user behaviour

With regard to understanding user behaviour, this thesis contributes to knowledge in two ways. First, it extends existing research with regard to ways in which students undertake revision before examinations. In particular, it deals with the pattern of students' use of online course materials during revision. The survey results described in Chapter 3 reveal that the sample of students at the University of Warwick were worried about the large amounts of learning resources they had to review, as well as the short time period in which to review these materials. Parts of the survey were analysed and integrated with various types of cognitive tools to produce a conceptual revision framework, which revealed a common pattern of students' use of learning resources. This answers research question RQ1.1. The sample of students at the University of Warwick commonly started their revision by considering lecture slides; they then gained further detailed information from other materials, especially their lecture notes and past exam papers. If they did not understand the content, they would search for more information or ask their peers. The results of the survey also provide evidence to answer research question RQ1.2 with regard to identifying potential issues involved in supporting student revision. Since revising a large amount of materials in a short time is a major difficulty for students during the revision period, they responded about their need for a tool to support them in gaining a quick overview of information, as well as a tool to support them in organising these materials for simple navigation during the revision process. In addition, the results show that students preferred to search for more information when faced with difficulties regarding content. This suggested that improving the performance of the search and navigation features of course websites was another issue requiring further consideration.

Second, this thesis also contributes to an understanding of students' perceptions of using the proposed features available from the SRECMATs framework for revision, compared with the corresponding traditional course website. The students' activities were recorded in order to understand their pattern of accessing both systems while revising. Although more students accessed the traditional course website than the SRECMATs, some groups of students preferred to use the proposed system. During the revision, the students were also asked to rate their perceptions of using the SRECMATs tool. The average rating of the SRECMATs system was 4.0 out of 5.0, suggesting positive perceptions of the tool. These results show that the proposed features were of benefit to some groups of students, providing evidence to answer RQ2.1. Adding this feature to the traditional course website to deliver online materials would provide students with more alternatives and increase the benefits of revising online. In addition, the results of the usability evaluation of the features described in Chapter 5 provide answers to RQ2.2. The results indicate that all four features were simple to use, with an average score higher than 4.0 with regard to all features of the system being easy to learn. However, some features, such as obtaining a quick overview and making recommendations, still require further improvement in terms of effectiveness and accuracy of the results in order to be more useful to students.

7.3.2 Contribution to architecture and framework

With regard to the architecture and framework, the proposed conceptual revision framework described in 3 contributes to its development in terms of using it as a guideline to build cognitive tools to support the revision process. It may also be used to validate features of existing tools with regard to the level of features that a tool provides to support the revision process. In addition, this thesis has applied this conceptual revision framework using NLP techniques to construct the SRECMATs software framework to support students' revision. The SRECMATs framework detailed in Chapter 4 was designed to answer RQ2 regarding how online course materials might be enhanced to support students' revision. NLP techniques, such as automatic term extraction (ATE) and cosine similarity calculations, were used to develop four interactive features to support students' navigation experience: (i) direct access to e-materials using keyword browsing; (ii) direct access to e-materials using keyword searching; (iii) gaining a quick overview using keywords; and (iv) easy access to related materials. These features aimed to reduce students' workloads in terms of organising content for revision, and allowing them to organise and navigate through e-materials more simply and effectively.

7.3.3 Contribution to term-weighting scheme

Lastly, this thesis contributes to knowledge by introducing a novel technique to improve the results of searching for relevant learning materials by using a classical term-weighting scheme (particularly with regard to lecture slides and past exam papers). Classical term-weighting methods are appropriate for materials that contain a large amount of content, such as textbooks, papers and journals. However, lecture slides and past exam papers contain far fewer terms than textbooks. In order to use classical term-weighting methods, a novel technique was proposed to adjust the weighting of terms based on TL and TI components. The first experiment described in Chapter 6 aimed to test the possibility of improving classical term weighting (TF and IDF) with TL and TI through four datasets in order to answer RQ3.1. The results reveal that there were sufficient candidate terms in all four datasets that met the criteria for applying the TI component. In addition, all of them contained a set of candidate terms located in the header, which also allowed the classical term weighting to be adjusted through the TL component. Furthermore, an experiment was conducted to compare the use of classical term weighting, with and without adjusting weightings, using the proposed components. The results of the comparison provide answers to RQ3.2, revealing that the TI component may improve the classical TF-IDF scheme by increasing the cosine similarity score of relevant documents, while the TL component has little effect.

7.4 Limitations and Future Research

Certain limitations of the experiments conducted in this thesis may have had an impact on the quality of findings. These are as follows.

- **Number of participants**: To obtain information on experiences of using the SRECMATs system, a semi-interview case study was designed and volunteer participants were sought. Unfortunately, only one student was willing to be involved in this experiment. Consequently, the result could not be included in this thesis.

- **Learning material repository**: To generalise the view that the proposed term-weighting techniques might improve the results with regard to recommending related materials to students, the techniques needed to be evaluated for a variety of learning materials from different universities. Requests for learning materials were sent to five lecturers from different universities who taught courses similar to the Data Structure course. Unfortunately, none was prepared to provide the necessary materials.

These limitations raise a number of challenges with regard to further experiments in the future. Recommendations for future work are listed below.

- The survey data collected to deduce a common pattern of students use of learning materials was based on a single case study of five departments at the University of Warwick. To provide stronger and more reliable evidence to support the proposed conceptual revision framework, further surveys should be conducted involving more departments and universities. However, obtaining data from other departments and other universities may be problematic.
- The usability evaluation of features provided in the SRECMATs software framework should be applied to more courses. An interview case study should be developed which could be used to obtain further evidence to support the framework.
- The results for automatic recommendations of materials indicate a need for improvement. Allowing users to amend the results is a potential challenge, for example by giving a usefulness score for each term in a document or a relatedness score for retrieved material.
- This thesis only considered the application of NLP techniques to improve learning materials. As a result of the rapid development of current technology, other techniques such as learning objects or semantic web might in future offer options to maximise the benefits of online materials.
- The proposed term-weighting techniques were applied only to the Design of Information Structure and Database System course materials. It remains to be seen whether or not the proposed techniques might be used with a wider variety of courses and different author styles.
- Other features to support revision need to be further studied, such as integration of Web2.0 for student collaboration during revision.

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Appendix A

Questionnaire Survey on the Use of Learning Materials for Revision

I am a PhD student and I am interested in education issues in improving e-material for revision. The purpose of this activity is to explore a pattern of student make use of learning resources through revision period. The data I receive will be kept confidential and will be stored anonymised. The data will only be seen by myself and my supervisor, Dr.Mike Joy. The Departments ethical procedures have been followed, and ethical consent has been granted for this questionnaire.

Section1: Background Information

Please respond to the following question based on your past experience during your MSc course and your previous BSc in general, rather than focus on your experience during a particular course. **University**: The University of Warwick **Department**:...... **Degree Title**:...... **Degree**: BSc. / MSc. **Year**: 1 / 2 / 3 / 4 **Nationality**:...... **Previous place of study**:...... **Gender**: M/F

1.How long do you start to review a course material before an exam?

Select one box only. *

- ◯ As soon as I know an exam date
- ◯ More than 5 weeks
- ◯ 3 – 5 weeks
- ◯ 1 – 3 weeks
- ◯ Less than 1 week

2.What is the approximate percentage of your understanding on your course that you think you obtain from a lecture?

Select one that apply * ----

3.How much do you think your memory of the material in a lecture decreases from the date the lecture was delivered until the revision period?

Select one that apply * ----

Section 2: Use of Learning Resources.

Please select the answer and provide some explanation (if required) that best identifies your behaviour to each corresponding questions.

4.What resources do you use to revise a course before exam?

- ☐ Lecture note
- ☐ Lecture slides (read direct from the PowerPoint file)
- ☐ Lecture slides hand-out(printed form PowerPoint slides)
- ☐ Textbook
- ☐ E-Book
- ☐ E-learning websites both formal and informal (e.g. Udacity, Wikipedia, Blog)
- ☐ VDO Streaming (e.g., YouTube, coure website)
- ☐ Assignment/Essay you was working on during a course
- ☐ Past exam paper

Other Material (please specify) __________

5.For each of the following provided resources, what percentage do you use each of these resources for revision? 0% I do not use it at all, 100% I mostly use it

Please provide percentage of use for each resources*	0% not use	10%	20%	30%	40%	50%	60%	70%	80%	90%	100% mostly use
Lecture note	◉	○	○	○	○	○	○	○	○	○	○
Lecture slides (read direct from the PowerPoint file)	◉	○	○	○	○	○	○	○	○	○	○
Lecture slides hand-out(printed form PowerPoint slides)	◉	○	○	○	○	○	○	○	○	○	○
Textbook	◉	○	○	○	○	○	○	○	○	○	○
E-Book	◉	○	○	○	○	○	○	○	○	○	○
E-learning websites both formal and informal (e.g. Udacity or Wikipidia)	◉	○	○	○	○	○	○	○	○	○	○
VDO Streaming (e.g.YouTube or coure website)	◉	○	○	○	○	○	○	○	○	○	○
Assignment/Essay you was working on during a course	◉	○	○	○	○	○	○	○	○	○	○
Past exam paper	◉	○	○	○	○	○	○	○	○	○	○
Other materials	◉	○	○	○	○	○	○	○	○	○	○

6.During the revision period, which resource do you prefer to start revising first?

Select one box only.

- ◯ Lecture note
- ◯ Lecture slides (read direct from the PowerPoint file)
- ◯ Lecture slides hand-out(printed form PowerPoint slides)
- ◯ Textbook
- ◯ E-Book
- ◯ E-learning websites both formal and informal (e.g. Udacity, Wikipedia, Blog)
- ◯ VDO Streaming (e.g., YouTube, coure website)
- ◯ Assignment/Essay you was working on during a course
- ◯ Past exam paper

Other Materials (please specify)

Please state the reason why you have selected that option

Section 3: Revision Strategy.

Please select the answer and provide some explanation (if required) that best identifies your behaviour to each corresponding question.

7.Which activities do you use for self-revision?

Select all that apply

- ☐ Organize all learning materials (e.g. to decide which one to read first)
- ☐ Read and try to define potential parts that could be in examination
- ☐ Read and try to link between relevant topics of a course
- ☐ Listen to a lecture from voice recorder/ vdo streaming
- ☐ Make new summary notes by copying from available learning material
- ☐ Make new summary notes in your own words
- ☐ Do exercise from a past exam paper or old assignments

Other activity (please specify)

8.Which activities do you prefer when you do not understand content in your lecture note?

Select all that apply.

- ☐ Search for more information on relevant textbooks
- ☐ Search for more information on the Internet
- ☐ Borrow a classmate's lecture notes
- ☐ Ask a classmate a specific question
- ☐ Ask a classmate to give you a tutorial
- ☐ Ask a lecturer or teacher for assistance

Other activity (please specify)

9.Do you normally prefer self-study revision or peer group revision?

Select one box only *

- ○ Self-Study Revision
- ○ Peer Group Revision

Please state the reason why you have selected that option

10.Would you be happy to share your lecture notes with friend?

Select one box only. *

- ○ Yes
- ○ No

If 'no', please state the reason why you do not want to share your note:

Section 4: Issues and Solutions.

Please select the answer and provide some explanation (if required) that best identifies your behaviour to each corresponding questions.

11.What do you find difficult when it comes to revising?

Select all that apply.

- ☐ A large amount of learning material to review
- ☐ A short period of time for revision
- ☐ It has been too long that you learnt this module (i.e. module in term 1)
- ☐ Not enough information in the revision materials (e.g., too few example)
- ☐ Content is difficult to understand
- ☐ Structure of content is difficult to follow

Other difficulty(please specify) ______

12.Please specify the following functions of e-material that you think it would support you through you revision.

- ☐ Organise content of all available resources in my own way
- ☐ Integrate and group all materials together to be revised as a single item
- ☐ Share lecture notes among my classmates
- ☐ Share an answer or idea of understanding in an e-material
- ☐ Navigate through relevant pre-requisite material
- ☐ Navigate through relevant exercises from other learning resources
- ☐ Extract an overview of key information on the material
- ☐ Extract detail of key information based on student demand

Other suggestion (please specify) ______

13.Are you willing to be an interviewer of this research in the future?

- ○ Yes
- ○ No

* **indicates a required field**

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Appendix B

A Post Questionnaire Survey on the Use of the SRECMATs system for Revision

Thanks for trying SRECMATs system. We'd love to know your thoughts on the experience you received. The purpose of this activity is to collect students' attitudes towards the SRECMATs system in order to improve the traditional course website to support students' revision in the future. The data I receive will be kept confidential and will be stored anonymised. The data will only be seen by myself and my supervisor, Dr.Mike Joy. The Departments ethical procedures have been followed, and ethical consent has been granted for this questionnaire.

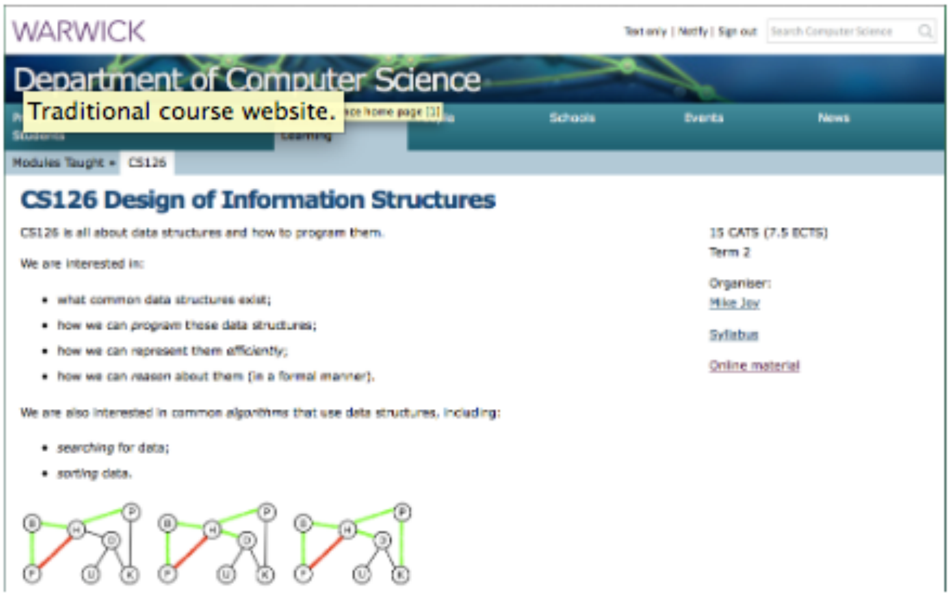
*** indicates a required field**

Username on SRECMAT *:

Section1: Students' participation in the use of traditional system.

Think about the FIRST TIME that you used traditional course website.

The traditional course website.



1.How difficulty was it to "FIND SPECIFIC INFORMATION" in e-learning materials that are provided on the traditional course website*

(*** Please think about when you were using the system for the first time)***

	1	2	3	4	5	
Very difficult	○	○	○	○	○	Very Easy

2.Did you feel that you had enough functions to support your navigation through e-materials on the course website?*

- ○ Yes, it is enough for me
- ○ Neutral
- ○ No, I need more supporting functions

3.Do you think the e-materials in the course website need to be more organised? *

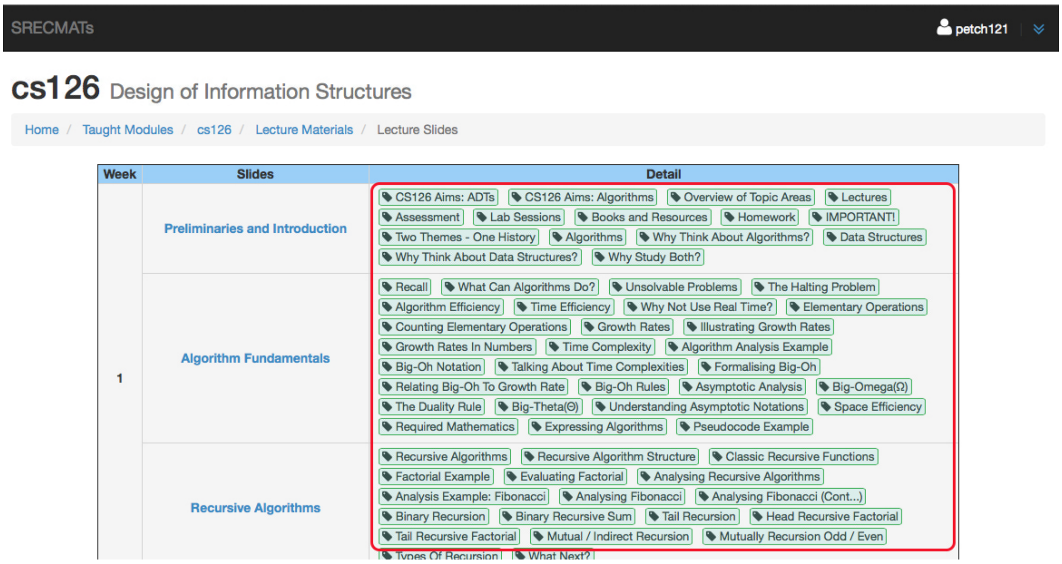
(Please rate from the following scale.)

- ◯ Yes, it need to be more organised.
- ◯ Neutral
- ◯ No, I like it this way.

Section 2: Attitude towards SRECMATs application.

Think about the functions you used in SRECMATs during your revision.

Browsing by keywords.

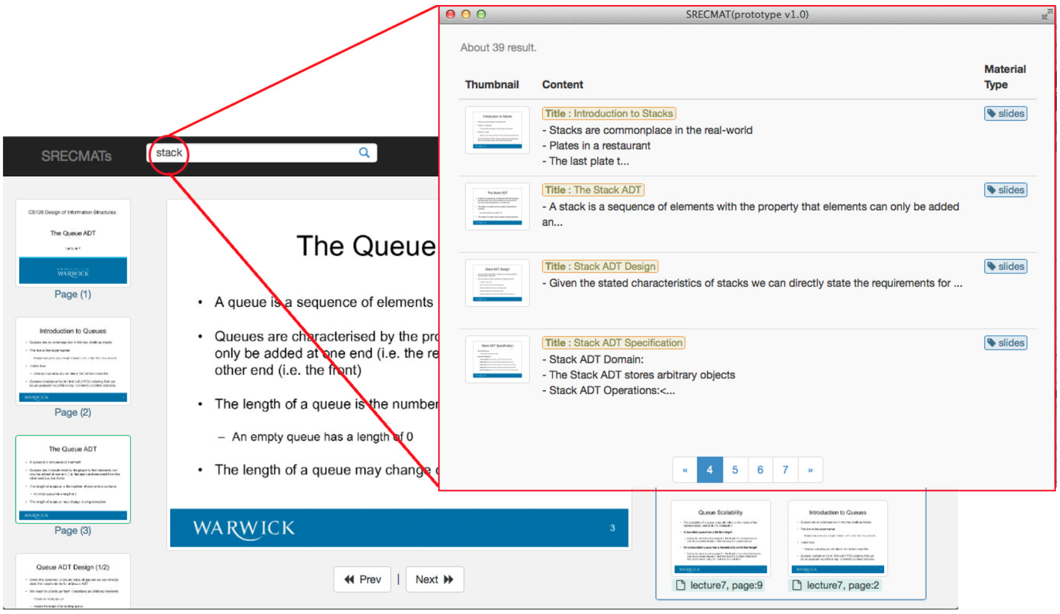


4.How would you rate ”BROWSING BY KEYWORDS” function, based on the following statements: *

(Please rate from the following scale.)

	Totally Disagree	Disagree	Neutral	Agree	Totally Agree
I can start using this function without any tutorial.					
This function allows me to navigate through e-materials easily and precisely.					
I found that this function disturbs my ability to navigate through e-materials					
This function reduces time I spend on browsing e-materials.					
This function returns the right materials which I expected.					
I prefer to have this function on the course website.					

Searching by keywords.

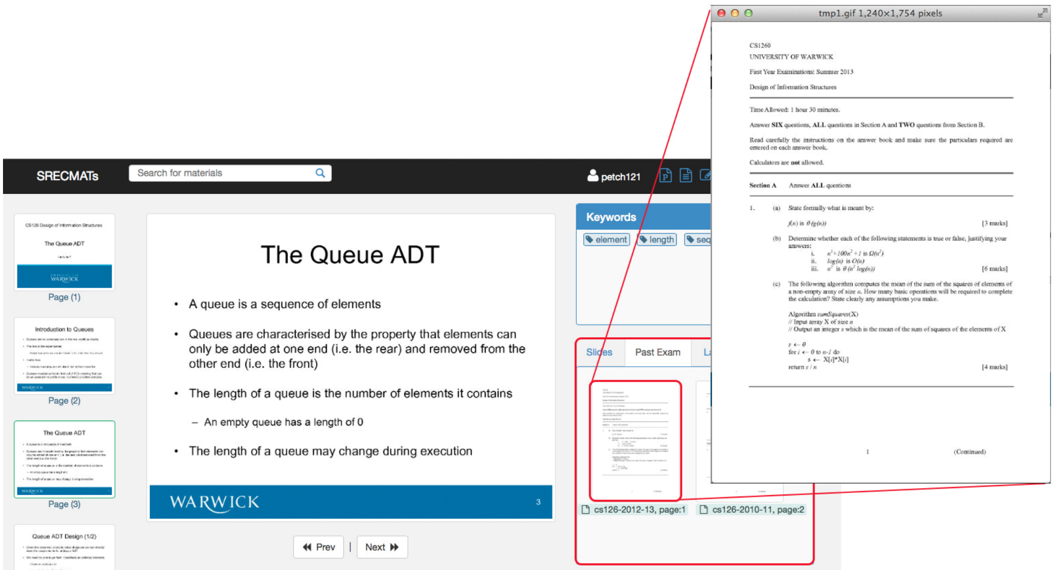


5.How would you rate "SEARCHING BY KEYWORDS" function, based on the following statements: *

(Please rate from the following scale.)

	Totally Disagree	Disagree	Neutral	Agree	Totally Agree
I can start using this function without any tutorial.	○	○	○	○	○
This function allows me to navigate through e-materials easily and precisely.	○	○	○	○	○
I found that this function disturbs my ability to navigate through e-materials	○	○	○	○	○
This function reduces time I spend on browsing e-materials.	○	○	○	○	○
This function returns the right materials which I expected.	○	○	○	○	○
I prefer to have this function on the course website.	○	○	○	○	○

Recommending Related Materials.

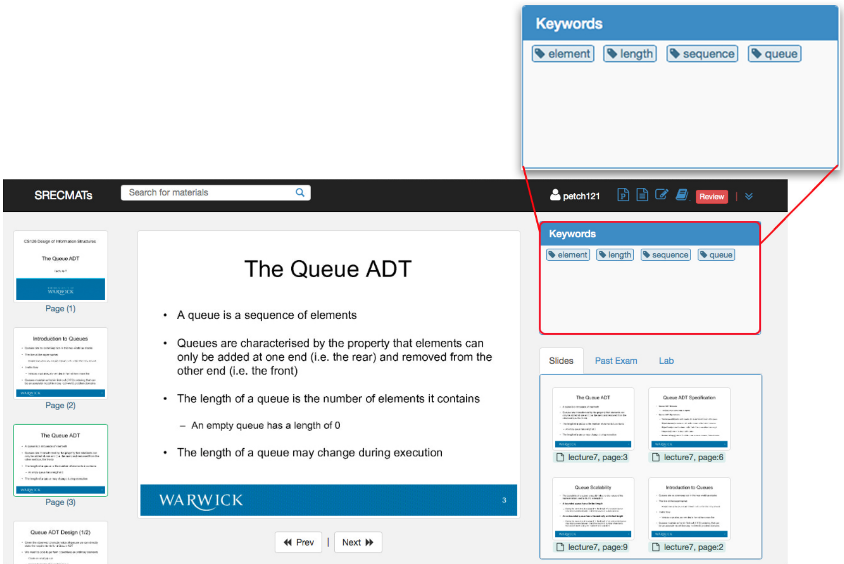


6.How would you rate "RECOMMENDING RELATED MATERIALS" function, based on the following statements: *

(Please rate from the following scale.)

	Totally Disagree	Disagree	Neutral	Agree	Totally Agree
I can start using this function without any tutorial.	○	○	○	○	○
This function allows me to navigate through e-materials easily and precisely.	○	○	○	○	○
I found that this function disturbs my ability to navigate through e-materials	○	○	○	○	○
This function reduces time I spend on browsing e-materials.	○	○	○	○	○
This function returns the right materials which I expected.	○	○	○	○	○
I prefer to have this function on the course website.	○	○	○	○	○

Keywords Tagging.



7. How would you rate ”KEYWORD TAGGING” function, based on the following statements: *

(Please rate from the following scale.)

	Totally Disagree	Disagree	Neutral	Agree	Totally Agree
I can start using this function without any tutorial.	○	○	○	○	○
This function allows me to gain overview of e-materials easily and precisely.	○	○	○	○	○
I found that this function disturbs my ability to understand e-materials	○	○	○	○	○
This function reduces times I spend on reading e-materials.	○	○	○	○	○
This function returns the correct technical terms which I expected.	○	○	○	○	○
I prefer to have this function on the course website.	○	○	○	○	○

8.Are there any comments or suggestions you’d like to share with us in order to improve the traditional course website or SRECMATs system?

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Send form