Lightweight Adaptive Personalised E-Advertising

By

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To My Mother's soul

To whom my heart belongs;

My Father and Brothers,

My Wife and Children.

Declaration

This thesis is submitted to the University of Warwick in support of my application for the degree of Doctor of Philosophy. I hereby declare that, except where acknowledged, the work in this thesis has been composed by myself, and has not been submitted elsewhere for the purpose of obtaining an academic degree.

Alaa A. Qaffas

Signature: _______________________________________

Date:____

Publications

Below, the publications written during the PhD research are listed, and their connection to the current thesis is explained. The work presented (including data generated and data analysis) was carried out by the author. In all of these cases, the contribution by the author has been greater than 80%.

1. **Qaffas, A. A.,** and Cristea, A. I., (2016). Lightweight Adaptive E-Advertising model. IADIS International Journal on WWW/Internet (to be submitted).

2. **Qaffas, A. A.,** and Cristea, A. I.,"An Adaptive E-Advertising Delivery Model: The AEADS Approach." The International Conference on e-Business (ICE-B 2016), Lisbon, Portugal, 2016 (Accepted).

3. **Qaffas, A. A.,** and Alexandra I. Cristea. "Large Scale Evaluation of an Adaptive E-Advertising User Model." E-Business and Telecommunications. Springer International Publishing, 2015. 137-157.

4. **Qaffas, A. A.,** and Cristea, A. I.,"An Adaptive E-Advertising User Model: The AEADS Approach." The International Conference on e-Business (ICE-B 2015), Colmar, Alsace, France, 2015.

5. **Qaffas, A.,** and Cristea, A.I., “How to Create an E-Advertising Adaptation Strategy: the AEADS Approach,” in The 8th Saudi Students Conference (SSC’15), London, UK, 2015.

6. **Qaffas, A. A.**, and Cristea, A. I., "How to Create an E-Advertising Adaptation Strategy: The AEADS Approach." E-Commerce and Web Technologies. Springer International Publishing, 2014. 171-178

7. **Qaffas, A. A.**, and Cristea, A. I., “How to create an E-Advertising Domain Model: the AEADS approach,” in The 2014 International Conference on e-Learning, e-Business, Enterprise Information Systems, and e-Government (EEE'14), Las Vegas, United State, 2014.

8. **Qaffas, A. A.**, Cristea, A. I., and Shi, L., "Is Adaptation of E-Advertising the Way Forward?" In Proceedings of 2013 IEEE Conference on e-Learning, e-Management and e-Services, Kuching, Sarawak, Malaysia, 2013. IEEE Computer Society (IC3e), 117-124.

I have also co-authored another set of publications as follows;

1. Shi, L., Al Qudah, D., **Qaffas, A.**, & Cristea, A. I. (2013). Topolor: a social personalized adaptive e-learning system. In *User Modeling, Adaptation, and Personalization* (pp. 338-340). Springer Berlin Heidelberg.
2. Shi, L., Cristea, A. I., Foss, J. G., Al Qudah, D., & **Qaffas, A.** (2013). A social personalized adaptive e-learning environment: a case study in Topolor. *IADIS International Journal on WWW/Internet*, *11*(3), 1-17.
3. Shi, L., Al Qudah, D., **Qaffas, A.**, & Cristea, A. I. (2013). To build light gamification upon social interactions: requirement analysis for the next version of Topolor. In *Proceedings of the Sixth York Doctoral Symposium on Computer Science and Electronics (YDS2013)* (pp. 1-5). Department of Computer Science, University of York

Abstract

Adaptation and personalisation is aimed at improving the user experience in e-systems. Personalisation was initially applied in the fields of distance learning and web-based educational systems. Adaptation can be also used in e-advertising, to increase customer satisfaction and encourage repeat visits to websites. Several models/frameworks have been designed for adaptation, for instance AHAM, LAOS, AdRosa, and MyAds. Many systems have been developed based on these frameworks. Most previous models/frameworks were primarily designed for personalised educational experience and were aimed at standalone systems, which cannot be (easily) integrated into existing websites in a lightweight manner. In addition, some of them are used in the portal model of advertising, since they match the interests of the publisher and the advertiser.

The aim of this work is to overcome the limitations and weaknesses of these models and systems to deliver adaptive advertising. This work firstly attempts to support and *facilitate the integration between adaptive systems and business websites*. It also introduces a method to control and adapt advertisements located and owned by businesses. This thesis further proposes *a generalised model, the Layered Adaptive Advertising Integration (LAAI)*, as the starting point for the development of an adaptive advertisement system. In a second stage, it presents a study that assesses the effectiveness of a *system (AEADS)* based on this model, via a trial run of a model prototype with users (*both customers and business owners*). In a third stage, social networks are used as inputs for the user model of customers, to enhance the efficiency of acquiring user information, as an addition to the user registration process. Furthermore, *social interactions*, such as the facility to use “like”, are added to the user model, and the delivery process has the ability to apply actions based on this data. Finally, an *evaluation of the whole system* proposed is conducted, with business owners and Internet users alike.

Keywords: adaptive e-advertising, personalisation, user modelling, user centred methodology, adaptation model, adaptation delivery, lightweight system.

Abbreviations

ADE	Adaptive Display Environment
AEADS	Adaptive E-Advertising Delivery System
AH	Adaptive Hypermedia
AHAM	Adaptive Hypermedia Application Model
AHS	Adaptive Hypermedia System
AM	Adaptation Model
DM	Delivery Model
DM	Domain Model
HTML	Hypertext Mark-up Language
JSP	Java Server Pages
LAAI	Layered Adaptive Advertising Integration
LAG	Layers of Adaptation Granularity
LAOS	Layered WWW AH Authoring Model and their Corresponding Algebraic Operators
MOT	My Online Teacher
SLAOS	Social Layered WWW AH Authoring Model and their Corresponding Algebraic Operators

UCD	User-Centred Design
UCE	User Centred Evaluation
UM	User Model
WebML	Web Modeling Language
XAHM	XML-based Adaptive Hypermedia Model
XML	Extensible Mark-up Language

Chapter 1

Introduction

1.1. Background and Motivation

Adaptive hypermedia systems can improve the efficiency and accuracy of the information distribution [23], by displaying or concealing the content to be adapted. They depend on storing user data that are represented by the user model, and adaptation specifications that are represented by the adaptation model [146]. The user model is initialised by user registration, and updated by the observation of user behaviour. The adaptation model is managed by the content owner. It contains the author's rules and strategies for managing the adaptation processes.

In modern times, the majority of online advertising systems are based on customer-based targeting [88]. Adaptation in this field aims to increase advertising effectiveness, by ensuring that the right person receives the right message at the right time and in the right context [3]. Design of appropriate adaptive hypermedia systems plays an essential role in adapting advertisements in a wide range of websites for Internet users.

The process of creating adaptive advertising is, however, complex [118], since there are many criteria that must be considered. When determining the most suitable advertisements for a particular user, several factors must be considered, including webpage content, users' interests, users' locations, search and buying history of the users, advertisement format, current user activity, advertisement home page content and the history of advertisements that a user has already been shown [86].

Whilst adaptive hypermedia has been the focus of many studies, the topic of lightweight adaptive advertising, on top of existing business websites, has not been properly researched and requires further investigation. This concept is important, especially for small businesses, since it can easily support the adaptation integration process. Most small businesses need to adapt their advertisements for their users, without any concerns about adaptation definition or techniques. In addition, they need to preserve their website's status, without modifying the structure. However, most adaptive hypermedia models attempt to provide adaptive content in the field of education [32, 50, 53, 67]. The models used in adaptive advertising are few and have some limitations regarding lightweight adaptive advertising, as well as the breadth of adaptation types facilitated.

This thesis presents *a new theoretical model to deliver personalised advertisements to Internet users with respect to lightweight personalisation specifications*. Based on this model, *a new system was implemented to adapt advertisements, which can be integrated with wide range of websites*. This model and its associated system aim to overcome the limitations and disadvantages of the previous models/frameworks, by using different views and structures. Essentially, the research identifies how they can be improved and enhances the generalisation, portability and efficiency of the user model and delivery model, to help a range of businesses adapt their advertisements, based on the users' profiles and behaviours, to enrich their satisfaction.

Finally, the evaluation shows that the AEADS system built based on the LAAI model chooses the most appropriate advertisements for the users, based on their data. It is successful in most instances, as will be shown in Chapters 8 and 9, sections 8.3 and 9.4.

1.2. Research Questions and Objectives

The research aimed to address the following main generic research question, which has an exploratory nature:

R0: Does adaptation/ personalisation of advertising make sense?

This research question can be explored in many ways, but here it is assumed that lightweight adaptive advertising is superior, by offering a set of tools for the creation and authoring of adaptive advertising, which support the delivery of personalised advertisements to Internet users. These tools are implemented based on a new model, designed to support and facilitate the integration between adaptive systems and most websites. Therefore, the main research question (**R0**) can be addressed by answering the following sub-research questions.

R1: Is adaptive advertising useful for businesses and users?

R1.1: Is it more acceptable for users to have adverts personalised to them and their environment? (i.e., do users find personalised adverts more acceptable than non-personalised)

R1.2: Is it more acceptable for businesses to deliver adaptive advertising? (e.g., do business users find adaptive advertising more acceptable when compared to non-adaptive advertising, and do they expect the former to provide a better income)

R1.3: What is a good source of information for adaptive advertising?

R2: How can we create a model for lightweight adaptive advertising and design the corresponding system that can be integrated with most websites?

R3: How can we support website owners in the creation of adaptive advertising, in order to be able to efficiently add adaptive advertising in a lightweight manner to their website?

The following objectives are defined, to answer the research questions mentioned above. The connections between research questions and objectives are illustrated in Figure 1.1.

O1: Review the state of art in the area of adaptive advertising, as well as related areas such as web personalisation and e-advertising, in order to find information for creating a model of adaptive e-advertising.

O2: Design a set of preliminary studies with businesses and users, to establish the current state of art in the area of adaptive advertising and to gather the requirements for the design and implementation of an appropriate theoretical model and system.

O3: Based on the outcomes from O1and O2, propose an appropriate theoretical model (new or extended) for lightweight adaptive advertising.

O4: Based on the outcome from O3, implement tools for the theoretical model, to support the creation of adaptive advertising by website owners.

O5: Implement a delivery engine that resides on the businesses' own websites, to support delivering personalised advertisements to the users.

O6: Evaluate each design and implementation step, both technically and, where appropriate, with real businesses and internet users.

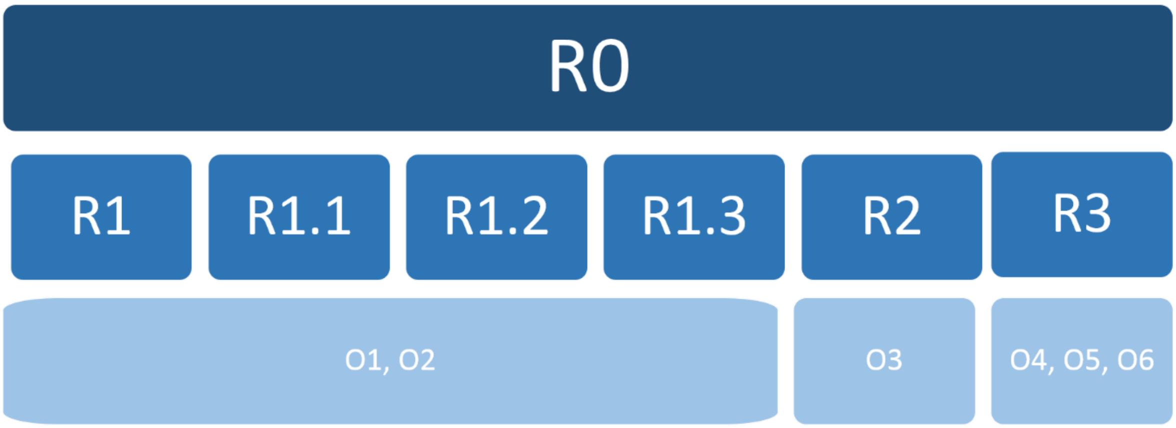

Figure 1.1 Research Questions and Objectives Connection

1.3. Original Contributions of the Thesis

A short preview of the original contributions of this thesis is summarised below.

- A flexible, extendible *theoretical model* for lightweight adaptive e-advertisements (see Chapter 5).
- A *system* for lightweight personalisation specifications, which can be added to existing business websites, implementing and illustrating the above model, as well as providing the opportunity to test and evaluate it (see Chapters 6-9).
- Innovative functions and features in an attempt to facilitate the authoring of adaptive advertisements; these include a simple (lightweight) *domain model tool* (see Chapter 6) that allows easy creation and organisation of adaptive advertisements, and a simple (lightweight) *adaptation model tool* (see Chapter 7) that enables easy application of adaptation rules.
- *Adaptation rules* in the *adaptation model*, which are separated into two groups – *general* and *behaviour* – in order to facilitate authoring and to ensure that advertisement adaptation is

simple, yet relatively comprehensive – giving thus clear hints to businesses of the type of adaptation rules expected from them (see Chapter 7).

- A *lightweight user model*, which includes several features, such as *simple user profiles*, *social media layer*, *automatic data retrieval*, *handling negative responses to advertisements displayed to end users*, and *future advertisements* (see Chapter 8).
- The *future advertisements* component in the user model includes advertisements that will be shown to each user in the future, based on the previous components in the user model and delivery model (see Chapter 8).
- Furthermore, the methodology includes a *lightweight and integrated delivery model*, which incorporates three engines (*inference*, *decision* and *modifier*) to facilitate adaptation and personalisation. The advertisement's location on the webpages can be easily chosen by business owners – for their own convenience, or for the convenience of Internet users (see Chapter 9).
- An evaluation of both theory and the real system by business owners (see Chapters 6-9).
- As well as an evaluation by a large number of Internet users, whose data usage has also been tracked (see Chapters 8, 9).

1.4. Thesis outline

The thesis consists of ten Chapters organised as follows:

Chapter 1 provides an introduction to the aims, background and motivation of the study. It presents the questions posed by the researcher and their aims, and a précis of the means by which the study was undertaken.

Chapter 2 provides the research methodologies that were used in this study and how they directed data collection, implementation, and evaluation.

Chapter 3 presents relevant related work, initially providing an introduction to advertisements adaptation, including the evolution of adapting frameworks within hypermedia and their various schemes. Consequently, it assesses the models and frameworks for adaptive hypermedia in general, and the models and frameworks for e-commerce in particular, to assess their benefits and shortcomings, and determine the course of this study. Finally, it presents the adaptive hypermedia system, to describe the innovation's design and implementation.

Chapter 4 contains a description of the experiments undertaken. The User-Centred Design (UCD) methodological approach was applied to assimilate real-life requirements of businesses and Internet users. It indicates the initial requirements for proposing and developing an appropriate model and system for adaptive advertising, as a result of the experiments, and gathers the implementation needs.

Chapter 5 contains details on the LAAI model that has been proposed based on previous models, and explains each layer and component separately. To assess this model, a new system, AEADS, was implemented, tested and evaluated by businesses and Internet users.

Subsequently, **Chapter 6** introduces a domain model and tool for lightweight adaptive advertising, which is the main tool for authoring adaptive advertising. It can be used by business owners to organise, label and categorise advertisements. In addition, companies in the United Kingdom and Saudi Arabia evaluated this tool. Furthermore, this Chapter includes a comparison with other domain models from different fields.

In **Chapter 7**, a model and tool for creating personalisation specifications for businesses (adaptation model) based on adaptation rules is introduced. The Chapter implements and evaluates a version of this tool. Moreover, this Chapter includes a comparison with other adaptation models for other systems.

Chapter 8 focuses on an automated, simple, lightweight user model, which can be easily integrated into an existing system (storage and operation), thus acquiring the ability to retrieve the user's general data and monitor their behaviour, while browsing the website. It also presents a study that assesses the effectiveness of a tool based on this model, via a trial run of a model prototype with users.

Chapter 9 presents the integrated model for lightweight adaptive advertising implementation, which is resident on the same server, to deliver advertisements to Internet users. This part parses the contents in XML files and uses adaptation rules to send the appropriate advertisements to the appropriate user, based on their user model. Internet users and business owners were used to test and evaluate this model. This Chapter also contains the implementation of the second iteration of the toolset of the AEADS system.

Finally, **Chapter 10** assesses the thesis with regards to a generalised research progression, and a discussion of general attainments, affects and contributory elements. It also suggests areas for future research in this field.

Chapter 2

Methodology

2.1. Introduction

This Chapter aims to introduce the research methodologies that have been used in this study and how these have directed data collection, implementation, and evaluation. The main aim of lightweight adaptive advertising is to deliver personalised advertisements to Internet users. As stated in Chapter 1, this research examines a set of tools for authoring and delivering adaptive advertising, and facilitating the integration of this advertising into most websites. The currently applied research strategy comprises a variety of key stages, including the literature review, user-centred design, iterative and incremental development and implementation, evaluation and investigation, and user-centred evaluation, as outlined below.

2.2. Literature Review

The first stage of the work within the thesis includes the stipulation of the overriding research question, both described and advanced within the former section. The literature review included in Chapter 3 was completed to assess the contemporary objectives and uses from former experience. The period of review commences in 2012, and is further modernised, up to the completion of the study, to 2016. This focuses upon the areas of adaptation with regard to e-advertisement, adaptation techniques and technology, adaptation models/frameworks, as well as previous adaptation systems, in both the field of e-advertisement, targeted in this thesis, and e-learning, which is the main original field of application of e-adaptation. Chapter 3 provides an appropriate and relevant definition of each of these, and identifies the value of this research in the context of the current state of the art.

2.3. User-Centred Design (UCD)

User-centred design (UCD) is defined as a multidisciplinary design approach that endeavours to actively involve users, with the aim of improving the understanding of designers, bettering the quality of technological products, fulfilling task requirements, and iteratively designing and evaluating products to achieve optimal functionality [100]. As a result, it is posited by some [100] that user-centred design is considered key to product usability and usefulness. That is, user-centred design is a fundamental method of working, through which designers can overcome the limitations associated with conventional system-centred approaches.

Thus, the use of *user-centred design (UCD)* [107] must be considered from the initial construction stages onwards, so that more user-friendly systems can be built [112]. When systems are built specifically answering the needs of end-users, they are inevitably far better at providing what end users actually want. Potentially, end users will also be motivated to use additional features, thus enabling them to get more out of the system at an earlier point.

Especially in business ventures and commercial applications, involving users early on can render benefits [15, 56, 65, 135].

The methodology used in this research thesis, which is focusing on advertising, which is a major component for any business, is thus the *user-centred design (UCD)*. The primary step in consulting users, both advertisers and consumers, is gathering a pool of design needs that should be addressed in the theoretical model and system's construction.

At the initial planning stage, *user-centred design (UCD)*, *questionnaires* and *interviews* methodologies, were adopted, in order to specify users and businesses' requirements. Chapter 4 outlines the exploratory study that has been carried out using these methods, with the aim of identifying a set of requirements for an *initial theoretical model* and *adaptive e-advertising system*, as well as correlating concerns and preferences for future research.

Thus, the benefit of using this method is to produce an appropriate methodology for authoring and delivering adaptive advertising. Helping business owners to adapt their advertising, and for their

Internet users to receive personalised advertising, is the main focus of this research. The reasons for using this methodology results from the discussion points outlined above, and its primary connection to the research questions.

Nevertheless, there are some drawbacks associated with the user-centred design methodology. For example, it can result in extra costs and slower development. These issues may present themselves during the process of creating experiments, examining results and determining the validity of findings. [112].

Given the above background information on user-centred design, the research presented in this thesis adopts UCD due to its emphasis on the need to explore the desires, interests, and needs of users, as well as the uses they intend for adaptive e-advertising. The significance of user involvement in design and development processes can no longer be ignored, because of their contribution to the effectiveness, efficiency, and safety of products [1]. For this reason, this study made use of *existing businesses* and *Internet users*, as can be seen in Chapter 4.

Various design methodologies have been investigated and explored with the conclusion that, given the focus on UCD, the one best suited to this research is the *ISO-standard 13407* [78]. The user-centred design process has been described as a collection of "Human-centred design processes for interactive systems" [78]. This standard outlines methods through which to attain high levels of quality, by utilising the UCD process for interactive computer-based products. The standard explains UCD as an iterative system, which involves human elements, and an understanding of ergonomics and methods, with the aims of bettering effectiveness and efficiency, improving employee conditions and preventing any possible negative effects on health, well-being and performance. Four user-centred design stages are adhered to, as shown in Figure 2.1, and this needs to be carried out, starting from the earliest point of the research [99, 139].

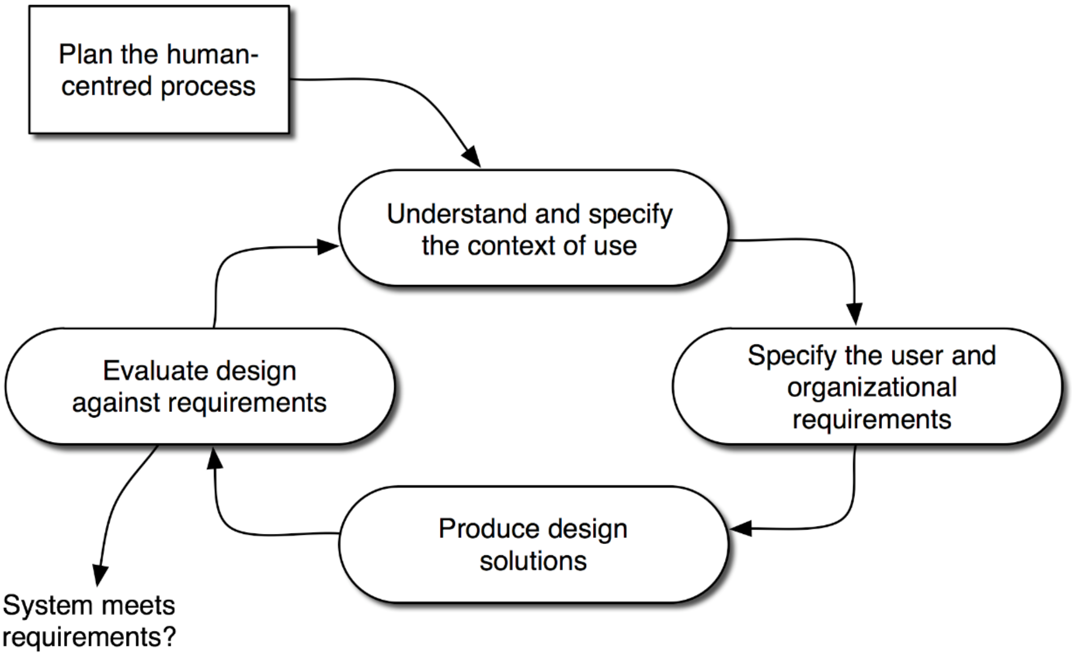

Figure 2.1 The user-centred design process, ISO-13407 [78]

2.3.1.First Stage: Understand and Specify the Context of Use

Figure 2.1 shows the scheme of the iterative user-centred design process, as described by the ISO-13407 [78, 99]. This methodology was adopted at this stage of the research by applying the ISO-standard 13407 process. When using ISO-standard 13407, *'understand and specify the context of use'* must initially be applied. This was implemented during the early stages of the research, as presented in Chapter 3. The intention is to specify the suitable and applicable concept, while readdressing the developmental stage and providing a synopsis of the advantages and risks. This will enable others to see how the research is most useful and provide a context for its use.

However, the crucial step was to make a decision regarding the main participants in the experiment [17]. This needed to be completed, prior to the planning of the experiment. Following the decision regarding participants, gathering the necessary materials for the experiments was required. Finally, an appropriate process to carry out the experiment needed to be selected. In this research, both the end-users and the business owners are required to participate in the e-advertising domain research, as further discussed in section 2.5 below.

2.3.2. Second Stage: Specify the User and Organisational Requirements

The next stage is to *identify the specific users and businesses' needs*. To ensure that the users are an integral part of every stage of the process, there are several empirical methods that can be used, such as interviews and surveys. Each method has its own advantages and disadvantages. Nevertheless, Henrik Lindström and Martin Malmsten [99] propose interviews, questionnaires and field studies as appropriate initial steps. These steps involve comprehending and identifying the conditions of use, and identifying the user and organisational needs. This means that users need to be identified, as does the context in which they will use the system, and the reasons for their use. Thus, interviews and questionnaires are highly appropriate for creating real design solutions. As a result, some of the principal empirical methods used by researchers centre on the objective of identifying the needs of the user and organisation (second step) through the use of *questionnaires* and *interviews*. These methods are employed, as they are proven to be the most suitable means of obtaining information [9, 143]. They were chosen as the most effective methods of gathering data for the research in this thesis and were used to collect information and identify needs. The description of the way the questionnaires and interviews are applied in practice is provided in Chapter 4, section 4.2.

2.3.3. Third Stage: Produce Design Solutions

The third stage involves *constructing designs and prototypes*. To bring together elements of primary importance, as identified by businesses and users, along with those founded on previous hypermedia adaptation models and frameworks, this research proposes a new, extendable, model called *Layered Adaptive Advertising Integration (LAAI)*. The model attempts to initiate typical concepts to form a foundation for the creation of advertising adaptation applications and to enhance the portability of such applications. The model guarantees the separation of content, adaptation needs and delivery in an adaptive advertising application, as detailed in Chapter 5. Furthermore, a system is proposed as the means of assessing the LAAI model's suitability for advertisement adaptation. The system enables business owners to classify their advertisements and alter them according to their users' needs and responses, as detailed in Chapters 6-9.

2.3.4. Fourth Stage: Evaluate Design Against Requirements

Implementing a user-based analysis of the system comprises the fourth stage in the process. When collecting data for analytical research, there are two possible methods that can be used. The first involves using *direct answers from users*, which can be completed by direct surveys and asking them to assess the system after trying it. The other method involves *monitoring users' behaviour* on the system and gathering information on their usage. Each implemented tool has been evaluated with, when appropriate, Internet users and business owners, as detailed in Chapters 6-9.

2.4. Iterative and Incremental Development and Implementation

This study is conducted using the iterative and incremental development model [95], which was established in order to address the Waterfall model's limitations [124] as a cyclic system development process. Using this model, it was possible to utilise iterative (i.e. repeated) cycles that occur incrementally. Both technological changes and alterations to the specification can be met effectively through the use of iteratively-looped process flows. A clear set of objectives are contained within each iteration. Furthermore, every iteration entails evaluation, implementation, design and other development processes. The system's refinement and evolution is achieved through a series of iterations, each of which extends upon the prior iteration. This approach allows to effectively maximise the understanding of both the early system version and development iteration through the adoption of the iterative process. Chapters 4-9 of this thesis discuss the design, implementation and evaluation stages involved in the iterative process with regards to the method's ability to balance, thread and combine the degree of social interaction and adaptation.

XML [57, 136] was used as an internal format for the AEADS system. The XML format was used to represent data within the AEADS system, instead of using a relational database, for a few reasons. This choice of format supports the integration process of the AEADS system within a wide range of websites, as well as it is also an easy-to-use, straightforward format, which thus corresponds to the major goal of this research. This is because this method allows the AEADS system to be integrated into a wide range of websites, regardless of the type of database that can be supported. In addition to this, the *lightweight* concept that is supported by this research is ultimately achieved by using the

XML format. This method overcomes the potential complexity of the relational database design. Decreasing the number of tables – merged and replaced by an XML file – and adjusting and simplifying the structure to support the type of queries required in order to retrieve data, is a very important reason to utilise the XML format. Furthermore, some of the adaptive hypermedia systems have proposed using semantic web languages (mainly XML) for the internal representation of the various authoring tools [48, 144]. For this reason, XML was also used as internal format for the AEADS system.

The Java language [8, 18] was used for the AEADS system implementation, as it is an independent platform and so it can (in principle) be run on any machine, regardless of the hardware and software present. Aside from this, the available packages within the Java language can ease the developing process of the AEADS system. The Java language also allows various facets of the AEADS system to be designed as an applet, which can enhance the interface and overall performances of these parts. This can also support any future moving of any part of the system within the server and so it can be accessed by any client. Furthermore, some of the adaptive hypermedia systems have proposed using the Java programming language – such as, e.g., ADE [127]. For this reason, the Java language was also used for the AEADS system implementation.

2.5. Evaluation and Investigation

A number of case studies have been undertaken, to collect responses from end-users, including business owners and Internet users, through authoring and presenting personalised advertisements. Businesses and Internet users are required to fill in a questionnaire that uses a Likert scale [98] and retains their anonymity. Additionally, oral responses from a number of businesses and Internet users are assimilated. Several elements of the system are assessed on their efficacy, proficiency and user content. A user model tool is utilised to assess logging information, to both determine the customer's behavioural trends and to comprehensively understand the means by which innovation affects the customer's experience. More discussion about user centred evaluation is presented in section 2.6 below.

As the target users of e-advertisements are all Internet users in the whole world, the ideal sample for an e-advertising study should come from a cross-section of this population. There are currently around 3 billion Internet users around the world [77]. A suitable sample group in this case requires 267 participants to provide a confidence level of 90; alternatively, a sample group of 377 would result in a confidence level of 95 [120]. Members of the sample group should ideally come from different countries.

However, in reality, it is often difficult to find such a large spread of population to involve in a study, and hence, alternatives must be found. For instance, prior research [128] has used a smaller spread population of 21 participants for the study, while a further study [4] used a sample size of 47 participants.

Moreover, the AEADS toolset (as introduced in Chapters 8 and 9) have been evaluated by students studying different subjects and modules (Introduction to Business, Principles of Marketing, Management Information System and E-Marketing) at King Abdul-Aziz University in Jeddah, Saudi Arabia. Students were deemed to be a relevant and appropriate sample population for testing for several reasons. The majority of students are Internet users and regular online shoppers, and are thus familiar with current online providers. Furthermore, as the study required a large sample population of users, students were deemed suitable participants, as it simplified access. It must be noted that, although all students within the sample population were familiar with the Internet and Internet use, they were not all Computer Science specialists, as the sample incorporated students studying a wide range of subjects, from different backgrounds, with a variety of knowledge and interests. However, using a sample of students does also present some drawbacks to the approach, as, whilst they represent the young population knowledgeable about the Internet and its tools, especially e-business tools, they do not represent the population as a whole.

Moreover, there are formulas to compute the ideal sample size for target population. For e-advertisements, as stated, the target population size is of 3 billion [77], and thus the ideal sample size is of 377 for a confidence level of 95 [120]. However, in practice, it is also very difficult to carry out a study with such a large scale sample. In fact, as mentioned, prior researchers have drawn conclusions from much smaller studies, such as in [4, 128].

The sample sizes have been kept as close as possible to the ideal number in this thesis, as follows.

1. In the data gathering stage, 138 Internet users responded out of 380 invitations (as described in Chapter 4, section 4.2).
2. In the evaluation of the user modelling tool, there were 134 Internet user responses out of 305 invitations (as described in Chapter 8, section 8.3).
3. In the evaluation of the whole AEADS system, including the domain model (DM) tool, adaptation model (AM) tool, user modelling tool, and delivery model (DM) tool, the sample was made up of 381 Internet users out of 450 invitations (as described in Chapter 9, section 9.4).

An important point is that both the end-user and the business owners are required to participate in the e-advertising domain research. Prior research does not always take this into account, for instance [5] only looked at the impact on the users, and not on the business owners. In contrast to this, evaluations have been carried out with both end-users, as well as business owners, in this thesis.

1. In the data gathering stage, two questionnaires have been designed, one for the Internet users and one for the business owners, to identify both points of view (as described in Chapter 4, section 4.2).
2. In the evaluation of the domain model (DM) tool, an evaluation with business owners has been performed, as this is one of the authoring tools and will be used for authoring advertisements (as described in Chapter 6, section 6.3).
3. In the evaluation of the adaptation model (AM) tool, an evaluation with business owners has been performed, as this is one of the authoring tools and they will use it for authoring their advertisements (as described in Chapter 7, section 7.4).
4. In the evaluation of the user modelling tool, an evaluation with Internet users has been performed, as this is one of the tools they will use (as described in Chapter 8, section 8.3).

5. In the evaluation of the whole AEADS system, including the domain model (DM) tool, adaptation model (AM) tool, user modelling tool, and delivery model (DM) tool, an evaluation was carried out with both Internet users and business owners, as both points of view were needed for the overall picture (as described in Chapter 9, section 9.4).

For business owners, the number of individuals interviewed is less important, as they can be considered experts, and their interviews represent gathering of expert opinions. Moreover, the spread of Internet businesses they represent is more interesting than their actual numbers. Prior research has only been carried out with Internet users [4]. In the research presented in this thesis, a good spread of businesses over the Internet has been included.

1. In the data gathering stage in Chapter 4, the business types involved were financial, manufacturing, real estate, transportation and marketing.
2. In the evaluation of the domain model (DM) tool in Chapter 6, the business types included communication, construction, consulting, media, online education, trading, training and transportation.
3. In the evaluation of the adaptation model (AM) tool in Chapter 7, the business types were media, transportation, consultation, retail, telecommunications, construction and web-based education services.
4. In the evaluation of the whole AEADS system including domain model (DM) tool, adaptation model (AM) tool, user modelling tool, and delivery model (DM) tool in Chapter 9, the following business types were represented: construction industry, online education industry, telecoms industry, retail industry, consultation industry, transportation sector and the media industry.

2.6. User Centred Evaluation (UCE)

The evaluation of user centred systems is notoriously difficult, primarily as the field is subject to a large degree of bias and there are also numerous factors to take into account. The first stage is a subjective evaluation, which is made on the basis of questionnaire responses and interview findings

[75]. The second stage involves an objective evaluation, carried out based on the data log files that are generated through the practical usage of the software [68].

The most popular and widely used method of evaluating user experience is the *user centred evaluation (UCE)* framework, which analyses the attitude of the users and their perception of the quality of service offered by the application, from a subjective standpoint. This approach is an effective means of appraising experimental systems and evaluations [72, 140].

In this research, the evaluations concentrate primarily on *effectiveness* and *efficiency*, as these attributes can be applied to evaluate which specific aspects of the software played a key role in satisfying businesses and users expectations and eliciting businesses and users' acceptance as well as systems' high level performance.

Likert designed a summative ranking scale referred to as the *Likert scale* [98]. This scale is widely used in the field of research, particularly when using questionnaires, as it is the simplest rating scale to compile [81], as respondents are asked to indicate the extent of their agreement or disagreement with a given statement [34]. For the purposes of the research presented in this thesis, a Likert scale was provided, as a response option for the closed-ended questions. Moreover, each statement had a corresponding *neutral midpoint*, using five ordered response levels (e.g. 1, 2, 3, 4, and 5) in the Likert scale, to prevent an acquiescence bias.

Furthermore, as usability is generally connected to system functionality, this study assesses system granularity on two levels, in terms of *effectiveness* and *efficiency*. These levels include the overall system and sub-system functionalities.

The highly regarded *System Usability Scale (SUS)* [22] is employed to evaluate the first level, the overall system, and contains a ten-item Likert scale to provide a broad overview of business owner's and Internet user's perceptions, regarding overall usability. This scale was designed by Brooke in 1966, to quickly determine the response of consumers to a specific product or service. This scale is widely used in the field of research and business and is also cheap, as it is non-proprietary. Furthermore, as this scale is technology agnostic, SUS can easily be adapted to assess a variety of items, such as websites, applications, software or hardware. The scale is also quick and easy for both researchers and respondents to use, and generates one score on the scale, which is simple to interpret [10]. These ten items or statements are listed below.

1. I think that I would like to use this system frequently.
2. I found the system unnecessarily complex.
3. I thought the system was easy to use.
4. I think that I would need the support of a technical person to be able to use this system.
5. I found the various functions in this system were well integrated.
6. I thought there was too much inconsistency in this system.
7. I would imagine that most people would learn to use this system very quickly.
8. I found the system very cumbersome to use.
9. I felt very confident using the system.
10. I needed to learn a lot of things before I could get going with this system.

A five-point *Likert scale* which ranges from ‘strongly disagree (1)’ to ‘strongly agree (5)’ is used to measure the ten statements in the SUS. This scale switches between being positive and negative, thus, a more effective rating scale would assign higher values to Questions 1, 3, 5, 7 and 9 and lower values for Question 2, 4, 6, 8 and 10. The score generated by the SUS falls between zero and one hundred with a higher score indicating a higher degree of usability. Thus, an outstanding system would obtain a score of 90+ while a good system would obtain a score of between 70 and 80 [10].

The *Likert scale* was also applied in further questions, which were posed to judge the *effectiveness* and *efficiency* of sub-system functionalities. In doing so, each question referred to a single system function or feature, with particular emphasis on its *effectiveness* and *ease of use*. A five-point Likert scale was provided which ranged from ‘very useless/hard to use (1)’ and ‘very useful/easy to use (5)’. The evaluation processes discussed in Chapters 6-9, sections 6.3, 7.4, 8.3 and 9.4, utilised this *Likert scale* questionnaire.

The validity and credibility of the questionnaire must be guaranteed by the analysis method used to process the data collected using the research methods discussed [122]. Descriptive statistics were then applied to synthesise and discuss the findings.

For the purposes of this study *Cronbach's Alpha* [51], is employed to measure reliability, as this method is suitable for the measurement of internal consistency, particularly as the present study includes *Likert scales*.

Cronbach's Alpha has a theoretical value, which ranges from 0 to 1. Although there is no minimum value for this measurement, a higher level of internal consistency is indicated by a score close to 1.0. As illustrated in Table 2.1 [66], George and Mallery argue that a *Cronbach's Alpha* value of at least 0.8 is desirable [69]. Therefore, to determine the reliability of the evaluation processes in this study, a baseline *Cronbach's Alpha* value of 0.8 has been set (sections 6.3, 7.4, 8.3 and 9.4).

Table 2.1 Rule of thumb for describing internal consistency [66]

Cronbach's alpha	**Internal Consistency**
$\alpha \geq 0.9$	Excellent (High Stake Testing)
$0.7 \leq \alpha < 0.9$	Good (Low Stakes Testing)
$0.6 \leq \alpha < 0.7$	Acceptable
$0.5 \leq \alpha < 0.6$	Poor
$\alpha < 0.5$	Unacceptable

In order to ascertain if two sets of data are significantly different, it is necessary to apply a statistical hypothesis test which, for the outcome of this study, is the *T-test* [125] and this deals specifically with inference difficulties related with having "small" samples. In sections 6.3, 7.4, 8.3 and 9.4 the evaluations are all based on the paired T-test and they each contain a comparison of the average score of all of the features and functions with the neutral response of (3). It was found that the result was significant at $p \leq 0.05$ (which is the normal significance threshold expected within statistical significance research areas). Furthermore the *Mann-Whitney U test* [125], which is a nonparametric test, has also been used in all of the evaluations found in sections 6.3, 7.4, 8.3 and 9.4 and again contains a comparison of the average score of all of the features and functions with the neutral response of (3). The *Mann-Whitney U test* is important as it performs two functions; firstly it compares two population means from the same population and secondly it also tests whether two population means are equal or not. In this case, it was found that the data reflected a normal distribution at $p \leq 0.05$.

2.7. Conclusion

This Chapter has introduced the methodological approaches that have been used during the course of this research. The literature review has been used from the outset of the research to specify the appropriate and relevant definition, and readdresses the development stage, providing a summary of benefits and problems, as well as identifying the value of this research. Based on the ISO-standard 13407, a user-centred design methodological approach is also used in this thesis, to examine the preferences of Internet users and business owners, and to collect data on adaptive advertising that lacks clarity. In addition, the iterative and incremental development model has been used for a cyclic system development process. Moreover, the user centred evaluation approach is employed in this research to assess system's usability, usefulness, credibility and accessibility. The discussions of the pros and cons of each evaluation in this study are also discussed in this Chapter. Next, the literature review and background literature for all the research performed in the thesis will be briefly presented in the following Chapter.

Chapter 3

Background and Related Literature

3.1. Introduction

This Chapter aims to address the research objective **O1:** "*Review the state of art in the area of adaptive advertising, as well as related areas such as web personalisation and e-advertising, in order to find information for creating a model of adaptive e-advertising*". Moreover, this Chapter of the thesis discusses the literature review and background research conducted to support the answering of research questions **R1:** "*Is adaptive advertising useful for businesses and users?*", **R1.1:** "*Is it more acceptable for users to have adverts personalised to them and their environment? (i.e., do users find personalised adverts more acceptable than non-personalised)*", **R1.2:** "*Is it more acceptable for businesses to deliver adaptive advertising? (e.g., do business users find adaptive advertising more acceptable when compared to non-adaptive advertising, and do they expect the former to provide a better income)*", and **R1.3:** "*What is a good source of information for adaptive advertising?*".

As part of the purpose of the research presented in this thesis, the literature review has been conducted as a major data collection exercise that was used to gather information to address the specific objectives. From the background of the study, it would be noted that there is great deal of literature about adaptive e-systems. I approach the literature instead from a perspective that narrows the scope of review solely to adaptive e-advertising systems. Therefore, it was considered important to discuss means by which adaptive advertising could be made easier for businesses, and more appealing to customers, and the aim of this literature review is to provide a detailed discussion on the different types of adaptive hypermedia models and frameworks, adaptive e-advertisement models, adaptive hypermedia systems such as MOT and ADE, and adaptive e-advertisement systems, including AdRosa and MyAd.

The Chapter is structured as follows. The next section discusses advertisements in general, including e-advertisements, and ways of targeting customers before adaptation. The following section contains definitions of the meaning and principles of *adaptive e-advertisement*. This is followed by descriptions of the various adaptive hypermedia models and frameworks that have been proposed, such as AHAM and LAOS. Next, various adaptive hypermedia systems are presented. Following that are explanations of the adaptation techniques, the structure of the user model, and insertion of the social interaction in the adaptation process that are used in this research. The current Chapter finally wraps up with a conclusion.

3.2. Advertisement in General

The type of advertisement is one of the most important decisions that a marketer has to make as it determines how the public will receive the products or the services offered. This, in turn, affects the revenue, profitability and the competitive advantage that the company will have over its rivals or those that deal in the same line of business. Initially, the main aim of advertising was to bring to the attention of the consumers the products or services offered by the business. However, Johnson [80] argues that currently firms have come to the realisation that for advertisements to be effective, they should be carried out in the right way and directed at the right people or audience. The advertisement also has to be adaptive to the needs of the population or consumers.

Companies therefore have to have the knowledge and the capabilities of directing their advertisements to each segment of the consumers in the market. This ability is only achievable due to the changes in the market that dictate the information that the consumers have about the products and the services, their preferences and how the media presents the products in the market [79]. This has been helped by the ability to collect, collate and process information about consumers and ensures that the advertisement meets the desires, attitudes, values and demands amongst other aspects of the consumers' needs. *Targeted advertisement*, r*ecommended advertisement* and *adaptive advertisement* are the basis of effective e-adverting in the current global market.

Targeted advertising is where advertisements are positioned to reach customers based on various traits, for example demographics [90]. Recently, the introduction of social media sites, such as Facebook, Instagram and Twitter has created new consumer demographics. Most companies use these sites to advertise and assist them to reach new customers [39]. Unlike adaptive advertising that utilise modern technology, targeted advertising uses both modern technology, such as the Internet, and traditional broadcast methods, for example television, to reach its customers. As such, this method does not require customer feedback for it to function efficiently [111], unlike in adaptive advertisement, where it is crucial. Thus, customers in targeted advertisement may not receive the best quality products, since there is no way to ensure that the products offered to them are the ones they require. Due to this reason target advertisement may not assist a company in attaining competitive advantage.

Recommended advertisement is where a person relies on information they get from a friend, relative or a website [73]. Information from a friend is usually conveyed through word of mouth and can influence an individual to purchase an item, thus acting as a form of advertisement for the company. This method of advertising is usually valuable for a corporation and can increase the sales of a product, due to positive publicity [108]. Further, recommended advertisements also appear on websites, potentially also related to the content of that webpage or search.

Adaptive advertisement, further discussed in the next section, can potentially be more effective than recommended advertisement with regards to reacting to customer feedback, since it provides a platform for customers to air their views.

3.3. Adaptive E-Advertisement

Adaptive hypermedia (AH) [28, 33] represents an opportunity to increase personalisation, whereby links to other relevant websites or content are tailored to the individual, to create a more personalised experience. Such technology helps customers by improving the efficiency and accuracy of the delivery of information. E-learning is the first, and most famous, field of adaptive hypermedia research. While e-advertising is an increasingly profitable industry that continues to grow rapidly year-on-year, adaptive e-advertising is becoming a key to maximising the effectiveness of advertisements [118], as the research presented in this thesis shows in a more thorough manner, from various points of view. This thesis is based on the adaptive hypermedia research area as a source to provide or to guide in developing a model and system for adaptive e-advertising.

In the adaptive e-advertising model, advertisements are designed to adapt in line with the evolution of customer behaviour and the country or region a company operates in. This form of advertising typically helps companies to cater for various customer needs, and thus can assist an organisation in its efforts to penetrate new markets, and build and maintain its brand. Technology advances and the emergence of new ways of selling products – such as online marketing – have enabled organisations to develop advertisements that enable them to adapt to changes in the environment [11]. As such, these methods challenge the traditional modes of advertising in which advertisements are presented to a general audience with little direct feedback. Adaptive advertising has, therefore, improved the ability of companies to present the right product to the right customer base, by improving the level of feedback they receive regarding each advertisement [11, 137].

In principle, organisations that implement adaptive advertising enjoy many operational advantages, compared to those that utilise traditional methods. A key benefit of the use of adaptive advertising is the generation of commercial value in the form of higher sales and a clearer picture of how they can improve their products [123]. As such, organisations that act on the feedback provided by customers on their product pages can gain a competitive advantage, by implementing suggestions on how to improve their products. This approach helps to ensure higher levels of satisfaction for existing customers by ensuring they are getting the goods that they want or need [14, 130], and can also help to attract new customers by building the company's reputation for quality. That, in turn, can help to build brand awareness.

Adaptive advertisement models have allowed organisations to explore new opportunities, due to the fact that they utilise modern technology that can reach people who are miles away from the company's traditional markets, unlike the traditional methods of advertising, which tend to be more localised. Technological innovation has provided a crucial platform for the advancement of adaptive advertisement. For example, the adaptive advertising method enables real-time delivery of information to its audience and also direct feedback from the customers.

The earlier adaptation models and frameworks were mostly targeting the education field, which is not appropriate for adaptive advertising. There are some major differences in terms of educational adaptation and adaptation for advertising. One of the most important is the need for a coherent narrative for educational adaptation, which is often irrelevant in adaptive advertising. Another one is related to the type of user model attributes that play a role in the adaptation process: knowledge, for instance, is vital in educational applications, whereas taste is more relevant in adaptive advertising. Even for user model attributes which seem similar, there are differences. For instance, whilst both application fields can benefit from tracking the user behaviour, in education, this refers mostly to the learning process, whilst in adaptive advertising, the viewing and buying profile are of importance. Thus, taking into account the differences in user information, user behaviour tracking, domain, adaptation rules that can be applied, and in the delivery process are key for developing a precise model or framework for adaptive advertising. For this reason, just applying previous models and frameworks cannot be performed, without properly ensuring the correct elements are present – and the unnecessary elements are dropped. Moreover, although there are a few (a very limited number of) frameworks that were specifically designed for adaptive advertising, these frameworks are not specifically targeting systems that can be lightweight and integrated easily within a wide range of websites, which are the main goals of the research presented in this thesis.

As this thesis addresses the application of an adaptive advertising model for e-advertisements, I have addressed the main aim of *easy integration and lightweight adaptive e-advertising*, by proposing a set of tools for the creation and authoring of adaptive advertising, which support the delivery of personalised advertisements to Internet users. These tools are implemented based on a new model designed to support and facilitate the integration between adaptive systems and websites.

3.4. Adaptive Hypermedia Models and Frameworks

For the most parts of the birth of e-commerce, a major criticism of early e-commerce sites was that they offered too many links, making it difficult for users to ascertain which links will enable them to meet their needs [44]. The introduction of adaptive hypermedia is therefore seen by Garlatti and Kervella [64] as a solution to this situation, where users otherwise would get lost in hyperspace. Goodman and Litman [71] explained that, with adaptive hypermedia, links and contents that are relevant to the needs of users are provided. As a way of introducing adaptive hypermedia platforms, various adaptive hypermedia models are proposed. These models cover many areas in hypermedia – in particular education, although there are a few that cover advertising. However, all of them suffer from some limitation to produce adaptive systems that, for example, can support easy integration into websites, social interaction, the lightweight concept, and so on. The following subsection details the most well-known and effective models and frameworks for adaptive hypermedia.

3.4.1. Adaptive Hypermedia Application Model (AHAM)

AHAM [53, 144] is a Dexter-base reference model [53]. As such, AHAM focuses on the information nodes together with the link structures that connect those nodes. AHAM consists of three major elements, which are *domain model*, *user model,* and *adaptation model* [33].

The domain model is a major structural component of AHAM. In this model, the components used in the Adaptive hypermedia system are categorised in concepts and their relationships. The concept represents a summary of information from the application domain and can be atomic or composite [30]. The most used concept relationship is the type link, which is similar to the link component in the Dexter model. In AHAM, the prerequisite is an important type of concept relationship. When a concept C1 is a prerequisite to C2, then the user should first read C1 in order to read C2. It thus shows that for a user to understand C2 there is various information that they need to acquire by first reading C1 [33].

The user model in AHAM stores information as an *overlay model* on the domain model, and as *free variables*. For the former, the user model is characterised by many attributes that help to explain the manner in which the user is related to the concept. The user model may keep information about the nature of the information acquired about a concept, or whether those concepts have any relevance to the user.

The adaptation model of AHAM is a set of rules covering both generic and specific adaptation [144]. The rules guide the process of adaptation and form the basis on which the Dexter model connects to the user model, and the presentation that is to be generated [110]. In specific adaptations the rules are always stated by the author.

While the AHAM model is one of the earliest and most effective means of creating adaptive hypermedia systems, it is not without some limitations. For example, the contents in the domain model are concepts or composite concepts and cannot describe any related elements that are not a concept. In addition, the structure of the user model is a rigid table-style structure that is unable to easily manipulate private and public information. Finally, this model, although claimed to be generic, is designed mainly for adaptation in the field of education, making its structure less suitable for advertising adaptation. For instance, the user model structure needs further components, to reflect a user's social interaction. In addition, the adaptation model and the domain model should be simple for authors, to be created easily. Moreover, the adaptation model needs to be related to specific user characteristics, which are required for adaptive advertising, such as age and gender.

3.4.2.LAOS

LAOS [50] is a theoretical framework for authoring adaptive hypermedia systems that attempts to resolve the issue of concealed adaptation information. LAOS is a universal representation of a layered model for generic authoring of adaptive hypermedia [43]. Cristea [44] states that functionality and semantics guide the separation of adaptive hypermedia components into layers, in order to group the components based on their potential usage, mainly for later use and reuse. In short, the LAOS framework is made up of the following layers [44, 50, 127], as illustrated in Figure 5.1.

- The *Domain Model* (DM). Expresses the conceptual model and consists of sub-layers comprising atomic and composite concepts, each of which have their own respective attributes. The model contains concept maps with linked concepts to represent resources in addition to their characteristics.

- *Goal and constraints Model* (GM). Goals provide a well-focused presentation, while constraints seek to limit the search space, in order to achieve a focused orientation of the material. This model sorts and regroups the domain model with regard to a specific goal. In addition, it allows for ordering and 'AND/OR' style relationships between attributes, and the actual analysis is conducted in the adaptation model.
- *User Model* (UM). As with the user model in AHAM, which is an overlay of the DM, the user model in LAOS is also an overlay of the goal model. Therefore, different user information can be assigned to different concepts, based on user experience.
- *Adaptation Model* (AM). The adaptation model is the layer containing the specification of the adaptive behaviour of the online system. It allows for various granularity representations of adaptation, starting from simple IF-THEN rules, triggered, e.g., when an event occurs, such as accessing a page, all the way to full adaptation strategies, that could, in the learning domain, correspond to a specific pedagogical strategy.
- *Presentation Model* (PM). The presentation model stores metadata on the presentation options, and drives the final presentation to the end user.

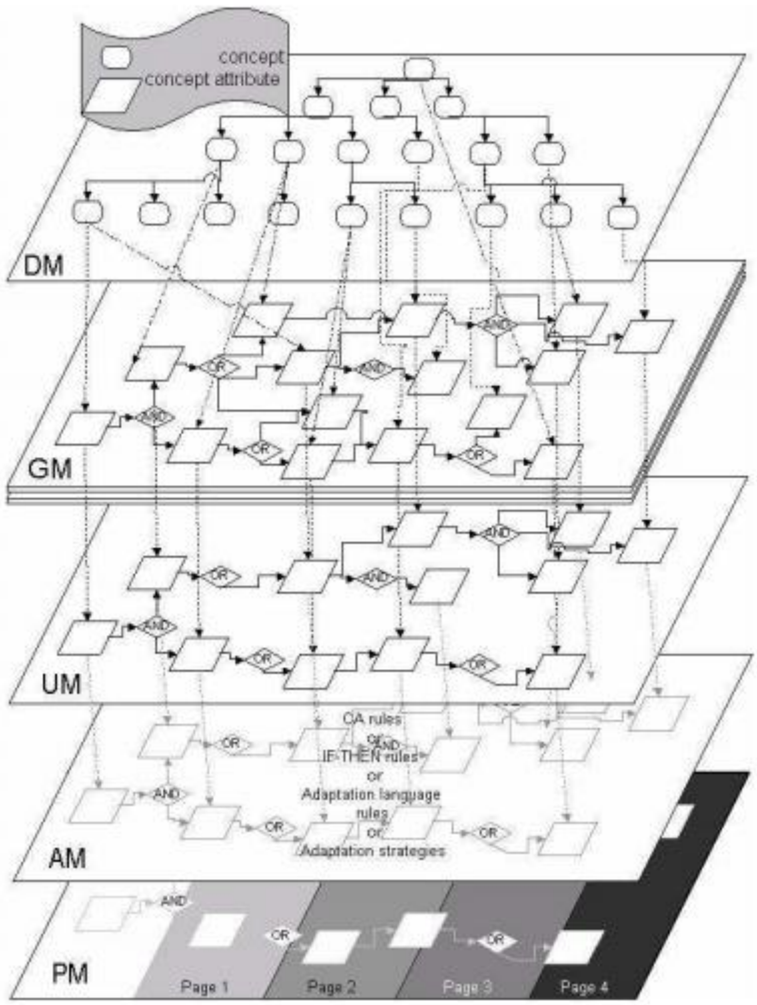

Figure 3.1 The five-layered adaptive hypermedia model based on LAOS framework [50]

LAOS clearly separates information- and presentation-goal to enhance information reuse, by separating chunks of information from a specific context. In this way, the approach simplifies the process of removing generality. This separation generates two major models – the DM and GM –, which allows a presentation to contain information relevant to a specific user, but which is drawn from multiple sources [44]. According to Cristea and Mooij [50], this separation provides high levels of flexibility. With the LAOS framework, it is possible to generate adaptive or flexible presentations, and the final presentation delivered to the user can include components of the domain model along with the components of the goal and constraints model. For example, the goal and constraints model can focus on clarifying a text attribute from the domain model's parent concept, thus allowing the author to show different presentations from the single parent concept [50].

While the LAOS structure offers clear ways to implement an adaptation system, and whilst it is also a generic framework, it has been applied mainly in the area of education. The structure of the framework allows interaction between its layers. The number of layers could render it too complex for business owners. Moreover, a layer such as the Goal and Constraints Model in LAOS is not necessary in adaptive advertising, as it is supporting a story line, and a coherent delivery, which is more appropriate for educational applications than for advertising. Moreover, it has been designed to allow for the creation of standalone applications, without specific focus on portability and easy integration, which are the main goals of the research presented in this thesis.

3.4.3.SLAOS

The SLAOS framework [67] is an extension of the LAOS framework. It adds a new layer, the social layer, which affects all five layers of the LAOS framework, as illustrated in Figure 3.2. SLAOS integrates users with their collaborative activities. Similar to the LAOS framework, this approach supports standalone applications. In addition, as illustrated above for LAOS framework, it also contains a Goal and Constraints Layer, just as LAOS, which is not directly relevant to adaptive advertising. However, unlike the LAOS model, this model introduces the great step forward towards using social data. It adds a social layer that can interact with the previous five layers of the LAOS framework. A social component is also used in the model proposed in this thesis. However, in this research, the social component is added only to the user model.

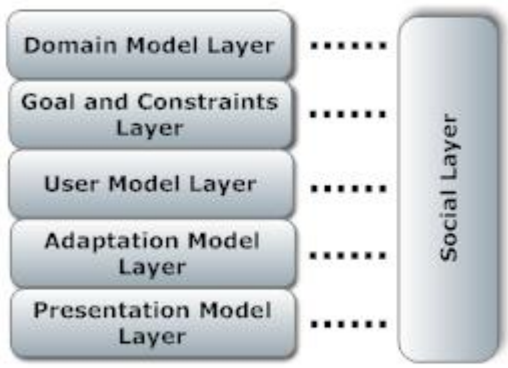

Figure 3.2 Social LAOS [67]

3.5. Frameworks resulting from Adaptive Advertising Systems

3.5.1. AdRosa

AdRosa [88] (Figure 3.3) makes automatic personalised web banners depend mostly on the specific browsing behaviour of a user. The AdRosa approach uses the portal model [16] of advertising to deliver the advertisements – where the publisher is responsible for advertisement management and cooperates with many advertisers – and can be easily extended to the broker model [16], by considering the publisher's portal as multiple publishers' portals. The main domain entities in the AdRosa system are advertisements. The domain model represents how to organise these advertisements. It categorises the domain of advertisements into groups (conceptual spaces) based on an advertiser's website, for example advertisements for travel, sports, and so on. If a page A in the publisher's website is about sports, then AdRosa will assign it to the sports conceptual space in the domain of advertisements. Information on the banner ads visited by users are stored in relevant vectors, to offer a clear picture of user behaviour. The delivery part of the AdRosa system applies advertising policy and priority features on advertisements that are placed beside user behaviour and are used to show the appropriate advertisements for each user. However, the structure of the AdRosa framework suffers from simplicity of the user model, which introduces limitations on its ability to develop accurate adaptive systems. In other words, the user data that can be collected is minimised to respect users' privacy. Moreover, this framework depends on usage and content mining techniques to cluster users based on some similarity.

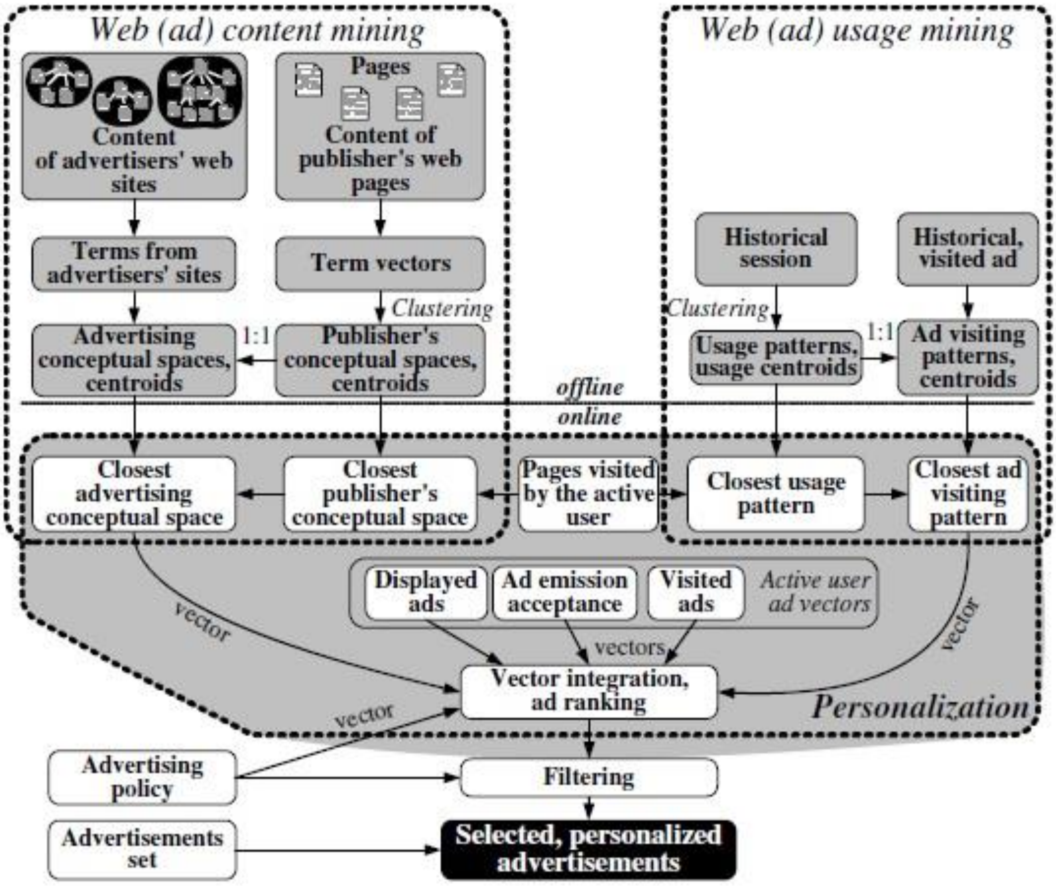

Figure 3.3: AdRosa Overview Method for Adaptive Advertising [88]

3.5.2.MyAds

A recent framework based on the LAOS framework called MyAds [5] (Figure 3.4) has been proposed as a social adaptive hypermedia framework that is used for online advertising. The first layer collects user data from social networks and user registration. In this approach, the user model is located on the second layer and places a user's profiles next to ads that they have seen. The adaptation and presentation layers in this model are similar to the LAOS framework and are located in the third and fourth layers. The final layer, the evaluation model, is responsible for tracking the user's behaviour to update the user model.

The research presented in this thesis has highlighted some issues with the MyAds model. First, the approach is aimed at supporting the creation of a standalone system, which depends heavily on collecting advertising information from multiple sources, which conflicts with my research that relies on advertisements that are owned or managed by the website. In addition, the user data collected can be moved to the user model easily, making the first layer redundant for my research. The final layer in this model suffers, in my view, from a design problem, since it should be connected to the user model layer, to update it.

Hence, whilst this model is serving a similar aim to the model created for this thesis, it was not directly possible to use this one, and the creation of a new model for adaptive advertising was deemed necessary.

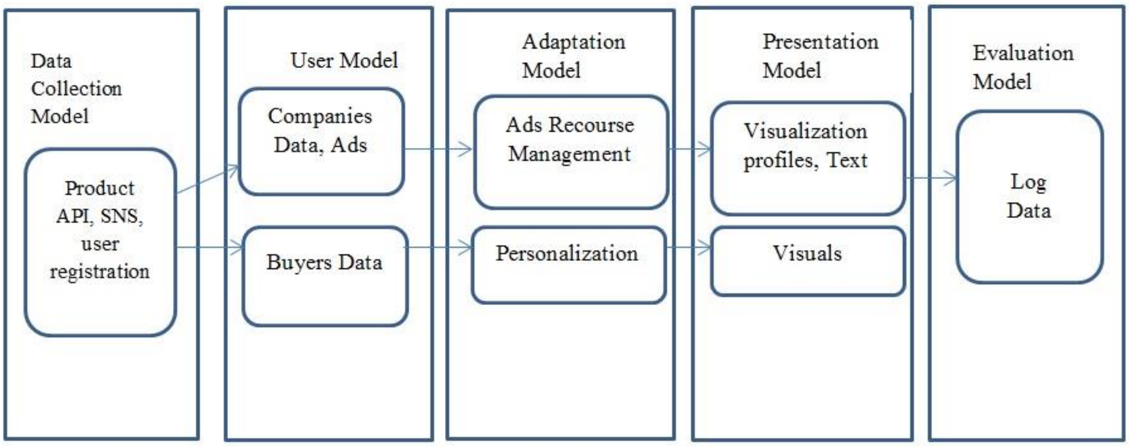

Figure 3.4 Theoretical Framework for MyAds [5]

3.6. Adaptive Hypermedia Systems

There is a wealth of evidence highlighting that personalised content – that which is tailored closely to the user's preferences – can boost the experience and engagement of that user [11, 137]. To support this personalisation, many adaptation engines have been developed, while others are still in the proposal stage [127]. However, these engines have some limitations and so tend to suffer from slow uptake.

Furthermore, the authoring process of adaptive hypermedia systems is constrained by the complexities of authoring tools, the lack of a standardised authoring mode, and the wide variety of tools [50]. Therefore, there arises one major question: how do we simplify the process of authoring while efficiently maintaining the advantages of the adaptive hypermedia capabilities? Scotton et al. [127] argue that bolstering the adaptation strategy's reuse can play an integral role towards simplifying the authoring process.

In this section, some of the best known adaptive hypermedia systems and authoring systems are briefly described.

3.6.1. MOT

MOT [49, 61] is a comprehensive adaptive hypermedia authoring system that can create material able to be delivered to different adaptation delivery engines. It has been specifically tested by delivery to AHA! [20] and ADE [127]. MOT exports adaptation strategies written in a dedicated language, the LAG adaptation language [43] and is based on the LAOS framework [50]. The MOT system utilises a LAOS-style domain model, in terms of a hierarchical conceptual layer of composite and atomic concepts consisting of several concept-specific attributes, in addition to a goal and constraints model. Domain maps consist of concept maps built of attributes and allow for relationships between hierarchical concepts as well as interconnected relations. Moreover, user maps hold essential attributes and initial values to represent the target user. Common variables include interests, knowledge level, learning styles and others. Difficulties associated with the MOT system include the use of LAG in the authoring section, which means the system requires a writer with a medium- to high-level of experience with coding.

The Programming Environment for Adaptation Language (PEAL) [62] is an environment that has been proposed for the LAG language specification [45]. It tries to simplify the authoring process of adaptive hypermedia systems, by addressing the complexity of the authoring process. PEAL creates adaptation strategies via the LAG language by using a wizard, auto completion, and code correction methods. While PEAL eases the pressure in terms of the experience required from the author, it still does require some good amount of work to be conducted by authors and so, again, it requires some initial level of knowledge.

3.6.2. ADE

The ADE system [127] is based on the AHA! adaptive hypermedia delivery system [20], and according to Moore et al. [102], it combines the characteristics of a typical adaptation engine with features including extended flexibility. ADE as an adaptability engine addresses issues related to content reusability, as well as adaptation specifications, and uses the LAOS framework for structuring the delivery of adaptive systems, which enforces the separation of concerns [127]. ADE tracks some user model attributes automatically. Information including the number of times a specific user has accessed a concept and whether or not a particular person has accessed a material are continuously inserted into the user model.

In ADE, adaptation strategies or specifications are independently stored from the content, to optimise their ability to be reused for several applications. The design of ADE mainly focuses on using a modular adaptation system and adopting an independent adaptation language – an approach that allows ADE to work with all adaptation languages. This modularity implies that execution of adaptation is free from any single adaptation languages [127]. The ADE system can adapt page or content presentation based on the device being used. In addition, ADE uses AJAX calls to actively track the network status of the current user's connection and updates the bandwidth variable in the user profile [127]. These network connection parameters can be used to tailor adaptation strategies according to a user's network connection speeds. Although this system offers a good method of delivery, it falls far outside the remit of this research because it is a standalone application, and does not support portability or easy integration into websites.

3.6.3. AdRosa

AdRosa [88], as described above, is an adaptation system that automatically personalises web banners for users. It integrates web usage and content-mining techniques to reduce the user input while respecting the user's privacy. The adaptation system employs those similarities that exist between individuals to dynamically reflect any changes in user interest. It is dependent on assimilating user data without any cooperation from the user. Thus, user identification is not necessary with the AdRosa system. Again, this system possesses a simplistic user model that depends on the categorisation of web banners for groups, based on similarities between individuals.

3.6.4. MyAds

In the MyAds system [4], the domain model is part of the data collection model, which contains information about various company products and user data from different sources. A tool called Product Crawler is used to construct the domain model, drawing in products from e-commerce websites based on the following metadata: price, image, description and the Amazon.com URL. The advertisement generator engine is connected to a Product Crawler to arrange the ads in the database.

On the server side, the Personalisation and Decision Making Engine and the Product Search Engine are located in the MyAds system to represent the adaptation model. This system is constructed using a new framework that attempts to update the structure of LAOS's adaptation model to support adaptation in the advertisements field. The Personalisation and Decision Making Engine matches the user to appropriate products. The difference between this system and the research proposed in this thesis is that the proposed work focuses on advertisements that exist and are already available on the website, rather than crawling across the Internet. The structure of the user model is also different, since the research in this thesis introduces new ideas for the user model structure that can enhance adaptive advertising. The proposed user model consists of four new components, each component storing different type of data (as further explained in Chapter 8). This structure is to enhance the adaptation process, as further discussed in Chapter 8. In addition, this system is superior to the MyAds system in terms of a more robust and flexible delivery engine, since it encapsulates the modification, inference, and decision process in it, which can make the integration process easier.

3.7. Adaptive Hypermedia – Adaptation Methods and Techniques, User Modelling, Social Interaction

3.7.1. Adaptation Methods and Techniques

Adaptation methods are required to perform the changes necessary in an adaptive hypermedia environment, and there are several ways in which the various methods can be employed [25]. These techniques are applied based on the information from the user model, which is used by an adaptation algorithm. For instance, in order to perform the following: "...hide the links to the concepts that are not yet ready to be learned", several different techniques can be implemented. Different adaptation technologies that are used in adaptive hypermedia have been introduced [25], as illustrated in Figure 3.5. These technologies are classified into two groups: *adaptive presentation* and *adaptive navigation*.

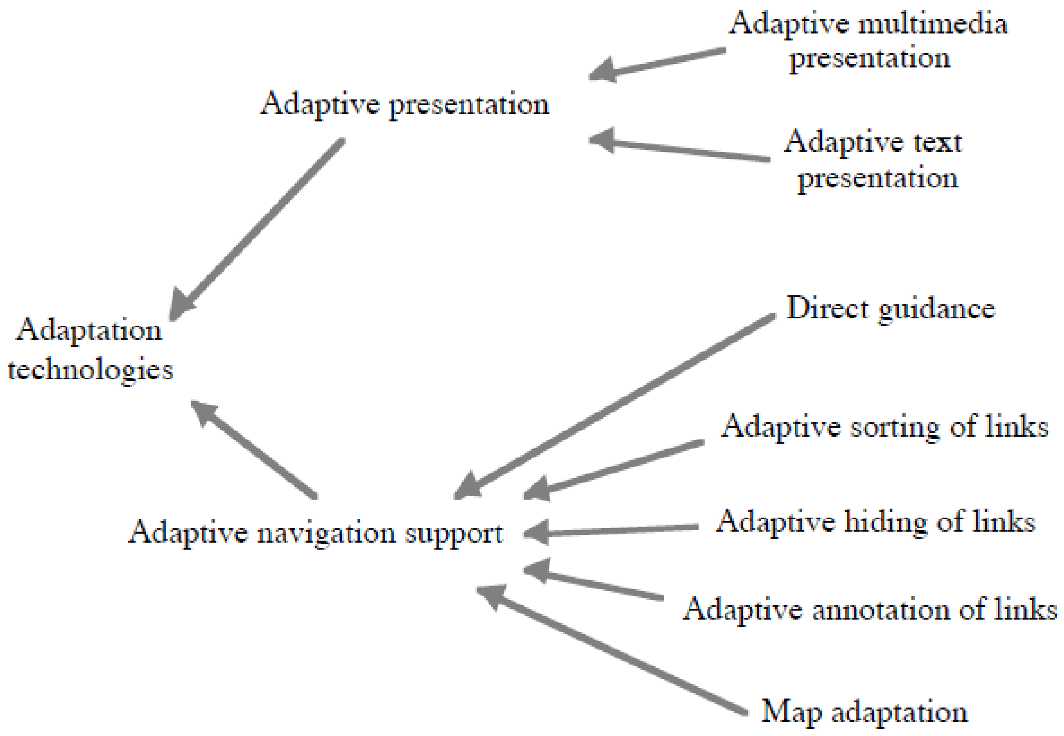

Figure 3.5 Adaptive Hypermedia Techniques by Brusilovsky [24]

Adaptive presentation techniques amend the content of pages for users based on their knowledge, and other characteristics. Novice users can access simple materials, while qualified users can get more complicated information. The contents of pages that can be adapted may be text or a variety of multimedia items. Therefore, these techniques can be categorised into two groups: text presentation, and multimedia presentation.

In contrast, adaptive navigation support leads the paths of users in hyperspace. These techniques adapt the links that appear to each user based on their knowledge and other characteristics. The main groups of these techniques are direct guidance, sorting, hiding, annotation, and map adaptation. Direct guidance invites users to 'follow me' by recommending the next best content based on their characteristics. In the sorting group, the links are sorted according to some characteristics of users. If the material is not suitable for users or if it is too complex, then hiding will be used. The adaptive annotation adds a comment to the links to give further information about them. It can be a text or graphic item, is relevant to all form of links, and is also a more powerful technology than other techniques. Finally, map adaptation technology adjusts hypermedia maps by amending their form, structure, or links.

These adaptation techniques can also be applied to the advertising adaptation field that is the focus of this research. For example, for the research in this thesis, sorting - based on some priorities - and hiding techniques are powerful tools which are used for adapting advertisements. In addition, adaptive annotation is used on each advertisement, by adding the 'alt' attribute to the HTML link only, to provide fast and relevant information to users.

3.7.2. User Modelling

A user model is a representation of the personal data of an individual user, recording adaptive changes to the system's behaviour. Table 3.1 (below) details the means by which the user model can be characterised, and the method of implementing it based on multiple factors, including the type and size of data, based on related literature [54, 85, 96].

Table 3.1 User Model Classification

Adaptive	**Adaptable**
The model is updated automatically by the system from the user's behaviour.	The model is updated by the user manually.
Static	**Dynamic**
The model does not change during the interaction with the user. Information is collected in an initial phase or at regular intervals.	The model is constantly updated, as new information is found.
Coarse Grained	**Fine Grained**
The knowledge domain is represented in the user model with only a few large concepts.	The knowledge domain is represented in the user model based on many small-sized concepts (for example, with pages, fragment of pages, or even images).

User modelling is the process of constructing, maintaining, and using user models, and covers data acquisition, representation, and inference tasks. The user modelling process can be divided into three tasks [91]: acquisition of user data, inference of knowledge from the data, and representation of the user model. These are further described below.

3.7.2.1. Acquisition Methods

The methods that can be used to acquire data for the user model will be described in this subsection. The acquisition process identifies information about users' characteristics, computer usage, and environment, and makes it accessible to the user-modelling server, where a user model is constructed.

Several methods of executing the acquisition process are used, depending on the class of data, as follows.

1. User and Usage Data Acquisition Methods

User data are the information about the personal characteristics of the user, for example demographic data. In contrast, usage data covers information about user interaction with the application, and is recorded directly from observation techniques, such as selective actions and ratings, or by analysing visible data, such as action sequences. Because the main objective is to tailor the system towards the user wherever possible, usage data are regarded as an important building block in the adaptation process, as it deals directly with the interactions of the user.

a. User-Supplied Information

Via this method, user data are acquired through questions asked by the system [91]. The process is most often run during the initial phase of system usage and is a potential method for acquiring data, including the user's name, address and phone number. The majority of websites rely on user-provided information, to categorise users as a means of personalising their experience of using that website.

b. Acquisition Rules

Acquisition rules [83] range from the very complex to the very simple. These support the construction of the user model by interacting with users. In [84] some simple acquisition rules are presented and the inference rules are executed when new information about the user is available. For example, to discover the user's level of experience with the application, the inference rules are based on knowledge of when the user last used the application. Using that information, the rules may be changed in the following way (for example):

> *If the user has been away too long: downgrade the experience level by 1.*
>
> *If the user has used the system for long enough since the last update: upgrade the experience level by 1.*

This technique was incorporated into this research, by adding some authoring policies that can affect the user model attributes, according to some user actions, as can be seen in Chapter 8.

c. Plan Recognition

Plan recognition refers to the task of inferring the plan of an intelligent agent from observations of the agent's actions or the effects of those actions [126]. This helps pinpoint the aim of the user based on their actions in a specific environment, thus narrowing the number of possible goals, in line with the actions performed. For example, in message centres and information systems, users often have specific goals, such as listening to new messages, accessing billing information, or receiving weather forecast information for a specific region. The plan recognition technique is applied in this research, by adding a plan library constructed by the author that is triggered according to user behaviour, as discussed in Chapter 9. By taking this approach, user behaviour has been combined with the much needed authoring aspects that are required for adaptive advertising.

d. Stereotype Reasoning

A simple method for making a first assessment of others is to classify them into groups sharing the same interests, according to a set of criteria – a stereotype [13]. Based on a stereotype that is associated with each category of the users, a prediction about them can be made. Stereotypes consist of a set of facts and rules applied to a group or class of users, and often consist of a set of activation conditions ("triggers") for applying the stereotype to a user, and as a set of conditions for retrieving information on a particular user from a stereotype group. For example, if the user model shows that the person is interested in childcare, the system may activate the stereotype "parent" [91]. In this research, stereotype reasoning can be added to the adaptation rules under the *general rules* type, as shown in Chapter 8. Each group of advertisements can be targeted to a group of users, according to criteria including age, gender, and so on. The technique is required to allow the author to categorise advertisements, according to their criteria.

e. Action Sequencing

Action sequencing is a technique employed to predict the future actions of the user, and therefore to recommend actions based on the sequences performed by other users, or perform some of these actions on behalf of the user [91]. This research tracks the selection sequence of advertisements of each user and stores the final ten selections to predict user actions, as discussed in Chapter 8. These data can be thus used to predict the future user actions [91]. However, this prediction process is postponed for future research, as in the research in the current thesis, only the data collection and storage are dealt with.

2. Environment Data Acquisition Methods

These are methods for acquiring data about the software and hardware environment, and location of the current user. This information is very useful for advertising adaptation, which has been used in this research to extract the software, device type, and browser version.

a. Software Environment

Information about the browser version, platform, and availability of plug-ins is important for websites, as many of them take the software constraints of the browser into account. Information about the web client can be obtained from the header of the HTTP requests that are received by the server. Each of these requests holds information on a number of different variables, which can then be extracted and used.

b. Hardware Environment

The hardware characteristics that influence the adaptation process include bandwidth, processing speed, display devices, and input devices. For example, mobile devices with small screens or low resolution require special software for web browsing or display. The AVANTI system [60] evaluates the available bandwidth based on the media download time, and automatically replaces high-resolution images and videos with those that are less bandwidth-intensive.

c. Locale

Location information covers more than just the geographic position of the user. It also includes details on the ambience of that location, for example information regarding background noise or how bright the environment is. Those details can then be recorded in a database and utilised to ensure the best possible user experience. Mobile devices provide locality information through general technologies such as the Global Positioning System (GPS) as well as through the cell sites that the device is connected to and surrounding sites. Many other technologies are also available today to assist in establishing the position of a user, such as optical recognition and ultrasound.

The user’s platform, browser version, bandwidth, device type, and location are exploited in this research for further adaptation in the future, as discussed in Chapter 8.

3.7.2.2. Inference of knowledge Methods

Some applications operate directly on usage results and environment models, whereas other applications need further data inputs. User modelling representation and inference rely on knowledge representation and machine learning techniques [91] and makes uses of deductive, inductive and analogical reasoning. These three forms of reasoning are used to infer adaptive measures to the system's reasoning, in conjunction with user model data. In this thesis, the research applies directly to data in the user model, as discussed in Chapter 9, section 9.3. Using these forms of reasoning inside the user model will be left for future work, as discussed in Chapter 10, section 10.5.

1. Deductive Reasoning

Deductive reasoning infers from a general case to a specific one by a process of logical conclusion. Using this approach, if something is true of a class of things in general, it is also true for all members of that class. For example, if Tom and John have the same parents, then they are brothers. This kind of reasoning can be ascertained using two approaches: logic-based representation and inference, and representation and reasoning with uncertainty. As stated above, this technique will be left for future work.

2. Inductive Reasoning

Inductive reasoning infers from a specific case to a general case, for example by monitoring a user's interaction (the 'specific') and forming a general case based on that information. An example of this process using basketball as the subject would therefore be that if the system observes that many players of the sport are very tall, then all basketball players must be tall. While this appears a logical process, it is important to bear in mind that the conclusion in an inductive argument is not guaranteed. As stated above, this technique will be left for future work.

3. Analogical Reasoning

Analogical reasoning tries to identify and recognise similarities between large numbers of users in web-based systems. The two approaches that can be used are Correlations Clique-based Filtering and Cluster User Profiles.

1) Correlations Clique-based Filtering [70] is another term for collaborative filtering [91], which is an approach employed to forecast unknown characteristics of the current user, based

on the behaviour of other similar users. In this approach, similar neighbours are determined, and then the set of closest users is selected and the prediction based on weighted representation of selected neighbours will be computed. For example, Amazon.com looks for users who have made similar purchases and makes predictions about other products they may like. A number of different algorithms for Clique-based filtering exist [6, 21].

2) Cluster User Profiles use machine learning techniques to form explicit user profiles [109]. In contrast to the Clique-based filtering approach, Cluster User Profiles depend on an explicit user profile. If profiles of different users are stored, the Cluster User Profiles approach tries to find similar users and form group profiles, and these are then compared with individual profiles. Several clustering algorithms use this approach.

3.7.3. User Model Representation

The user model representation refers to a data structure that stores users' characteristics. Data formats for representing user data can be given by attribute-value pairs, Boolean, and many other formats. Moreover, the structure of the user model can be represented in various different formats, depending on the user model extraction techniques used [7]. The most popular and widely used example of such user model extraction techniques is the domain overlay model.

In the domain overlay model, the user model is considered as an overlay of the domain model. A relation between the user and item in the domain model is established and certain attributes for each item in the domain are applied, to represent the user's knowledge or any other characteristics for this domain item. The overlay model may be binary – clicked or not clicked – or weighted – qualitative or quantitative. The overlay model has been employed in this research to construct the user model, since it can easily represent any kind of knowledge [31].

3.7.4. Social Data and Adaptation

Social networks are good sources of user information [59], from which user behaviour and characteristics to personalise advertising can be retrieved. Social networks have become a part of all of our lives, and the number of people using of social networking sites is increasing rapidly every year. These social networks reflect and record the social practices, behaviour, preferences, and concerns of their users [89, 119]. The various forms of social networks vary, from those in which users actively participate in content creation and production, to those that share content [82, 89].

For the research presented in this thesis, social networks are one of the inputs for the user model for advertising. Such sites offer a supplementary source of information that can enrich the information already available about a given user. The social concept will be used in this research to maximise the accuracy of the proposed research.

3.8. Conclusions

In this Chapter, details of the background and related work for this research have been presented. Adaptive e-advertising as a field of the adaptive hypermedia – the target of the research – is illustrated. The most famous models for designing adaptive hypermedia system are explained. AHAM, the Munich Reference, LAOS, SLAOS, AdRosa, and MyAds models and frameworks are discussed, to highlight the premise of the research; namely that a fresh model is required to construct an adaptive advertising system. In addition, various adaptive hypermedia systems from the education and the few from the advertisements fields are illustrated, and the difficulties and limitations of these systems highlighted. Finally, the adaptation techniques, user modelling processes and how to integrate the social concept in advertising adaptation are presented and explained, along with details on how those are applied in the research.

In summary, the information presented in this Chapter has looked at the research objective **O1:** "*Review the state of art in the area of adaptive advertising, as well as related areas, such as web personalisation and e-advertising, in order to find information for creating a model of adaptive e-advertising*". The procedure of analysing this objective is outlined and the outcomes have helped to start forming ideas about answering the research questions **R1:** "*Is adaptive advertising useful for businesses and users?*", **R1.1:** "*Is it more acceptable for users to have adverts personalised to them and their environment? (i.e., do users find personalised adverts more acceptable than non-personalised)*", **R1.2:** "*Is it more acceptable for businesses to deliver adaptive advertising? (e.g., do business users find adaptive advertising more acceptable when compared to non-adaptive advertising, and do they expect the former to provide a better income)*", and **R1.3:** "*What is a good* *source of information for adaptive advertising?*". These questions are partly answered in this Chapter, by reviewing the areas of adaptive advertising, as well as related fields, such as web personalisation and e-advertising. The concept of lightweight adaptive e-advertising is further discussed in the next Chapter, to further answer research questions **R1**, **R1.1**, **R1.2**, and **R1.3**.

Chapter 4

Lightweight Adaptive E-advertising Concept

4.1. Introduction

This Chapter aims to expand the knowledge of adaptive e-advertising and address the research objective **O2:** "*Design a set of preliminary studies with businesses and users, to establish the current state of art in the area of adaptive advertising and to gather the requirements for the design and implementation of an appropriate theoretical model and system*". In this Chapter, the appropriate research methods and design used to achieve the objective and to support answering research questions **R1:** "*Is adaptive advertising useful for businesses and users?*", **R1.1:** "*Is it more acceptable for users to have adverts personalised to them and their environment? (i.e., do users find personalised adverts more acceptable than non-personalised)*", **R1.2:** "*Is it more acceptable for businesses to deliver adaptive advertising? (e.g., do business users find adaptive advertising more acceptable when compared to non-adaptive advertising, and do they expect the former to provide a better income)*", and **R1.3:** "*What is a good source of information for adaptive advertising?*" are discussed. The focus of this Chapter is the presentation and analysis of information gathered via the research methods detailed in Chapter 2, in order to best address the research objective and expand understanding of e-advertising.

As discussed in Chapter 2, section 2.3, the methodology used in this study is *user-centred design (UCD)*. The primary step in consulting users, both advertisers and consumers, is gathering a pool of design needs that should be addressed in the theoretical model and the system's construction.

Based on the outcome from the first and second stages, in order to follow the *ISO-standard 13407* stages, this research proposes a preliminary version of a new extendable model called *Layered Adaptive Advertising Integration (LAAI)*. The model attempts to initiate typical concepts, to form a foundation for the creation of advertising adaptation applications and to enhance the portability of such applications. The model guarantees the separation of content, adaptation needs and delivery in an adaptive advertising application, as detailed in Chapter 5. Furthermore, a system (*AEADS*) is proposed, as the means of assessing the LAAI model's suitability for advertisement adaptation. The system enables business owners to classify their advertisements and alter them according to their users' needs and responses. The actual implementation of this system is described in Chapters 6-9 and the evaluations of the implementations are described in the same Chapters, respectively.

The current Chapter is structured as follows; the next section introduces the exploratory study with Internet users and business owners, followed by a discussion. The current Chapter finally wraps up with a conclusion.

4.2. Exploratory Study

In order to implement the user-centred experimental design process, and validate the hypotheses, a questionnaire for users and a structured interview for businesses were designed. The segment of the experiment focused on users lasted for approximately one month and was disseminated online, while each individual interview with a business representative lasted approximately one hour, with allowances made for the natural flow of each discussion. The purpose of the questionnaire and interviews was to develop a new advertising delivery system, which could help business owners and users to adapt advertisements. The target population in this thesis was international in scope and the questionnaire was sent to around 380 Internet users, while 15 business owners were asked to participate in interviews. These numbers would have corresponded to a confidence level of 90-95. However, of the groups selected, only 138 Internet users answered, which would correspond to a target population of approximately half the world's Internet users. Additionally, for the qualitative part of the study, only five business owners decided to participate. This is no surprise again, as business owners are notoriously busy [55, 141], and an interview takes a considerable amount of their time.

This experiment responds to the first research question and its sub-questions via the following hypotheses.

H1: *Users are more likely to accept adaptive advertising which is suitable for their characteristics and environment.*

H2: *Advertisers prefer to send the appropriate advertisement to appropriate users.*

H3: *Social Networks are a very good source for user behaviour extraction.*

These hypotheses were tested by surveying a subset of the population, as well as interviews with selected businesses and analysing their responses, as described below. Hypothesis H1 was tested with Internet Users. Hypothesis H2 was tested with business owners. Hypothesis H3 was tested with Internet Users (behaviour and preferences). Hypothesis H3 questions were also used with the business owners, to gather a different point of view – ease of input/relevance of input.

4.2.1. Internet Users

A questionnaire was provided for Internet users to complete. It was administered informally and contained fourteen questions. The majority of the questions were closed questions, for ease of use as well as fast processing. The first section of the questionnaire was concerned with demographic information. The next set of questions asked how often respondents visited the Internet, the purpose of their visits, and if they shopped online or offline – to better understand the way the respondents qualify as the target population for online shopping – and thus, adaptive advertising. The remainder of the questionnaire concerned advertisements: if the advertising they were exposed to was useful, and if it adapts to their preferences and characteristics to determine the status quo for advertising (the current state of the art). The questionnaire also asked if any adaptation took place for bandwidth and screen outline for their device, if social networks that provided them with advertising adapted to their characteristics, and finally, how the advertising attracted them (the questionnaire is in Appendix A). The results were then collected and are presented below.

4.2.2. Business Owners

Business owners participating in the study were interviewed in person. The structured interview used contained, on average, thirteen questions with the majority being open questions. The first questions were concerned with information about the type of business the respondent ran. The following questions looked at the current type of advertising the business used and the channels through which it was disseminated. Further questions then asked about current access rates, products sold and income made through e-advertisements. Respondents were then asked about the existing personalisation or adaptation in their online advertising, and, in cases where it was adaptive, whether this provided better income. The final question focused on their preference regarding advertising being categorised on hosting websites and directed towards specific groups of people (the structured interview is in Appendix B).

4.3. Results

The results section is divided into two sections, with the first presenting the results from the Internet users, and the second section presenting the results from business owners.

4.3.1. Users Responses

Of the 380 questionnaires distributed, 138 users provided responses. Two thirds of the respondents were female and 43% of respondents were in the 19-25 age bracket. The results show that all respondents visited the Internet at least once a day, with 69.57% spending several hours a day on the Internet (Figure 4.1). This confirmed them as the target population for the research work presented in this thesis. Interestingly, not even one respondent selected the available options of ‘Weekly’, ‘Monthly’, ‘Yearly’, ‘A few times’ or ‘Never’. Hence, the population segment analysed were clearly in possession of substantial Internet usage knowledge and experience, and thus could be relied on to provide insight into the type of advertisement necessary to address their needs.

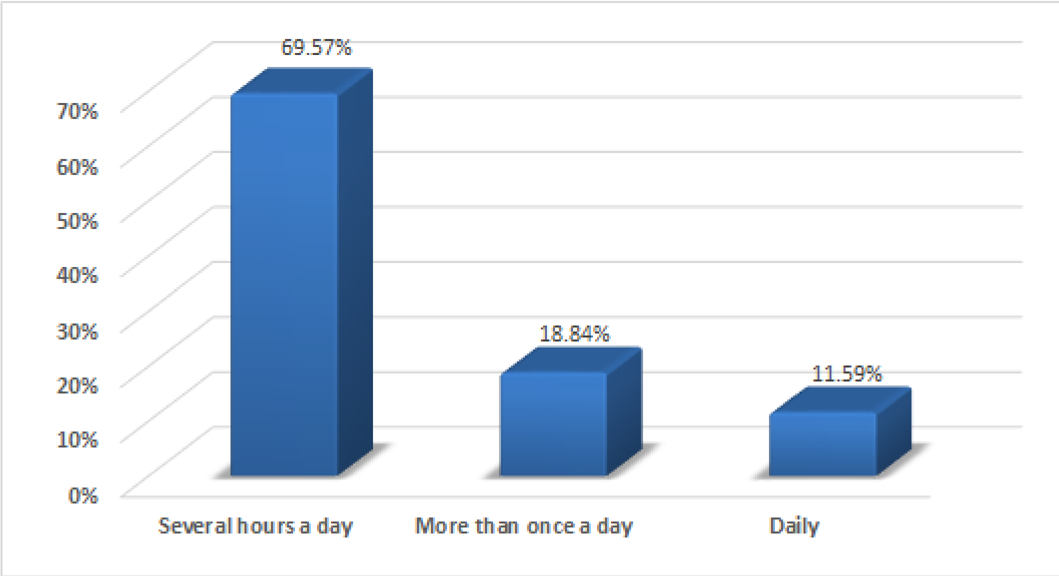

Figure 4.1 How often the Internet was visited

When asked why they used the Internet, the largest number (over 26%) mentioned social interaction, which appears to be a major incentive for the younger generations (see Figure 4.2). Another large number (over 25%) stated that they used the Internet to help with studying. Additional reasons for surfing the Internet included working (19.36%) and shopping (17.87%), with a minority stipulating that they would used it for play (8.3%). The relatively large number answering unprompted that they used the Internet for shopping shows that a large proportion of transactions have moved from traditional shops to the e-market, and that businesses need to make better use of the opportunities such a market offers, including the potential of adaptive e-advertising, and ensure they are making the most of this trend. Such a response additionally confirms that these participants are an excellent target audience for the research in this thesis.

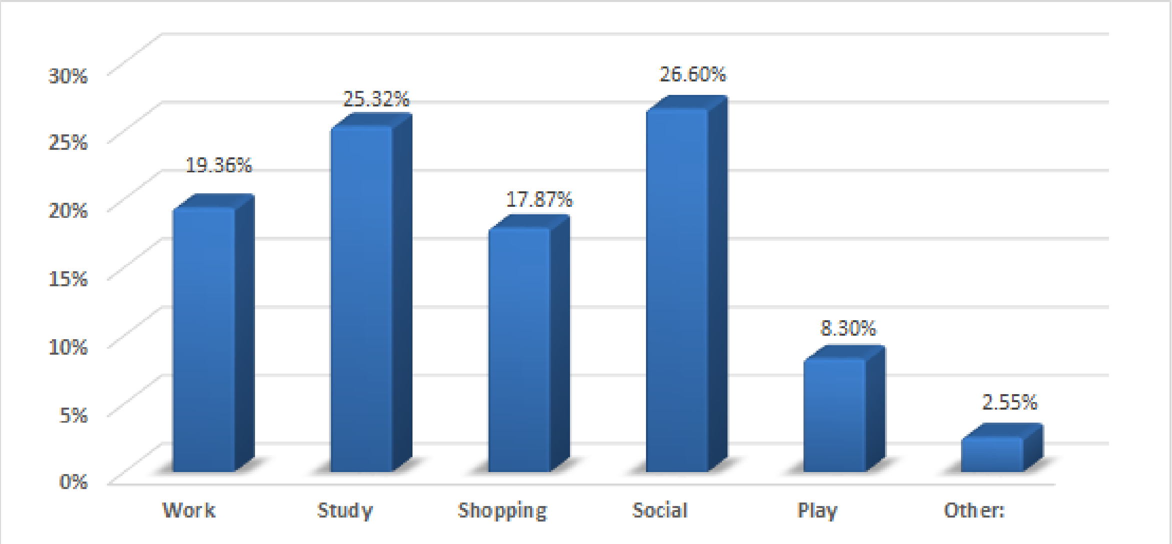

Figure 4.2 Purpose of visiting the Internet

When questioned specifically about shopping online, the majority of the respondents (54.35%) indicated that they sometimes shopped online. Moreover, 37.68% of the respondents indicated that they shopped offline, but would look up the items online first (see Figure 4.3). Both types of respondents are clear targets for adaptive advertising. Only 29.71% stated that they normally shop in offline shops, although the number of people declaring they normally shop online is low (13.04%), showing that most prefer a mixed approach.

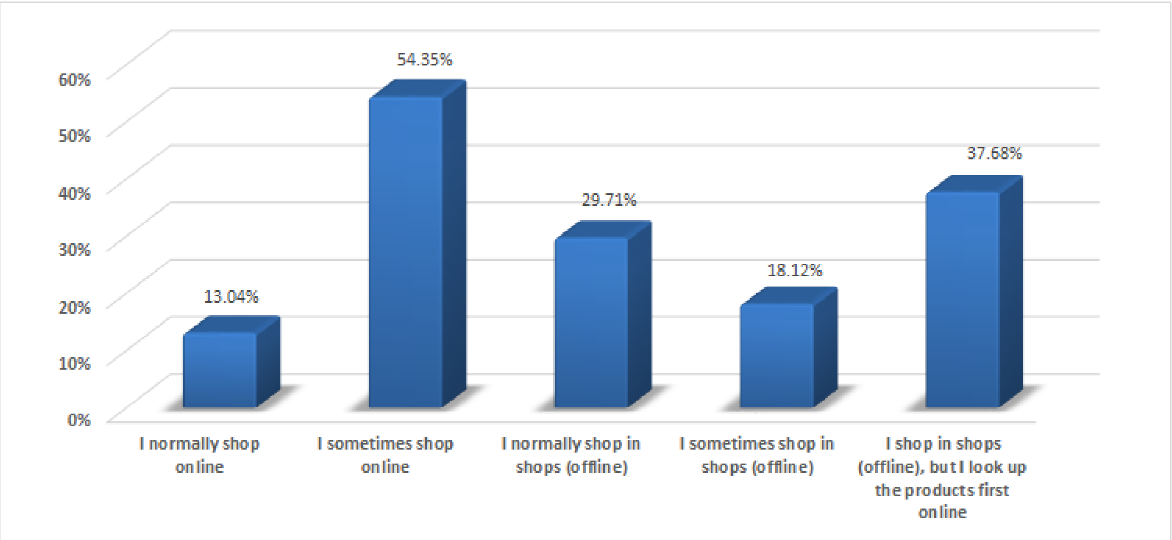

Figure 4.3 Responses to shopping online

Considering that a large amount of research shows that online advertisements have negative connotations [12, 97, 101, 142], it is surprising that a majority of respondents (52.9%) found advertising on the Internet useful on occasion, while 5.8% even indicated that advertising was always useful (Figure 4.4). This contrasts with the 26.81% who said that e-advertising was never useful. Explicit negative comments about Internet advertising provided by respondents included: “I find advertising annoying”, “I generally ignore it”, “It's just a load of rubbish”, and “Often deceiving”. These outcomes partially support hypothesis H1, as 79.71% (sometimes + never) do not feel that the advertising they are exposed to is useful very often.

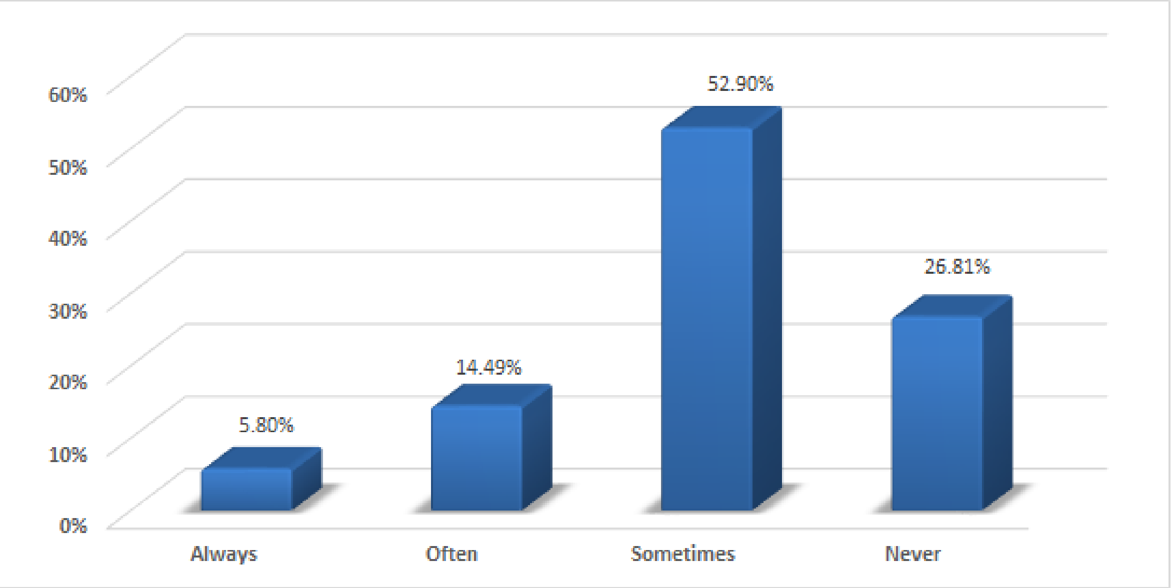

Figure 4.4 Responses to whether advertising exposed to was useful or not

When asked if the advertising they were exposed to was adapted to their user preferences, 53.62% indicated that this happened sometimes, while 9.42% and 36.96% indicated mostly yes and mostly no respectively (Figure 4.5). From the open text responses, Amazon, Facebook and YouTube were mentioned by name as websites that did adapt advertising to user preferences. These answers provide support for hypothesis H3, in that social networks are a good source for user behaviour extraction.

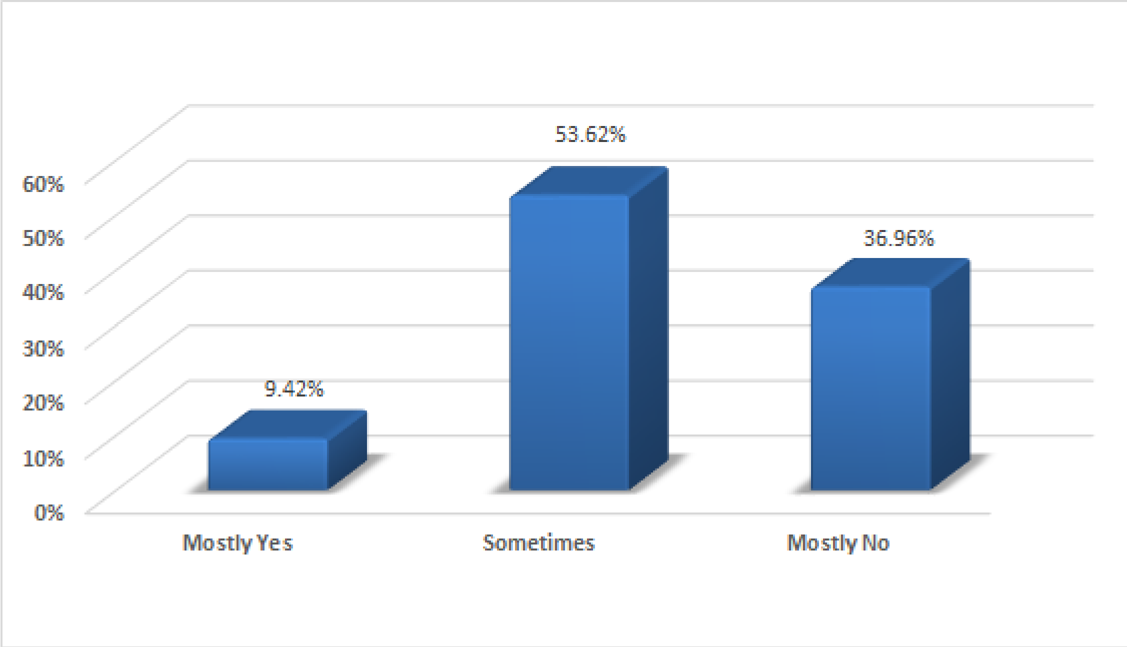

Figure 4.5 Responses to adaptation of advertising to user preferences

When asked if the advertising adapted to any other characteristics, 63.24% said that sometimes it did adapt to their behaviour, product history and websites visited, while 31.62% said mostly no (Figure 4.6).

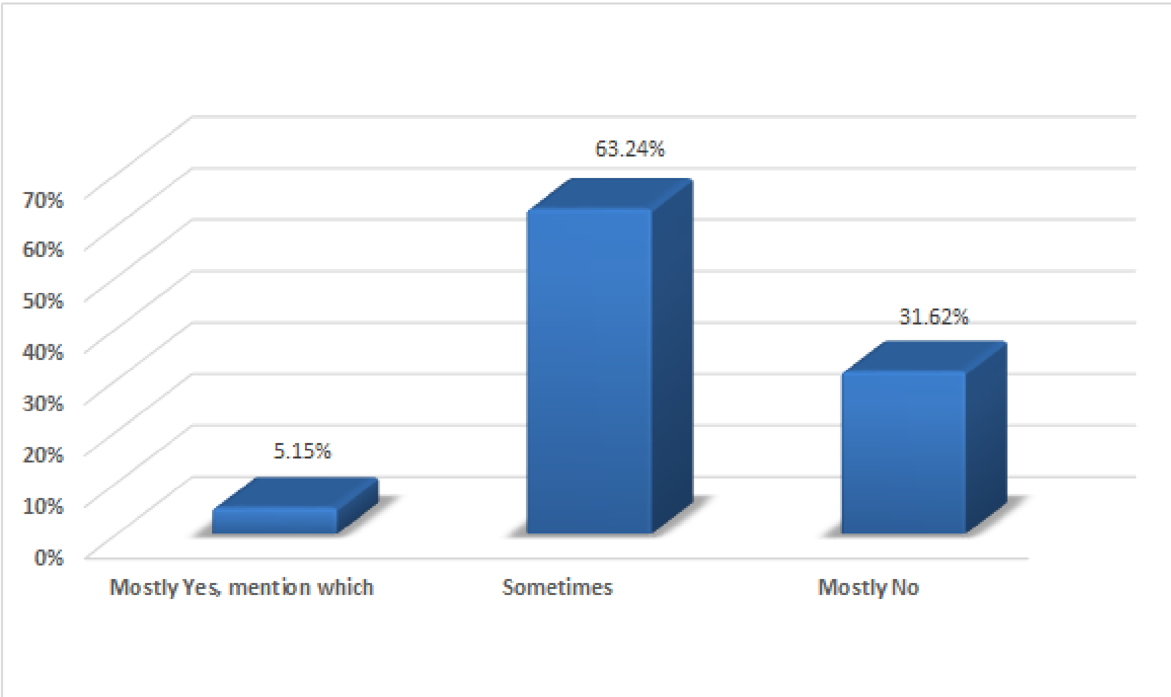

Figure 4.6 Responses to adaptation of advertising to other user characteristics

Of the respondents asked, 44.2% claimed that the social networks they were using did not provide useful advertising the majority of the time, but 43.48% also stated that on occasion the reverse is true. Social networks mentioned included Facebook, YouTube and Twitter. When answering a different question, the majority of respondents (73.19%) also indicated that social networks did not provide them with advertising adapted to their characteristics. From this statement one see that, although social networks can provide useful advertising, most of the time it is not adapted to user specific characteristics.

From the open user comments, three key categories of issues were recorded, regarding what attracted respondents to advertisements online. These included the following.

- *Design* issues, including use of bright colours, large fonts, simple messages or short display time.
- *Relevance* of the advertising message, i.e. is the advertisement relevant to the user or advertising a service the user is interested in?
- *Price*, i.e. is there an on-going sale or possible discount available?

From user comments that mainly fell into one or more of the above three categories, hypothesis H1 can be supported, that users are more likely to accept adaptive advertising, which is suitable for their characteristics and environment. If the information is more relevant to their characteristics, either by design or relevant advertisement or price, the user is more likely to accept such an advertisement.

When asked about the display of advertising content, for instance, whether reasonable media was used according to bandwidth, 24.64% said mostly yes, 46.38% said sometimes and 28.99% said mostly no (see Figure 4.7). These findings suggest that alternative methods of adapting advertisements in circumstances of differing bandwidth require further exploration.

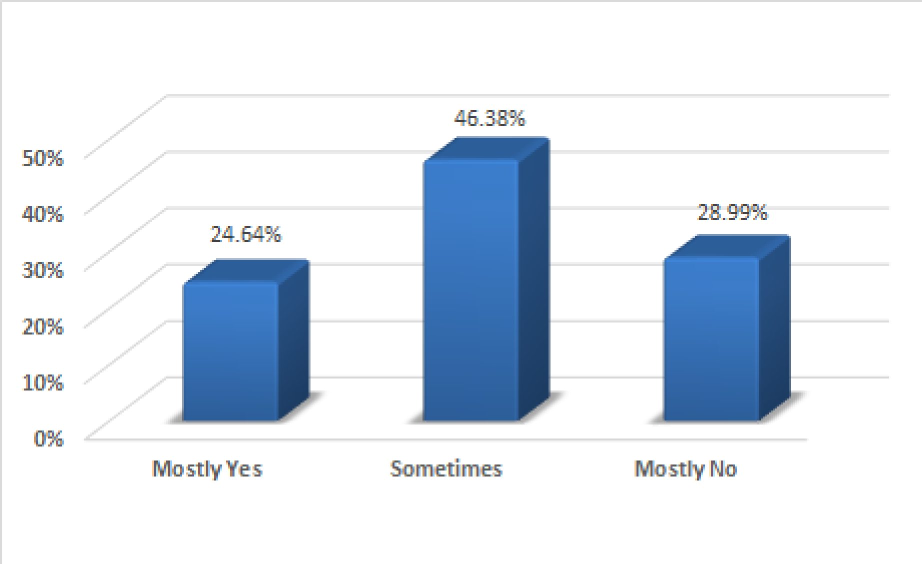

Figure 4.7 Use of reasonable media according to bandwidth

From the responses regarding whether advertising used a reasonable screen outline for the user devices, 40.58% said mostly no and only 14.49% said mostly yes (see Figure 4.8).

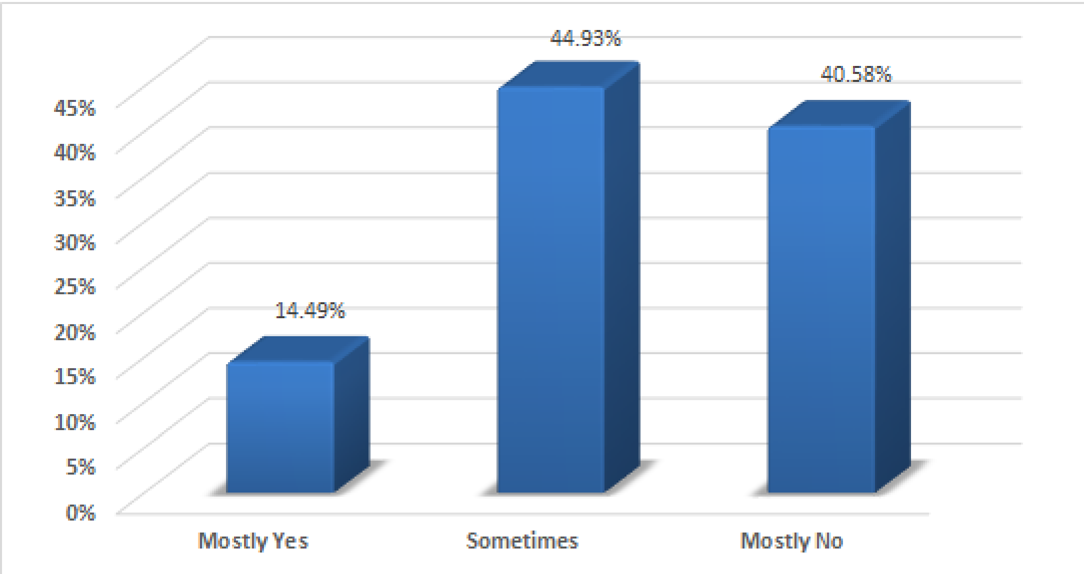

Figure 4.8 Use of reasonable screen outline for device

4.3.2.Businesses Responses

Receiving responses from businesses was more difficult, with only five agreeing to take part in an interview for the study. However, although small in number, the interviews that did take place resulted in the collection of some valuable data. Responses were obtained from businesses in the financial, manufacturing, real estate, transportation and marketing industries. Two of the businesses were classified as small, two as large and one as a medium enterprise. Additionally, four of the businesses were located in Saudi Arabia and one was in Egypt.

All of the businesses utilised online advertising, with 80% also utilising newspaper advertisements. Furthermore, 60% also utilised email advertising and another 60% made use of brochure advertising (see Figure 4.9). The difference in utilisation of the various types of advertising can partially be attributed to a variation in the content required, for example in the difference between traditional newspaper advertising and modern email advertising. Implementation of a common protocol between an adaptive delivery system and the advertising content is therefore considered a potential solution for adaptive advertising.

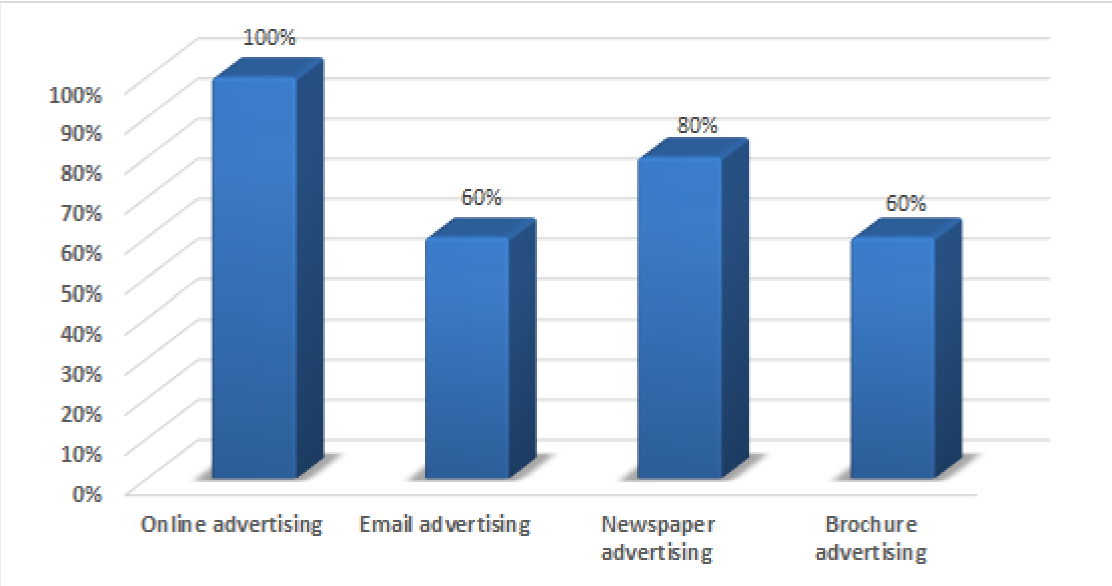

Figure 4.9 Type of Advertising

When asked about channels used for advertising, company website, social networks, online newspapers and email were the ones most frequently used (see Figure 4.10). Online journals, however, were least likely to be used. In addition, all of the businesses that used social networks as an advertisement channel specified that they used Facebook to publish their advertisements. However, one of them stated that, “Facebook is not enough, as a lot of users are now using Twitter as their main social network site. Thus, I am now using both sites to publish advertisements.” Moreover, one of the businesses considered a specialised site for real estate advertisements as their main advertisements channel. He said that, “I consider any other channel to be used in parallel with this channel, as this one is the most worthwhile.”.

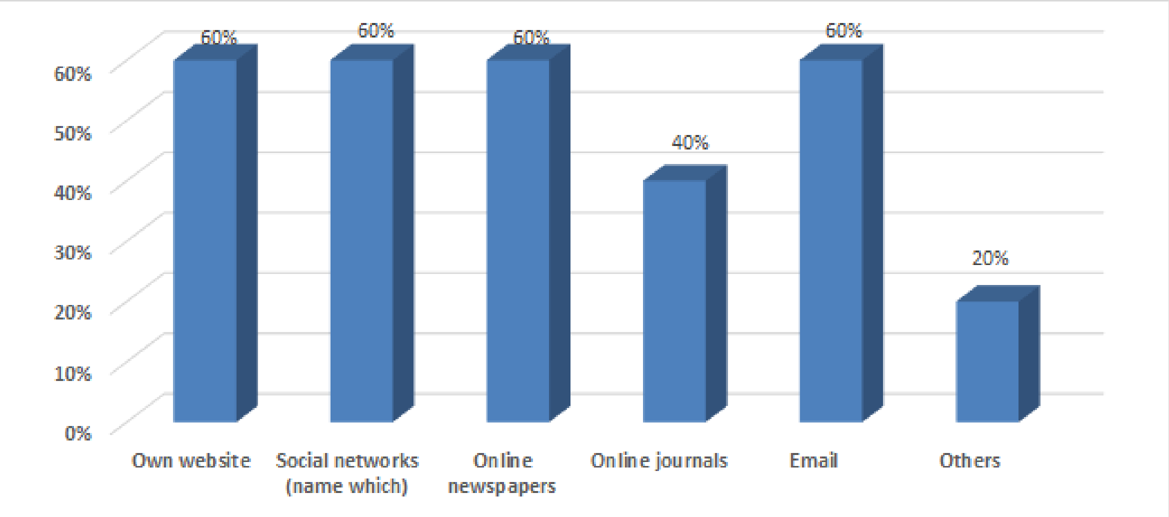

Figure 4.10 Advertisement Channels

When asked about the percentage of access versus display for their advertisements, all those who responded indicated that they did not have access to this figure. However, when asked about the percentage of products sold with respect to the access, half of the respondents could provide the percentages (20% and 10%). Additionally, one of the businesses indicated that, “If people like my advertisements the percentages will be high”, while another one specified that, “I don't know”.

For 25% of the respondents, their income is completely dependent on online advertising, while 50% and 25% of the respondents rely on online advertising for 40% and 20% of their income, respectively (Figure 4.11).

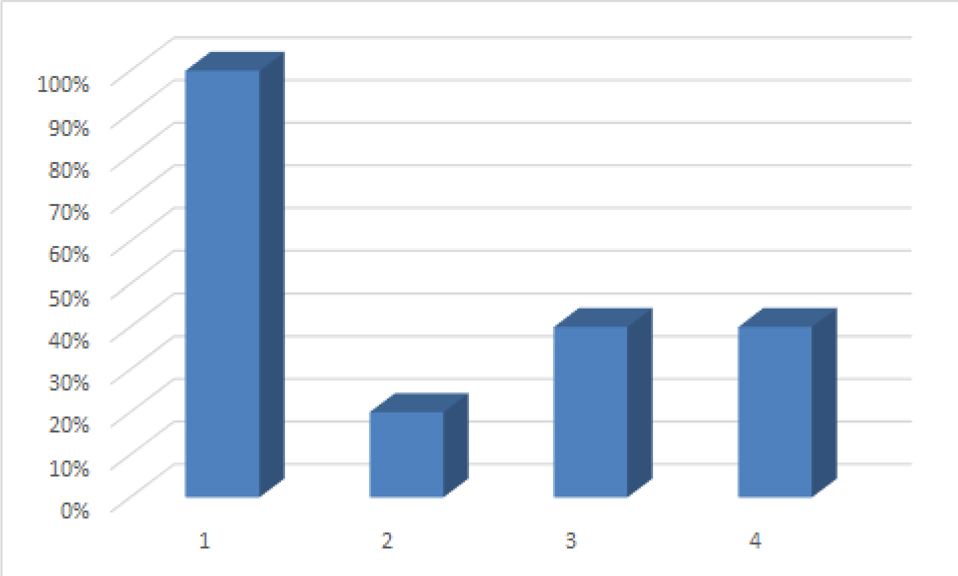

Figure 4.11 Percentage of Income from Online Advertising

None of the businesses whose representative was interviewed was currently using adaptive advertising techniques of any kind, yet all felt that advertising of this type would potentially lead to higher rates of income when compared to the non-adaptive forms they were currently using. Responses to this question included “I think so”, “yes” and “yes, but I don't use it”. Moreover, one respondent stated that, “if the real estate ad is categorised with respect to age and financial situation and every category is given to the suitable users, I guess we will get a high percentage of products sold”. All respondents also preferred their advertising to be categorised on hosting websites and directed to specific groups of people. Some respondents specified that, “I need to categorise my transportation packages and send them to a suitable person” and that thus “it would help me to send the adverts to the right person or company”.

4.4. Discussion

This section discusses the main features which adaptive advertisements needs to implement or consider implementing according to the overall results gathered from questionnaires and interviews.

The study that is presented here can be considered a preliminary study into adaptive e-advertising, especially with regard to the data gathered from businesses, given that the number of respondents (five) was low.

The first thing of note is that the user comments, as stated above, mentioned that Amazon did currently use advertising that was at least partially personalised. This is due to the fact that on Amazon, when one purchases or views a book, for example, they are also advised about similar books that other people who also looked at the selected book purchased [93]. This helps to direct a users' search towards additional products that may be of interest, as well as to enable a positive attitude to such advertising.

The second item of note regards the comments made by users about why they liked advertisements. Most of the comments were grouped into either design relevance or cost categories. According to the comments, most users were attracted by the design, thus suggesting that this is a key aspect to consider when developing advertisements. However, design can also have a strongly negative effect, such as in the case of pop-ups in front of user windows or information that loads slowly and does not have a "close" button [103]. However, this research will not treat the cost category, as there is no selling of any product in this research.

From the principles of human-computer interaction research, items that are close together on the screen are seen as related, and users view things that are the same colour or shape, or that move or change together, or reside inside an enclosure (e.g. a box) as related [104]. This closeness gestalt principle [106] needs to be incorporated into advertising design, to ensure that users do not overlook features due to layouts violating the closeness rule (e.g. buttons and dropdowns, etc. being too far from the objects being actioned). Additionally, research into Western world websites found users spend 69% of the time viewing the left half of the page and 30% of the time viewing the right half of the page, while the remaining 1% is generally used for viewing information that requires scrolling to the right [105]. Thus, horizontal scrolling should be avoided and the advertisement placed on the left-hand side of the screen for users speaking languages that run left-to-right (such as Western world languages), and on the right-hand side for users speaking languages running right-to-left (such as Arabic), to ensure increased levels of attention.

The third point of note concerns bandwidth. Displaying advertising content according to the bandwidth that is available to users is very important. For instance, displaying an advertisement in flash or video format needs a high bandwidth; in contrast, text format is suitable to display using just a low bandwidth.

The fourth thing of note relates to respondent comments on whether advertising uses a reasonable screen outline for different user devices. Large advertisements that don't fit the small screen of mobile devices may bother users. Similarly, the resolution of devices may be limited, and conflict with high-resolution advertisement formats.

From the responses provided by business representatives, it is to be noted that respondents would prefer to send appropriate advertisements to appropriate users, a service that requires personalisation of advertising. Based on the evaluation with business owners and Internet users, ‘appropriate advertising’ for businesses means that their advertising is to be categorised on *hosting websites* and directed to *specific groups* of people. Additionally, the definition of 'appropriate advertising' from the Internet users’ point of view is that of receiving suitable advertisements, based on their characteristics and interests. Whilst the number of participants in this study is low for the businesses, their importance is high, as they can be considered experts in the field, as owners of their own business, so the actual number of participants is less important, compared to their feedback.

In the next section, the lessons learned from the exploratory case studies are combined with a literature review, to propose a model for lightweight adaptive advertising.

4.5. Requirements for the Implementation Methodology

The results of the study presented in this thesis propose a clear set of features, which are specific to the advertising field. For instance, they recommend *linked and categorised advertisements* (business owner question in section 4.2.2 and Appendix B, the comments of business owners in section 4.3.2 and open comments in section 4.3.1, and further detailed and discussed in Chapter 6, section 6.2), *adaptation rules* (hypothesis H2, as defined in section 4.2, and further explored and discussed in Chapter 7, section 7.2), *user characteristics/behaviour* (hypotheses H1 and H3, defined in section

4.2, and further explored and discussed in Chapter 8, section 8.2) and *location on the webpage* (further discussed in Chapter 9, section 9.3). These are all necessary to identify the most suitable advertisements for each online user, and are not available and supported by previous existing models. Thus, a model that supports adaptive advertising has to implement all these features (see Chapter 5).

The requirements for the implementation methodology are identified, based on the outcomes of the exploratory case studies above and the literature review, as follows.

1. The methodology must prioritise flexibility and agility, thus prototyping should be applied to generate the AEADS system. A first version of the system will be generated, validated, tested, and finally evaluated (Chapters 6-9). The evaluation analysis data will then be used to generate the second version of the AEADS system (Chapter 9).
2. The methodology will rely on social networks as the primary source for extracting attributes of the user model form (Chapter 8).
3. The methodology permits the author to categorise the advertisements in the domain model (Chapter 6).
4. The methodology should enhance the user model structure, by dividing it into multiple levels. This will enhance the processes for storing and retrieving data (Chapter 8).
5. The methodology should introduce an easy graphical user interface tool, to easily create the adaptation rules (Chapter 9).
6. The methodology should ensure that the system monitors the use of advertisements (Chapters 8, 9).
    - Find out how many people click on each advertisement.
    - Find out how many people view an advertisement and do not click.
7. The methodology proposes to add a social interaction element to advertisements, such as ‘like’ or ‘stop’ options (see Chapter 9).

The proposed system for personalised advertisements is heavily based on e-learning adaptive systems, and that the application of similar systems in advertising is in its infancy.

4.6. Conclusion

In this Chapter, an exploratory study has been presented, in relation to the challenges and primary elements of the overall study. The user-centred design method has been utilised in this study, according to the ISO-standard 13407, so that the preferences of Internet users and business owners could be examined. Overall, the primary result of this Chapter, along with the outcome of the research, has shown that businesses would prefer to send out personalised or segmented advertising messages. Based on the research results, a new theoretical model and adaptive e-advertising system have been proposed, to enhance the organisation and adaptation of advertisements on any website it is introduced to. The purpose for this methodology is to create a generalised system that can integrate and work with any website. Moreover, the importance of social networks as the primary sites for extracting users' characteristics has been brought to the fore and discussed. To this end, social networks have an increasingly important part to play in identifying users' attributes. An evaluation methodology has been proposed for each layer of the system.

Furthermore, Internet advertising is a growing revenue stream that many businesses are considering. However, personalisation may be the key to ensuring effectiveness of the advertising. Social network analysis is a growing area of knowledge and, as shown in this instance, it is also an effective source of complex user data that have the potential to revolutionise e-advertising.

In summary, the research shown in this Chapter has implemented (the implemented parts are underlined) the research objective **O2:** "*Design a set of preliminary studies with businesses and users, to establish the current state of art in the area of adaptive advertising and to gather the requirements for the design and implementation of an appropriate theoretical model and system*". The procedure for analysing this objective has been outlined and the outcomes have helped to answer the research questions **R1:** "*Is adaptive advertising useful for businesses and users?*", **R1.1:** "*Is it more acceptable for users to have adverts personalised to them and their environment? (i.e., do users find personalised adverts more acceptable than non-personalised)*", **R1.2:** "*Is it more acceptable for businesses to deliver adaptive advertising? (e.g., do business users find adaptive advertising more acceptable when compared to non-adaptive advertising, and do they expect the former to provide a* *better income)*", and **R1.3:** "*What is a good source of information for adaptive advertising?*". The answers to these research questions are presented in this Chapter and were produced through gathering the requirements of business owners and Internet users. In addition, they will be answered through designing an appropriate model and system for adaptive advertising. The details of the model and system are discussed in Chapters 5-9, where the research questions **R2** and **R3** are answered.

Chapter 5

The Layered Adaptive Advertising Integration Model (LAAI)

5.1. Introduction

This Chapter aims to address the research objective **O3:** "*Based on the outcomes from O1and O2, propose an appropriate theoretical model (new or extended) for lightweight adaptive advertising*". This Chapter discusses in depth a layered theoretical model to support answering the research question **R2:** "*How can we create a model for lightweight adaptive advertising and design the corresponding system that can be integrated with most websites?*".

There are several models and frameworks through which adaptation information may be authored and delivered, for instance the Dexter Hypertext Reference Model [74], AHAM [53, 144], WebML [38], LAOS [50], SLAOS [67], and XAHM [35]. Each of these models and frameworks has different benefits and limitations, as described in Chapter 3. The SLAOS framework integrates users – authors and learners – with their collaborative activities. The social activities in this framework drive the delivery as well as the authoring process, by introducing adaptive materials for these users, based on communities of practice. The social layer in SLAOS interacts with all the five other layers of the LAOS framework. For instance, the user model layer contains new entities that describe the groups and roles that will be assigned for these social groups. Besides these models and frameworks that are designed mainly for the education field, there are a limited few frameworks that are designed for advertisement adaptation.

AdRosa [88], and, more recently, MyAds [5] are examples of advertisement adaptation frameworks. AdRosa makes automatic personalised web banners, depending mostly on specific browsing behaviours of a user. AdRosa uses a portal model of advertising to deliver the advertisements. The more recent MyAds system [5] is a social adaptive hypermedia system used for online advertising.

It is a standalone system based on its own theoretical framework, consisting of five main layers. The theoretical framework is rooted in the adaptive hypermedia theory [30].

However, none of these models has as a primary objective the lightweight integration of adaptive features on websites. In addition, a large number of them are designed for the educational field, which is not directly related to the research presented in this thesis. The two last models mentioned are more strongly related to this research, as they are designed for the advertising field. However, AdRosa uses a user model only based on user behaviour, and the model in MyAds has been only recently built, in parallel with the one in this thesis, and has a different purpose, that of a standalone system, so it's not directly applicable to this research, where the main aim is portability and generalisation.

5.2. Proposing the Layered Adaptive Advertising Integration Model (LAAI)

Based on the analysis of existing models and frameworks, and the fact that they cannot be directly applied to the current work, this thesis proposes a new adaptation model, named the *Layered Adaptive Advertising Integration (LAAI)*, which can be used to disseminate advertising, and which is based on previous hypermedia adaptation models. This model seeks to introduce common abstractions in order to provide a basis for the development of advertising adaptation applications and to support the portability of these applications. LAAI ensures separation of content, adaptation requirements and delivery within an adaptive advertising application [50, 53]. This is important for higher-level strategies, as it enables content to be reusable. The structure of the LAAI model is illustrated in Figure 5.1 and comprises four layers: *domain model (DM), adaptation model (AM), user model (UM),* and *delivery model (DM).*

The LAAI model aims to reuse certain features from previous models, such as AHAM [53] or LAOS [50], whilst increasing portability. Some elements of previous models, such as LAOS's Goal Model, have been discarded, as the Goal Model is based on pedagogical narrative, it is not useful in adapting advertising content. However, several features of the LAOS Presentation Model have been integrated as a sub-model in the User Model known as 'Future Advertisements'.

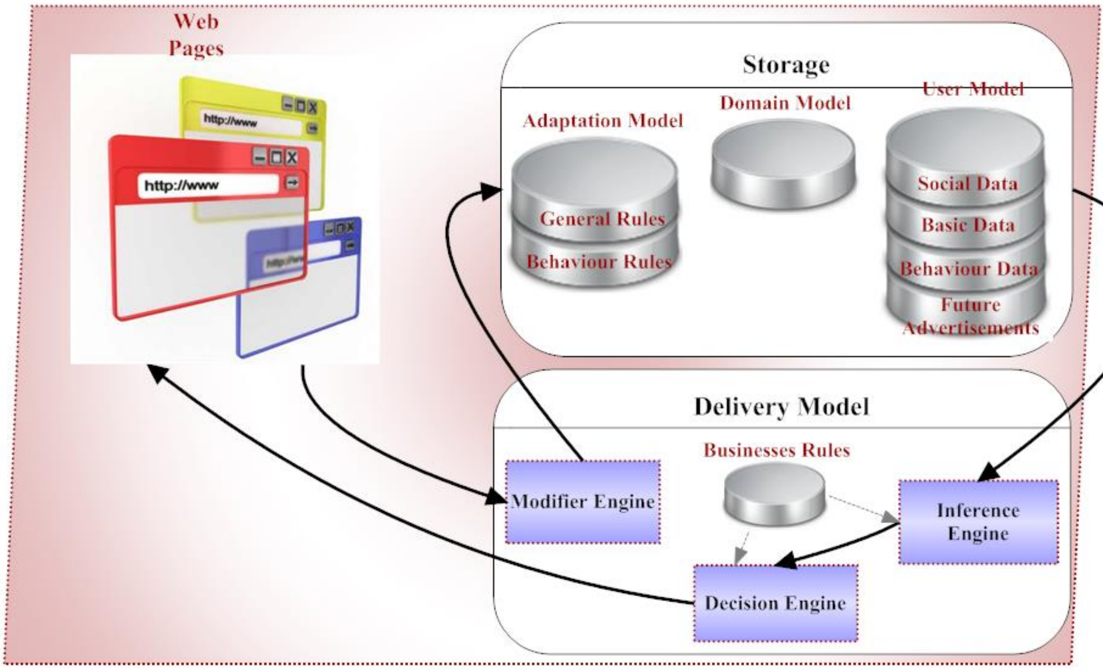

Figure 5.1 The Layered Adaptive Advertising Integration (LAAI) Model

The first three layers of the LAAI model comprise the storage area. The first layer, *domain model (DM),* describes entities in an application that represent advertisements and the relationships between them, which are represented by grouping the advertisements into levels. The next layer, *adaptation model (AM)*, includes the adaptation rules that adapt advertisements for each user. The *user model (UM)* layers store four different types of data: social data, basic data, behaviour data, and future advertisements data. The final layer, *delivery model (DM)*, uses the data stored in other layers to generate adapted advertisements. This layer also monitors user behaviour and updates the other layers with current user status. The business rules that are stored within the delivery model layer are a new concept within adaptation frameworks, and will enable businesses to modify the priorities and actions of inference and decision engines.

The framework design and initial analysis of this model supports objective O3, which states “Propose an appropriate theoretical model (new or extended) for lightweight adaptive advertising”. However, as described, the LAOS framework has been used as the initial basis, which then has been further developed. The architecture of the LAAI model and the ways in which this model may be employed to develop systems to adapt advertising that can be easily integrated within websites, will be described in the following sections.

5.3. Domain Model (DM)

In adaptive hypermedia applications, the *domain model (DM)* consists of concepts and of the relationships between these concepts. The most common relationships type is the hypertext link. The concept is classified within two categories – atomic or composite – with respect to the information structure [145]. Atomic concepts represent fragments of information, while composite concepts include sequences of sub-concepts. If the children of a composite concept are all atomic in nature, then this concept represents a page.

The domain models in previous adaptation models or frameworks, such as AHAM [53], the Munich Reference Model [92], the Dexter Hypertext Reference Model [74], XAHM [35], WebML [38], and LAOS [50], are similar but structured slightly differently. In the Dexter Hypertext Reference Model, the hypertext link relationship is the only type of relationship between components of hypermedia systems, i.e., link components. In AHAM, in addition to the hypertext link relationship type, a prerequisite type is added – for instance, users must read C1 before C2 if C1 is a prerequisite for C2. LAOS introduces the same idea but divides it across two layers – domain model and goal and constraint model – in order to contain concepts and their relationships.

The remainder of this section focuses on the domain model, which is the first layer in the LAAI adaptation model. Generating an efficient domain for adaptation systems is dependent on the underlying concept of advertising, which for the purposes of this thesis will be considered to be a tool used to sell an item by causing a customer to become attracted to it upon seeing or hearing an advertisement. As the domain model represents the author's view of the application domain, then the basic item in the domain model is the advertisement. Each advertisement in the domain model contains a number of attributes, such as the location of the advertisement in the storage medium and its name and description. These attributes form a model of the advertisement and include some information about the advertisement that will be used by the delivery layer to carry out adaptation of the advertisements. For example, the description of an advertisement may be used in many processes in the delivery layer, in addition to the adaptation rules, that are carried out to match advertisements to users. These attributes can also be easily extended by any application to reflect its particular requirements or in response to changes. These advertisement attributes can be considered to correspond to atomic concepts in other adaptive hypermedia models like AHAM.

As illustrated in Figure 5.2, advertisements are also grouped into categories on multiple levels determined by the author. This grouping process enriches the domain model and helps to overcome authoring difficulties. For example, as the author can divide advertisements into groups based on certain user characteristics – age, such as advertisements for children, for instance – it becomes much easier to write adaptation rules. As well, in this model, the author can add a relationship between advertisements by constructing plan libraries that represent a sequence of advertisements. These libraries can be used later by inference engines to display advertisements in sequence based on clicks.

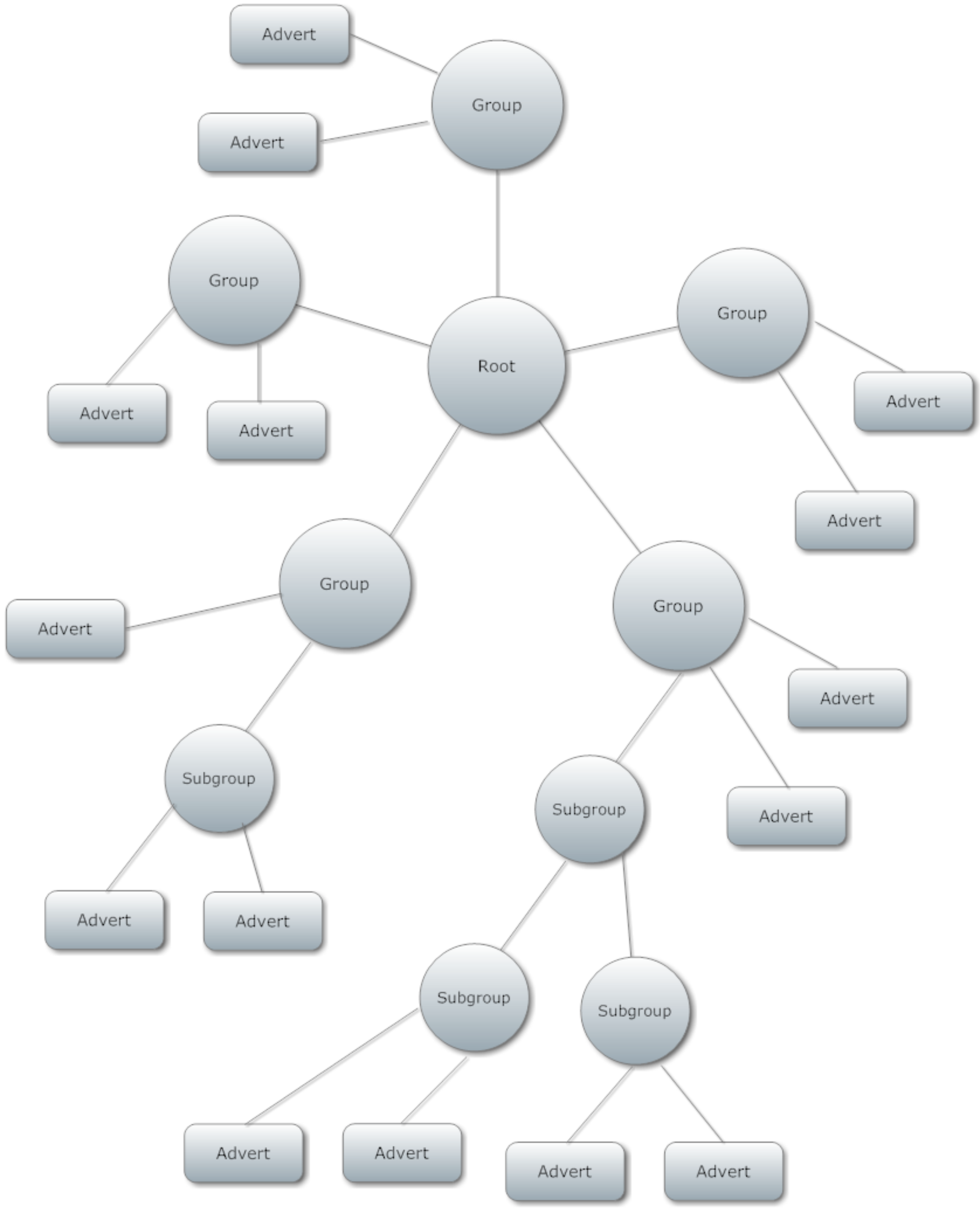

Figure 5.2 Domain Model Structure in LAAI

Thus, the domain concept in LAAI can be summarised as a single root concept that contains many composite concepts. These composite concepts can contain other composite concepts as well as atomic concepts as children. Advertisements are considered to be atomic concepts, and do not have any child concepts, only a set of attributes that describe each advertisement and that are used in various ways on subsequent layers. This summarisation is illustrated in Figure 5.3. This domain model is a simplified version of the traditional representation in adaptive hypermedia models (including LAOS); in addition, the categories are based on the features of the advertisements.

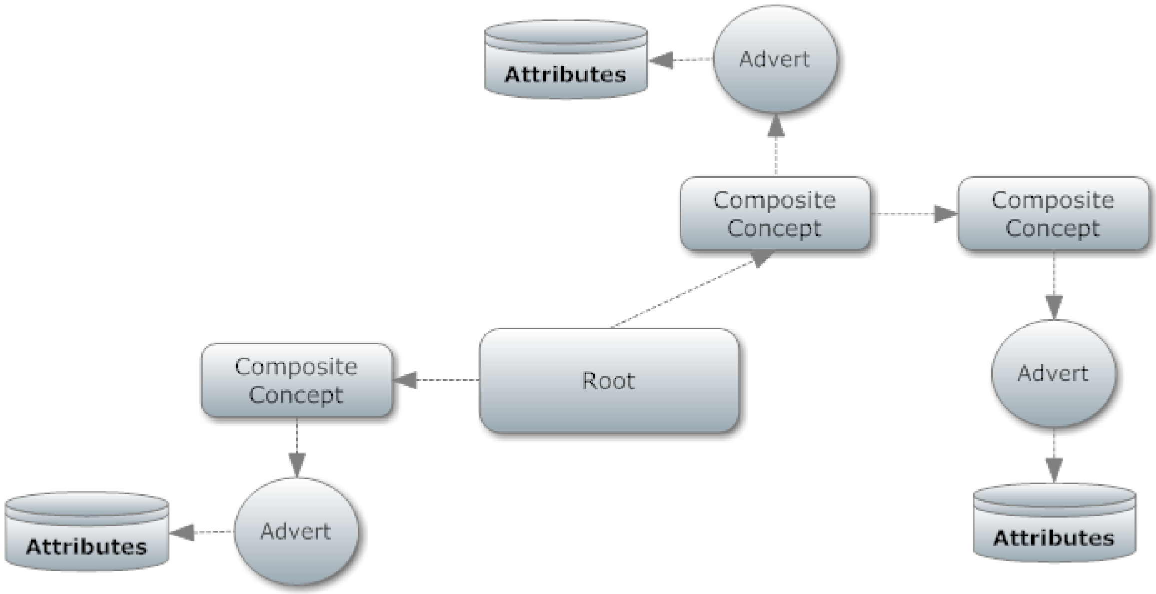

Figure 5.3 Composite and Atomic Concepts in LAAI

5.4. Adaptation Model (AM)

In general, an *adaptation model (AM)* will describe how the AHS should carry out adaptations in order to display appropriate information to each user. These adaptations are performed based on domain models and user models; there must therefore be a connection between these two models. The adaptation model consists of a set of rules and functions that are used to perform adaptations. In order to carry out adaptations in an adaptive hypermedia environment, an adaptation method is required [25]. Each method can be applied via a number of techniques. These techniques can be defined based on knowledge that exists in the user model and by an adaptation algorithm. For instance, in order to perform the following: "...hide the links to the concepts which are not yet ready to be learned", several different techniques can be implemented. Brusilovsky in [25] introduces different adaptation technologies that are used in adaptive hypermedia. These technologies are classified into two groups, based on adaptive presentation and adaptive navigation.

The adaptation model in AHAM [145] is defined as a set of adaptation rules – condition-action rules – that establish a connection between domain model, user model and the presentation that will be generated. As AHAM is AHS-dependent, it contains no fixed syntax of adaptation rules. By contrast, in LAOS [46, 50], the adaptation model consists of three layers in order to overcome the limitations of the inexperienced author and allow adequate flexibility for the advanced author. These layers, Adaptive Assembly Language, Adaptive Language and Adaptive Strategies, are distinguished by the type of rules they allow. The first layer, Adaptive Assembly Language, represents traditional techniques like the insertion/removal of fragments, sorting of fragments and links, link hiding/removal/disabling, and so on, as defined by Brusilovsky's taxonomy [25]. The second layer groups the elements from the previous layer to create adaptation mechanisms and constructs, which can be represented as a higher-level adaptation language, while the third layer uses the building blocks from the previous layer to build higher-level programs.

As in the AHA! system [20], an adaptation engine is required for the actual implementation of the AHAM model. The adaptation engine performs many tasks, such as updating user models, displaying concepts based on rules, and so on. In the LAAI model, these functions are isolated in the delivery layer.

The specification of adaptation in the LAAI model can be described by the adaptation model. The adaptation model layer contains the adaptation rules, which specify different styles of adaptive behaviour. This layer describes the relationships between domain models and user models, and based on these relationships, a group of advertisements can be assigned to each user. The adaptation rules in the adaptation model are separated into two groups – *general* and *behaviour* – in order to facilitate authoring and to ensure that advertisement adaptation is reasonable. This grouping of adaptation rules is also intended to facilitate any future extensions of the rules, by mapping the relationships between adaptation rules, user model and decision engine. Furthermore, applying template adaptation rules within these categories precludes the need to write complex adaptation rules by hand.

The *behaviour rules* assign advertisements to a user, based on the user's behaviour. This process involves a number of prewritten strategy templates that the author may choose from and control. This strategy overcomes the limitations of inexperienced authors, which have been highlighted in prior research [62, 127]. The author (here considered to be the website and business owner) controls these strategies by updating them to meet specific requirements. For instance, using an adaptation system based on the LAAI model, it is easy to add a behaviour rule that will instruct the delivery layer to display an advertisement after a user has clicked on another specified advertisement. As shown in Figure 5.4, after putting together a sequence of these rules, the author must then assign or un-assign advertisement to these rules.

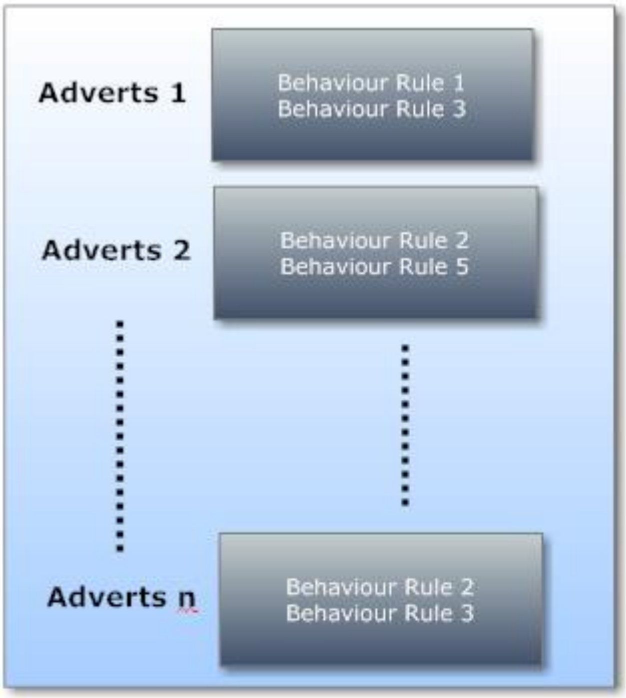

Figure 5.4 Behaviour Rules in LAAI

With respect to the nature of advertisements, in addition to grouping advertisements into levels within the domain model, the behaviour rules must also establish links between advertisements in the domain. Thus, for example, when using an application that has been developed based on this model, the author can add a behaviour rule to display two advertisements from a specified subgroup, if another specified advertisement in the same subgroup is clicked. In order to ensure flexibility, the application must allow the author to control the number of clicks to fire and the number of advertisements that will be shown.

By contrast, *general rules* generally assign advertising content to a user based on basic data from the user model such as age, gender, etc. The author must be able to add and remove these characteristics in order to maximise the portability and generalisability of the adaptation system. This type of adaptation rule has some similarity to stereotyping, as, for example, an adaptation rule may assume that if a user is employed as a judge, they are likely to be over age forty and well educated, and will assign advertisements based on this information.

General rules can make use of two types of data – discrete or range. The data type can be determined by businesses to maximise flexibility and efficiency. As illustrated in Figure 5.5, businesses can add a general rule named 'gender' using discrete data that will retrieve the gender of users. According to this rule, advertisements can be categorised by businesses for male and female users. By contrast, general rules can also be assigned based on range-type data. Figure 5.6 and Figure 5.7 illustrate the general 'age' rule using different data types. In other words, a business can assign a general rule, 'age', and can then assign the appropriate data type for this rule according to their marketing policy.

Gender General Rule	
Data Type	Discrete

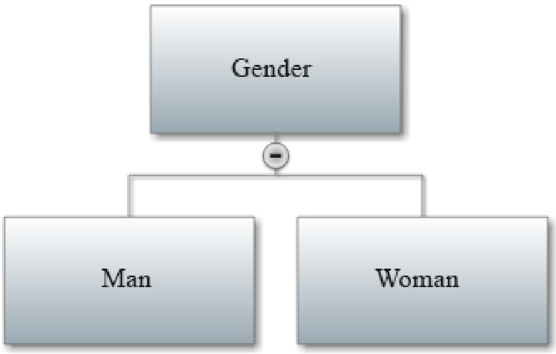

Figure 5.5 Gender Rule with Range Data Type

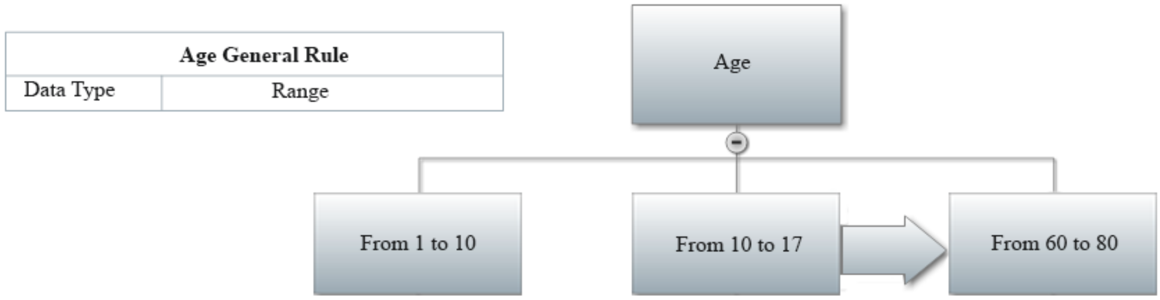

Figure 5.6 Age Rule with Range Data Type

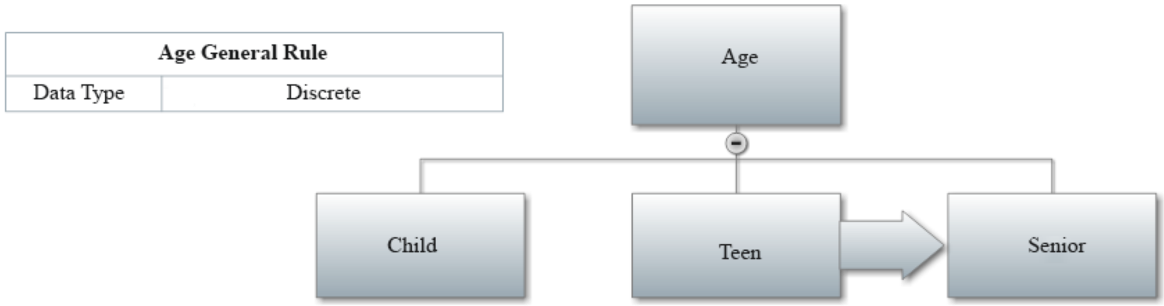

Figure 5.7 Age Rule with Discrete Data Type

Finally, the adaptation model allows for an easy match between rules and domain models, as rules only need to be written once and can then be assigned to any number of advertisements. With regard to flexibility, generalisability and portability, for any application based on LAAI, the adaptation model is considered as a storage layer, and any implementation for adaptation is isolated within the inference engine in the delivery model.

5.5. User Model (UM)

More often, users have unique behaviours, characteristics, interests, goals and so on. In order to personalise advertisements, these must be modelled, and a user model is a basic component in any system offering personalisation. All adaptive hypermedia frameworks and models have a user model as one of their components [35, 38, 50, 53, 74, 144]. A user model is a collection of data that describes a user's characteristics explicitly at a certain time, while user modelling is the process that manipulates the user model by creating and updating its components, as discussed in Chapter 3.

In AHAM [53], the user model includes a set of entities associated with a number of attribute-value pairs. Some attributes are typical for DM-related concepts, while others represent a user's background, preferences, and general data. Every concept in the domain model appears within the user model associated with user knowledge. LAOS [47] views the user model as a concept map, since the relationships between variables in the user model can be explicitly expressed as relationships in the user model and do not need to be "hidden" within adaptive rules.

The *user model (UM)* in LAAI was designed based on the LAOS framework. However, the LAOS model was extended by adding components relating to social input and future advertisements and by moving several functions, such as the inference function, to the delivery layer, in order to support the integration process.

The first component (*basic data*) contains basic user data, which are acquired directly and does not require inference or tracking of user behaviour. This component includes user characteristics such as age, gender, interest, bandwidth, device type, etc. The characteristics that are taken into account here must be appropriate for the adaptation of advertisements. Demographic information, interests, education level, age, gender and so on are all required in order to efficiently adapt advertising content. However, some characteristics, like bandwidth and device type, must be acquired automatically, in order to decrease the burden on the system and to maximise portability and generalisability.

Social networks are good sources of user information [59], from which user behaviour and characteristics to personalise advertising can be retrieved. Social networks have become a part of all of our lives, and the number of people using social networking sites is increasing rapidly every year. These social networks reflect and record the social practices, behaviour, preferences, and concerns of their users. The various forms of social networks vary, from those in which users actively participate in content creation and production, to those that share content. In general, however, a large amount of user data can be acquired from these sites, including gender and geographic region.

In this component of the LAAI model, basic data can be acquired from social networking sites, either through the registration process or automatically, as illustrated in Figure 5.8. The registration process is considered to be the traditional method of obtaining basic user data. Profile information – age, gender, etc. – can be taken from social networking sites without requiring registration/log-in, which can overcome some issues relating to portability and generalisability in the creation of adaptation systems for advertising content. The automatic acquisition of some basic data not only makes significant progress in achieving these goals, but also returns accurate data (which has been verified by other systems).

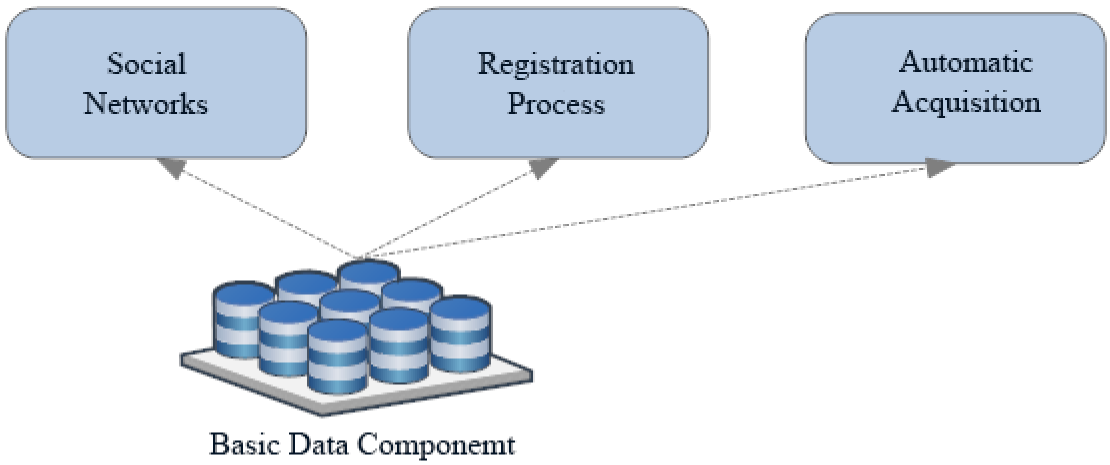

Figure 5.8 Methods to Collect Basic Data

The second component of the user model – *behaviour data* – contains information about the behaviour of each user. This information varies, according to the actions of the user. In order to design an application to effectively adapt advertising content, actions such as the number of displays and clicks for each advertisement, in addition to actions such as searching for and purchasing items, must be tracked and saved. This is illustrated in Figure 5.9. The application developed for the LAAI model will monitor user actions and store binary values (clicked or not clicked, sequence of clicks, etc.) for each user.

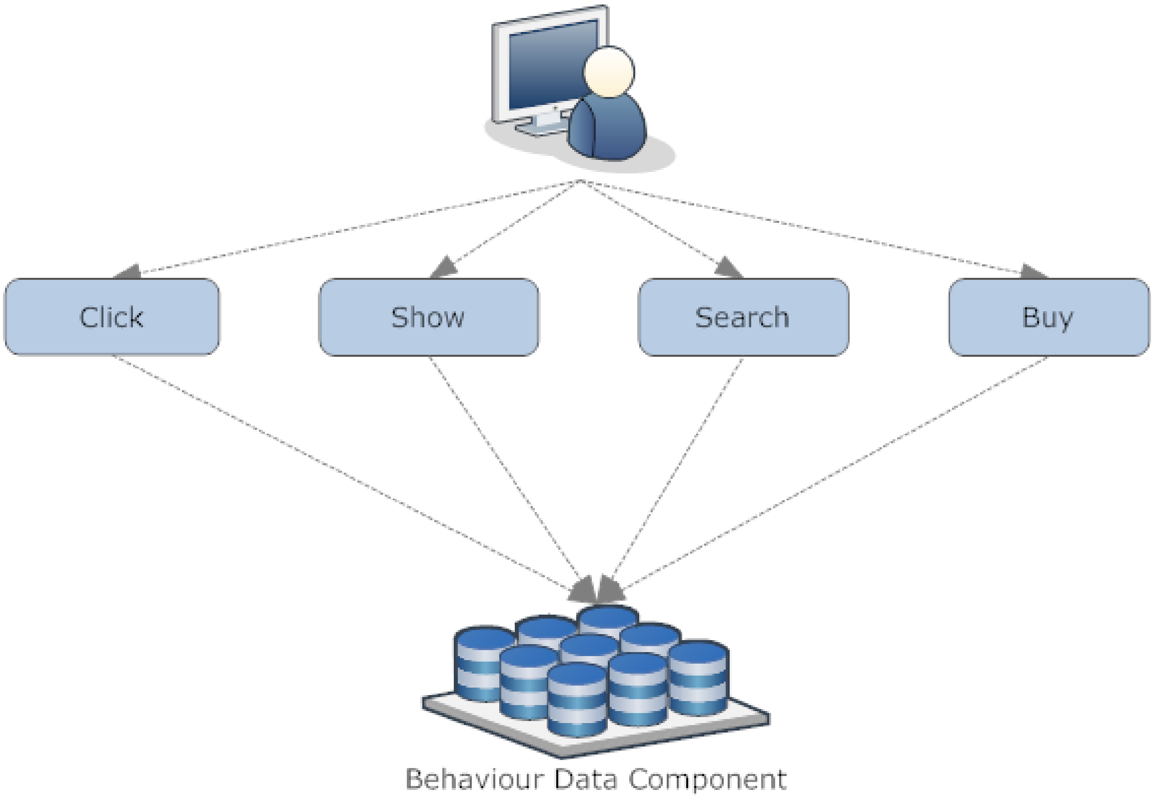

Figure 5.9 Method to Collect Information on the User's Behaviour

The third component – *social data* – is a creative component, and has been added to the user model as a new concept, supporting the evolution of the adaptation of advertising content. This component allows users to control advertisements in the domain model and to identify them with social data, such as likes and stops. Businesses may decide what happens based on this data – for instance, if a user stops an advertisement, the business may choose to stop this particular advertisement or to hide all advertisements within the same category for a fixed number of log-ins. The advertisements in the domain model are attached to the user model, as illustrated in Figure 5.10, that represents a user's actions, such as click, search, and so on. Additionally, as an application of the social features in the model, the advertisements can be marked as 'like' and 'stop', to support the adaptation process. In order to apply business decisions, these social data will be implemented in the delivery process.

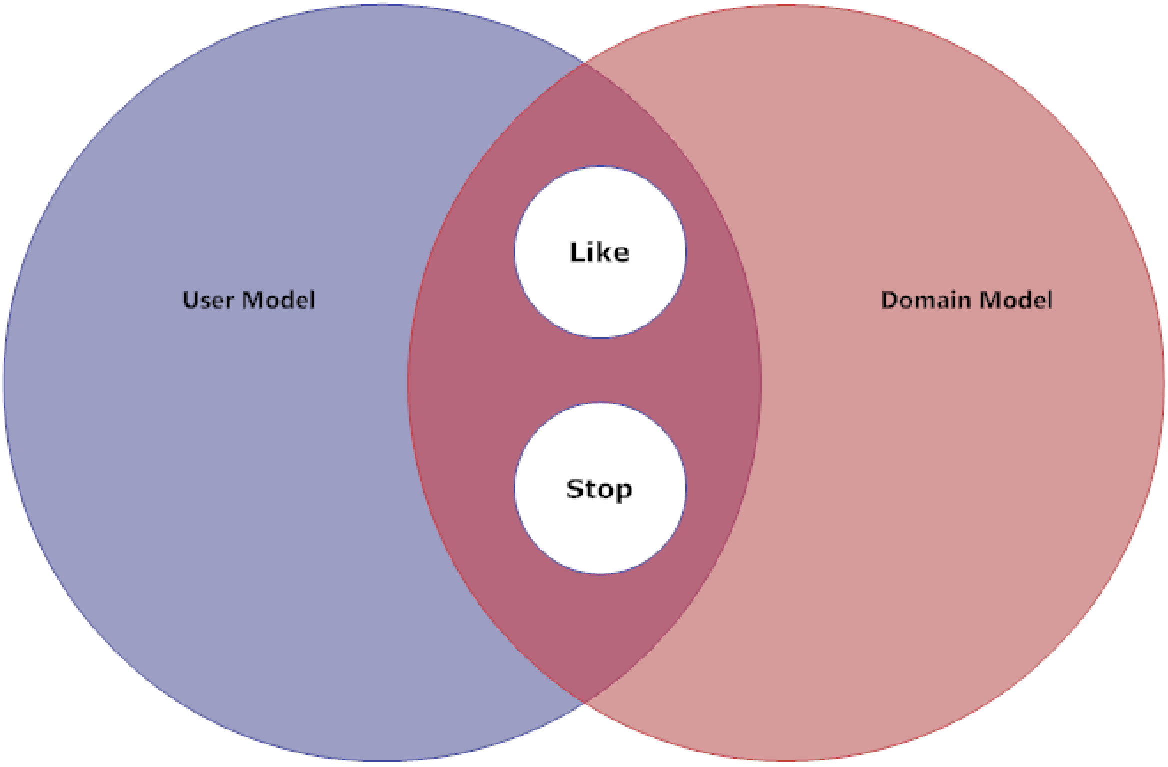

Figure 5.10 Social Data in the User Model

The fourth component – *future advertisements* – includes advertisements that will be shown to each user in the future, based on the previous components in the user model and delivery model. Based on the delivery model, this component stores advertisements that will be shown to users on their next log-in. The delivery model stores the remaining advertisements that will be shown to the user based on the decision engine, which is a component of the delivery model. These future advertisements will be stored and shown at a future login. For instance, the advertisements that will be shown to a user will be organised based on priority, as established by the application of the rules. This queue will then be saved in the future advertisements component, during log-out. Cookies and other similar techniques are commonly used in existing adaptation systems, but the future advertisement component introduces a more accurate, machine-independent and persistent process, since cookies can be blocked by many users. Finally, an initial user model can be generated by the registration process, social network log-ins and automatic acquisition of data.

5.6. Delivery Model (DM)

In the LAOS framework, the adaptation and presentation layers are responsible for delivering adapted content to users. An adaptation strategy is carried out based on the specifications in the adaptation layer, and the resulting data are passed to the presentation layer, which will display it to the user in a specific format. In the AHAM adaptation model, presentation specification and run-time layers form the delivery component that displays appropriate content to users. The adaptation model forms a connection between the user model and the domain model, in order to generate presentation specifications via the adaptation engine. In the LAAI model, adapted advertising content is delivered using the delivery model.

The *delivery model (DM)* developed for the LAAI model is further detailed and contains three engines: *inference*, *decision* and *modifier*. The reason for this design decision is to separate important stages in the delivery of appropriate advertisements to a client. Using these three engines, the delivery model generates advertisements that are suitable for the current user. The first engine, inference, carries out reasoning processes about the state of the user. The decision engine is based on adaptation rules, domain items and data generated by the inference engine, and retrieves appropriate advertisements for each user and displays these advertisements. Finally, the modifier engine updates the user model with current data. The modifier engine determines how to make transitions to the user model, and updates the data in the user model based on the behaviour of the user. The following subsections describe the actions of these three engines.

5.6.1. Inference Engine

As illustrated in Figure 5.11, the *inference engine* obtains data from the domain, adaptation and user models and carries out a series of processes based on these data in order to generate multiple sequences of advertisements to send to the decision engine. Adaptation rules from the adaptation model are executed in the inference engine. Firstly, it determines whether the current user is logged into the website. If the user is not logged in, the inference engine will only apply the *plan recognition* process, based on the current session and behaviour data only. *Plan recognition* refers to the task of inferring the plan of an intelligent agent from observations of the agent’s actions or the effects of those actions [126]. This helps pinpoint the aim of the user, based on their actions in a specific environment, thus narrowing the number of possible goals, by observation of the actions performed. For example, in message centres and information systems, users often have specific goals such as listening to new messages, getting billing information, or receiving weather forecast information for a local region. The *plan recognition* technique is applied in the research by adding a *plan library*, constructed by the thesis author, which is triggered according to user behaviour, as discussed in Chapter 9. By taking this approach, user behaviour has been combined with the much needed authoring aspects that are required by adaptive advertising.

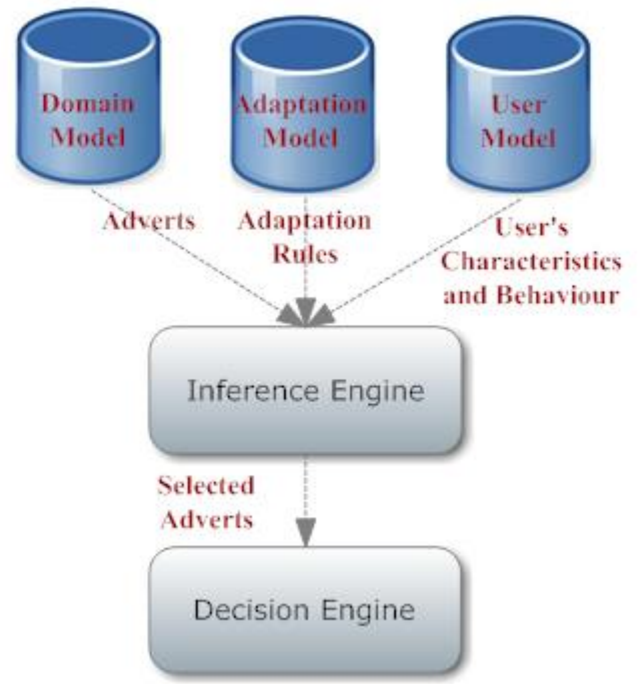

Figure 5.11 Inference Engine

The *plan recognition* process depends on the plan libraries (Figure 5.12), which the business will have previously created. The inference engine checks clicked items and then checks the plan libraries, in order to generate a sequence of advertisements, to be dispatched to the decision engine. For example, as shown in Figure 5.12, the author may construct a plan, such as follows: Advert 1 followed by Advert 3 and then Advert 6. This plan will be triggered by the inference engine when Advert 1 is clicked by a user. In this situation, the inference engine will place Advert 3 and Advert 6 in a queue that will be sent to the decision engine. In the case of two plans sharing the starting advert, AEADS will discard the advertisements from these plans and instead send a random advertisement to the user.

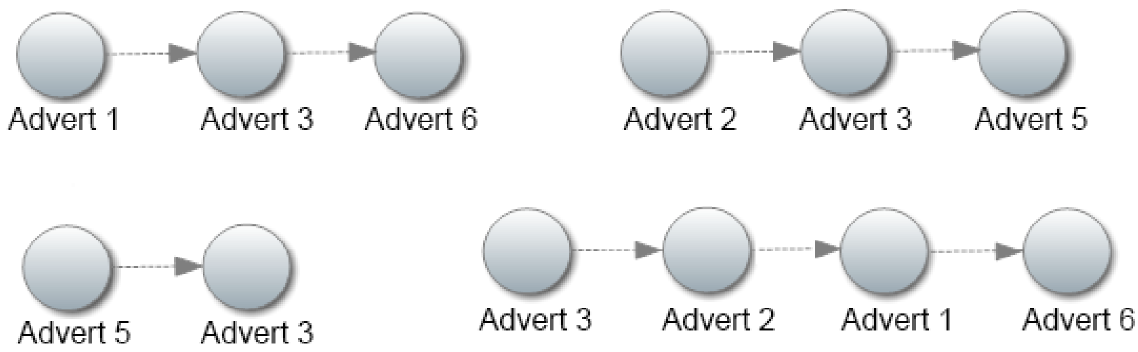

Figure 5.12 Plan Libraries from the Domain Model

On the other hand, if the current user is logged in, then the general rules from the adaptation model will be applied by the inference engine first, in order to assign a group of advertisements from the entire domain to the user, based on features such as gender, age and so on. The group of data relating to the current user will be sent directly to the modifier engine, which will update the user model with 'allowed' and 'not allowed' advertisements. The behaviour rules representing adaptation strategies will then be applied. The user model data that represents the user's behaviour – clicked advertisements, for example – is used by the inference engine to apply the behaviour rules. This process will yield a sequence of advertisements, which will then be sent to the decision engine.

A sequence of advertisements is also retrieved and passed to the decision engine based on the plan recognition process. When dealing with a user who is logged in, the inference engine will also apply the plan recognition process and pass the results to the decision engine. Moreover, the inference engine will apply a series of processes based on criteria developed by the business relating to user actions, such as searches, likes and purchases. These processes will also yield a sequence of advertisements to be passed to the decision engine.

The social data component of the user model will cause the inference engine to exclude certain advertisements based on 'stop' data and to display other advertisements based on 'like' data. The customised business rules included in the delivery model also help to determine how the inference engine deals with social data. Finally, all advertisements must validate the general rules that were applied in the first step. The inference algorithm is as follows.

Algorithm 5.1: Inference Algorithm

Algorithm #1. ***Inference Algorithm***

1- If user is logged in
   a. Get the advertisements from the inference engine that match and do not match the general rules for the current user.
      i. Send this information to the modifier engine to update the user model.
   b. Get the advertisements from the inference engine that were stopped based on 'stop' social data.
   c. Get the advertisements from the inference engine that were retrieved based on 'like' social data.
   d. Get the advertisements from the inference engine as per applied behaviour rules.

2- Listen for advertisement clicks to apply plan recognition process, then send the results to the decision engine.

3- End if

5.6.2. Modifier Engine

The *modifier engine* updates the user model based on the connections between the modifier, inference and decision engines. The modifier engine receives two groups of advertisements for the current user from the inference engine, which has applied general rules to generate these groups. The modifier engine then updates each user model with 'allowed' and 'not allowed' groups of advertisements, based on these general rules. The decision engine can also send advertisements to be displayed for each user to the modifier engine to update the user model. In addition, the modifier engine can monitor the user's behaviour to update the user model with new data such as clicks, searches, likes and so on. By collecting these data and updating user models, the modifier engine contributes to the portability and generalisability of the overall application design.

Algorithm 5.2: Modifier Algorithm

Algorithm #2. ***Modifier Algorithm***

---

1. Listener for decision engine to update
   - Number of shows for advertisements.
2. Listener for user behaviour to update
   - Advertisements that are clicked, and number of clicks.
   - Advertisements that are searched.
   - Advertisements that are bought.
   - …And so on.
3. Update user model with information obtained by the inference engine by applying general adaptation rules.
4. Update user model with information that describes inference engine actions on advertisements.
5. After log-out, the modifier engine stores the remainder of advertisements in the future advertisements component of the user model for the next login.

5.6.3. Decision Engine

The *decision engine* is responsible for displaying advertisements to the current user. First, the decision engine must check whether the current user is logged in or not. If the user is not logged in, the decision engine will randomly display advertisements from the entire domain. In addition to displaying these advertisements, the decision engine obtains the user's click data, in order to fire the plan recognition process generated by the inference engine. The advertisements generated based on this process will be displayed to the user with the highest level of priority.

On the other hand, if a user is logged in, the decision engine will retrieve the business rules strategy saved in the delivery model, in order to assign the priority levels determined by the business to the advertisements yielded by the inference engine. The decision engine will now also load the advertisements previously saved in the future advertisements component of the user model. This engine also retrieves advertisements that match data from the inference engine, such as 'like' and 'stop' social data, behaviour rules, general rules, and user actions (search and buy), and assigns concurrent priority levels to advertisements, in order to arrange them in a queue. If a user is not logged in, the decision engine obtains the user's clicks, in order to fire the plan recognition process from the inference engine. Advertisements that are generated by this process will be assigned to the tail of a queue.

The decision engine is now ready to display the advertisements from the queue to the current user on any page of the website. The engine displays advertisements from the queue, until the sequence is completed, and then randomly displays advertisements that match the general rules appropriate for the user's characteristics. If the user logs out while there are advertisements remaining in the queue, the decision engine will save these advertisements in the future advertisements components of the user model to be loaded as a first priority at the user's next log-in, as follows.

Algorithm 5.3: Decision Algorithm

Algorithm #3. ***Decision Algorithm***

---

1. If the user is logged in:
   a. Load previous advertisements which were assigned to the user at the last login, but were not displayed (these are stored in the *future advertisements* section of the user model).
   b. Find the advertisements from the user model which do not match the general rules for the current user.
   c. Call the inference engine (General Rules part) one time only at login, to find advertisements which match and do not match general rules, and add these to two lists labelled ‘match’ and ‘do not match’.
   d. Call the inference engine (Social part) to retrieve the advertisements that are stopped based on ‘stop’ social data.
   e. Call the inference engine (Social part) to retrieve the advertisements based on different social data ('like'), and add them to the social data list.
   f. Call the inference engine (Behaviour Rules part) to retrieve advertisements, and add them to the behaviour rules data list.
   g. Remove all advertisements listed in the ‘do not match’ list.
   h. Apply the priority algorithm determined by the business rules, in order to arrange advertisements according to the type of criteria used by the inference engine to obtain the advertisements.
   i. Loop while the user is logged in:
      i. Display the advertisements from the queue on the current page (with the condition of no duplication of advertisements within the same page).
      ii. Advertisement clicks listener:
         1. Call the inference engine (Plan Recognition part) to get the list of advertisements.
         2. Show the results to users as the first priority.
      iii. Call the Modifier Engine to update the user model.
   j. End loop
2. Else if user is not logged in:
   a. Load all advertisements in list.
   b. Loop
      i. Display an advertisement randomly from the list on the current page.
      ii. Advertisement clicks listener:
         1. Call inference engine (Plan Recognition part) to get list of advertisements.
         2. Show the results to users as the first priority.
   c. End loop
3. End if

5.7. Discussion

In addition to its lightweight structure, the LAAI model has introduced several further improvements in the adaptation of advertisements, over other models. Firstly, the domain model structure, which contains advertisements inside groups and subgroups, supports the lightweight concept of the LAAI model. The author needs only create groups and subgroups in the GUI and then insert the advertisement information between them, without writing any code, and the information held in the domain model is sufficient for the adaptation to advertisements.

Next, separating the adaptation model into general rules and behaviour-based ones is an addition which is new when compared to existing models. Producing one set of rules for a user's characteristics and another set for the user's behaviour is a practical method for adaptation to advertisements, ensuring a simple, yet comprehensive way for authors to specify a great variety of adaptive behaviour, broken down into simple parts. In addition, this division and simple addition of these rules support the lightweight concept of the model, since the author can create and classify these rules easily, without any need for writing code, by simply adding rules and assigning them to existing domain items.

With respect to the structure of the user model within the LAAI model, information in the user model is encapsulated in four different components, which support the implementation of lightweight systems. The user model can be easily updated in this case, by updating separate parts independently of each other; and it is also straightforward to pass the information from the user model, according to the type of information held in these components. The social data component of the LAAI model can reflect the user's preferences accurately. Although other models exist, which support both the social login and some interaction, for example SLAOS and MyAds, this model introduces a new idea regarding the user's social interaction, which is particularly designed for adaptation to advertisements. A social interaction for the user is recorded as a component in the user model, in order to lead the system to generate an accurate adaptation decision. For example, the "like" social data that is inserted by the user for any advertisement is stored within the user model, in order to guide the delivery model to generate further advertisements related to this existing advertisement. Using social interaction data in this way can improve the click rate. This increase in the number of clicks is related to the exploitation of the behaviour of the users, in order to show suitable advertisements. In addition, the 'future advertisements' component in the user model of the LAAI model is very important for advertisements, since none of the existing adaptation models contains this component. This storing of the remainder of the advertisements that have been generated by the delivery model, but not yet shown to the user during the current session is very important, since this component data can be loaded right-away from the 'future advertisements component' by the delivery model at the next login of this user, to show appropriate advertisements based on the previous user's behaviour.

Lastly, in order to facilitate the delivery engine process and support the lightweight concept of this model, the structure comprises three engines known as the inference, modifier, and decision engines. The use of this structure offers the capability of constructing a system which is straightforward to integrate into a wide range of websites. For example, the modifier engine is linked only to the user model, and can change only when the user model is altered. In addition to this, the decision engine is dependent on the inference engine and the domain model, producing a flexible and adaptable overall system, which can be easily integrated into a website. As discussed in section 5.6, the reason for this design decision is to separate important stages in the delivery of appropriate advertisements to a client. Using these three engines, the delivery model generates advertisements that are suitable for the current user.

A more detailed comparison between the LAAI model and various existing models such as SLAOS, AdROSA, and MyAds has been conducted, as can be seen in Table 5.1, below. The purpose and components of these models are compared, and the level of social integration within each model is described.

5.8. Conclusion

A new adaptation model, the *Layered Adaptive Advertising Integration (LAAI)*, for delivering adapted advertisements for users is introduced in this Chapter. This model can introduce a framework to design adaptive systems that can integrate easily in a wide range of websites, to adapt their advertisements, as will be show in Chapters 6, 7, 8, and 9. In addition, this model uses the concepts of social networks, to enhance and simplify the data retrieval process. It also uses interactive data about advertisements in the domain, to updated the user model. The LAAI model is composed of four components, *domain model (DM)*, *adaptation model (AM)*, *user model (UM)*, and *delivery model (DM)*.

Based on this model, a new adaptive system, *Adaptive E-Advertising Delivery System (AEADS)*, is introduced and explained in the following Chapters 6, 7, 8 and 9. This system will reveal the accuracy, effectiveness, and efficiency of the introduced LAAI model. A theoretical comparison between the proposed model and other important models/frameworks is presented in Table 5.1 below, which has been discussed in the introduction and discussion sections in this Chapter.

In summary, the research shown in this Chapter has accomplished the following (the underlined parts have been achieved): the research objective **O3:** "*Based on the outcomes from O1and O2, propose an appropriate theoretical model (new or extended) for lightweight adaptive advertising*". The procedure of implementing this objective is outlined and the outcomes have helped to answer the research question **R2:** "*How can we create a model for lightweight adaptive advertising and design the corresponding system that can be integrated with most websites?*". This research question is partly answered in the current Chapter, by proposing a model for adaptive advertising, built on existing models and frameworks, but extending them, according to the specifics of adaptive advertising. Furthermore, the implementation and evaluation of the system based on the LAAI model are discussed in the next Chapters 6, 7, 8 and 9, so that the research question **R2** can be fully answered.

Table 5.1 Comparison between Proposed Model and other Frameworks (main differences highlighted)

<table>
<tr><th>Models and Frameworks</th><th>Purpose</th><th>Social Integration</th><th>Domain Model (DM)</th><th>Adaptation Model (AM)</th><th colspan="2">User Model (UM)</th><th>Delivery Model (DM)</th></tr>
<tr><td rowspan="2">LAAI (current model) (differences further discussed in sections 5.1 and 5.7)</td><td rowspan="2">Advertisement</td><td rowspan="2">▪ login - to get data

▪ Action upon advertisements, shared with peers (like and stop)</td><td rowspan="2">▪ Advertisements
▪ Organised in groups and subgroups in an XML file
▪ based on author’s view (company's view)</td><td rowspan="2">▪ Adaptation rules
▪ Categorised into general and behaviour adaptation
▪ Can be extended</td><td>Components</td><td>▪ Basic data
▪ Behaviour data
▪ Social data
▪ Future advertisements</td><td rowspan="2">▪ Inference engine: obtains personalised advertisements
▪ Modifier engine: updates user model
▪ Decision engine: displays advertisements</td></tr>
<tr><td>Data Collection</td><td>▪ Registration
▪ Social networks
▪ Automatically
▪ Monitoring user behaviour (advertisements appear, clicked, bought, etc.)</td></tr>
<tr><td>SLAOS</td><td>Education</td><td>▪ Social layer affects all other layers (tags, feedback, group etc.)</td><td>▪ Concepts and sub concepts contain lessons parts and some features, like weight.
▪ Located in the domain model and goal and constraints model.
▪ can be output in an XML file</td><td>▪ Three layer model for authoring adaptation
○ Low level assembly-like adaptation language
○ Medium level programming adaptation language
○ Adaptation strategies language</td><td>Components</td><td>▪ Basic data
▪ Behaviour data (visited attributes and concepts)
▪ any data about users supported
▪ Future concept map
▪ Social data(groups)</td><td>▪ Presentation model
○ Concept can have a certain representation type on the screen
○ Independent representation types depending on user model</td></tr>
</table>

			▪ Based on the author's view (teacher, course creator)		**Data Collection**	▪ Registration ▪ Monitoring user behaviour	
AdRosa	Advertisement	No	▪ Advertisements ▪ Organised in groups (conceptual spaces) in the database ▪ Based on the advertiser's website	▪ Advertising policy (from the advertiser)	**Components**	▪ Behaviour data only	▪ Personalisation ○ First stage (user assigned to pattern) ○ Second stage (integrate all user information to obtain appropriate advertisement) ▪ Final filtering (use additional advertising policy to filter result advertisements)
					Data Collection	▪ Monitoring user behaviour (pages which are visited)	
MyAds	Advertisement	▪ Users with social network login, data collected from social networks ▪ in the implementation: social interaction based on a social interaction database	▪ Products (as part of the company user model) ▪ A separate data collection model ▪ In the implementation: ○ Arranged in a database ○ Based on e-commerce websites	▪ contains Ads Resource Management and Personalisation models ▪ in the implementation: applies adaptive hypermedia algorithms and data mining techniques (to deliver the appropriate advertisement mapped to the user)	**Components**	▪ User data ▪ Behaviour data (viewing history) ▪ companies' data ▪ ads	▪ Presentation model ○ contains visualisation, profiles, text and visuals models; ○ personalised content is presented to users
					Data Collection	▪ Registration ▪ Social networks ▪ Monitoring user behaviour (advertisements that were seen/ selected/ etc.)	

Chapter 6

Domain Model for Lightweight Adaptive Advertising

6.1. Introduction

This Chapter will partially address research objectives **O4:** "*Based on the outcome from O3, implement tools for the theoretical model, to support the creation of adaptive advertising by website owners*", and **O6:** "*Evaluate each design and implementation step, both technically and, where appropriate, with real businesses and internet users*". This Chapter will discuss the implementation and evaluation of the first model of the AEADS system. This supports the answer to the last part of the research question **R2:** "*How can we create a model for lightweight adaptive advertising and design the corresponding system that can be integrated with most websites?*". Moreover, it partially supports answering the research question **R3:** "*How can we support website owners in the creation of adaptive advertising, in order to be able to efficiently add adaptive advertising in a lightweight manner to their website?*". For all objectives and research questions above, the other parts are addressed by Chapters 7, 8, and are revisited as a whole in Chapter 9.

The domain model maps the structure and organises the resources of the specific application. The creation of the domain is meant to represent the key concepts and vocabulary of the domain problem, and helps to identify the relationships between the entities within the scope of the problem and their attributes [58]. The domain model reflects the design process of the information structure of the problem domain. The domain model is a conceptual model of the domain that describes some aspects of the problem. It helps to describe the various entities, alongside with their attributes, roles and relationships, within the constraints governing the problem domain. In general, the domain model is considered to be a representation of meaningful real-world concepts relevant to the domain that need to be modelled using software [94]. The domain models have entities and relationships that provide an effective basis for understanding and helping practitioners to design a system that is able to carry out maintainability, incremental development, and testability analysis of the system.

When building adaptive systems, the problem domain that is to be solved must be considered. Many different adaptive systems are designed to cover many areas. For example, adaptive hypermedia systems focus on adapting the hypertext (graphics, audio, video, plain text and hyperlinks) for users [26, 30].

New technologies, such as adaptive advertising systems, have emerged recently, as conducting e-business over the Internet has become more and more common for larger numbers of people. The *domain model (DM)* in these adaptive systems must contain the advertisements, and their relations according to businesses opinion, as well as any extra information to help the adaptation process. For the area of business adaptation, the concepts include the data involved in the business, and the relations between these concepts are based on businesses' decision [87].

In this thesis, the domain model is one of the components as described in Chapter 5, section 5.3.

The Chapter is structured as follows; the next section contains the description of the design and implementation of the domain model (DM), in an actual system, AEADS. This is followed by the domain model evaluation, including quantitative and qualitative evaluations. The final version of the domain model is not evaluated separately, but as a component of the whole system, in Chapter 9, section 9.4. Next, a comparison with other domain models and a discussion are presented. The current Chapter finally wraps up with a conclusion.

6.2. Design and Implementation of the Domain Model

The *domain model (DM)* is one of the main tools of the AEADS authoring tool set that has been implemented based on the LAAI model (as described in Chapter 5). The process of building the domain model must ensure that all entities and the relationships between them have been covered. The domain model includes advertisements and information about the entities, and describes how they are organised and classified. The advertisements in the domain model are organised in groups and subgroups, to reflect their categorisation based on author’s view (as explained in Chapter 5, section 5.3). The actual implementation is dependent on the provider's aims, as the LAAI model is to be a lightweight model, which can be adapted to different providers. It is not aimed at being comprehensive for all businesses, but instead, to provide a simple mechanism for any business to map their data onto this model. To illustrate this process, in the first implementation of the AEADS system, the domain model was selected to be a basic small company selling books, computers and TVs. They are keeping their books, computers and TV information on a database. In order to represent it according to the LAAI model, a mapping from that database to the AEADS system would in principle be straightforward. As illustrated in Figure 6.1, the advertisements are organised thus into two main categories – books and television – which in turn are split into further additional categories. The books category is further divided into sub-categories 'children' and 'computers', the leaves in any category representing the advertisements themselves (as stipulated by the model in Chapter 5, section 5.3). Each leaf additionally contains some attributes, to help the adaptation process (again, as stipulated by the model). Each advertisement includes a property name, a description and a hard disk name, which will indicate the advertisement's name, and any other information about the advertisement, respectively.

The domain model tool in the AEADS system, as shown in Figure 6.1, is a graphical tool that allows business owners to describe advertisements. The advertisements appear to the business owner as a graphical tree, which allows them to organise and classify advertisements in a simple way. The business owner can easily categorise advertisements manually, by adding groups and subgroups, which is done by simply clicking the Add Node button and writing the name of the group or subgroup. Groups and subgroups can also be deleted, by clicking the Delete Node Button. Finally, XML files are used by the AEADS system to save the output from the domain model tool. Using XML files should enhance the portability, easy processing and generalisation of the system as described in [115].

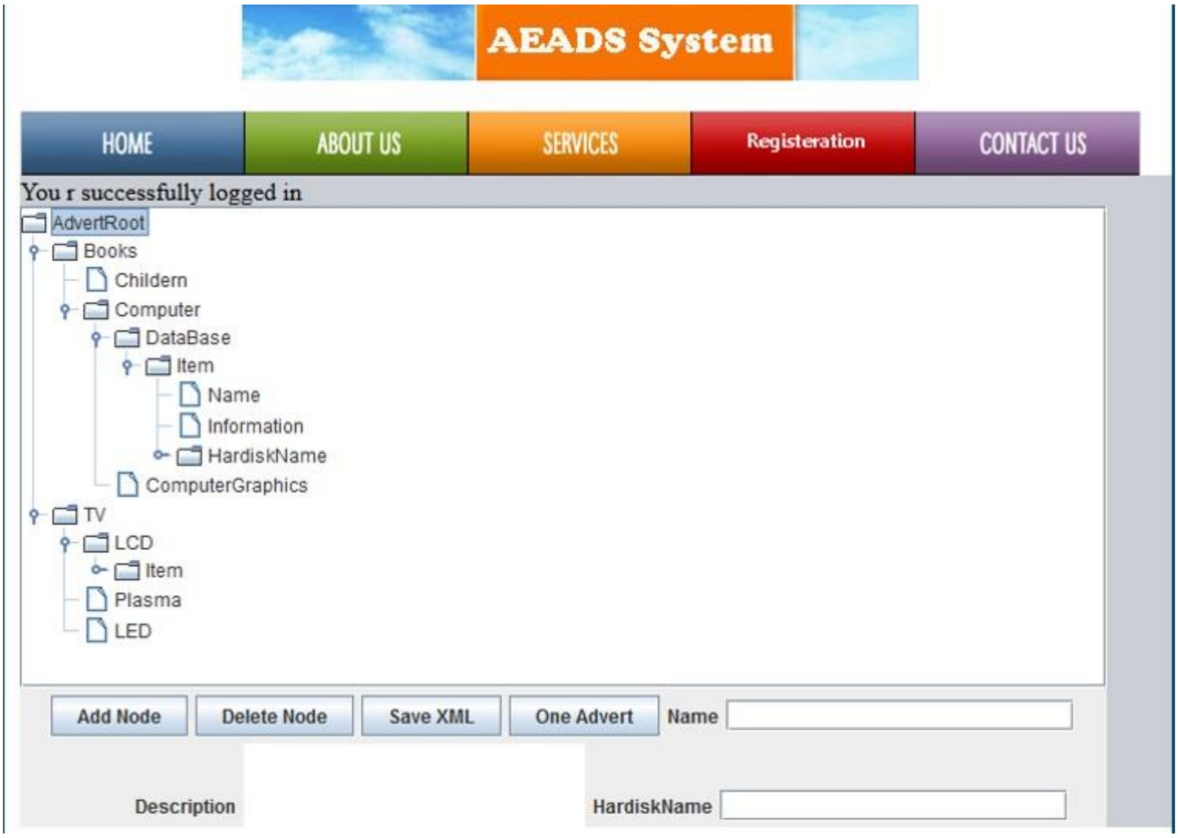

Figure 6.1: Domain Model Creation

A sample XML document containing a simple example with the hierarchy of categories, the advertisements and their attributes, is illustrated in Figure 6.2 (corresponding to the hierarchy and advertisements as created in Figure 6.1). Each advertisement is specified via the *Item* element inside any *group* or *subgroup*. The information associated with each element is specified using the *Name*, *Information*, and *HardiskName* elements. The *Name* element contains a unique and non-empty string, which represents the name of the advertisement, while the *Information* element contains a description of the advertisement, based on the author's view. This element assumes that the author is thus providing information useful for the adaptation process, since the *Information* element can be used by data mining techniques, to support and enhance the adaptation process. Finally, the *HardiskName* element represents a link to the advertisement's file location on the storage media.

```
  <?xml version="1.0" encoding="UTF-8"?>
- <AdvertRoot>
  - <Tv>
    - <LCD>
      - <LED>
        - <Item>
            <Name>ad1</Name>
            <Information>TV ad1</Information>
            <HardiskName>TV1</HardiskName>
          </Item>
        - <Item>
            <Name>advert2</Name>
            <Information>TV ad2</Information>
            <HardiskName>TV2</HardiskName>
          </Item>
        </LED>
      </LCD>
    - <Plasma>
      - <Item>
          <Name>ad3</Name>
          <Information>TV ad3</Information>
          <HardiskName>TV3</HardiskName>
        </Item>
      - <Item>
          <Name>ad4</Name>
          <Information>TV ad4</Information>
          <HardiskName>TV4</HardiskName>
        </Item>
      </Plasma>
    </Tv>
  </AdvertRoot>
```

Figure 6.2 XML Sample of Advertisements of categories

The next section evaluates the implemented domain model in AEADS with the help of business owners.

6.3. Evaluation

As this model and its implementation is aimed at adaptive advertising for businesses, it was crucial to evaluate it firstly with business owners.

The domain model tool was presented for evaluation to twelve business owners, who were selected from a variety of company types. The experiment lasted about an hour for each of business owner based on the natural flow of the interactions and discussion. The evaluation procedure is discussed below. The results have been published in [115].

6.3.1.Hypotheses

The following hypotheses have been written to evaluate the domain model tool, from a business owner's perspective:

H1: *The tool is important for the business owner's business.*

H2: *The GUI of the tool is attractive to business owners.*

H3: *The tool makes the advertisement work of the business owner easier.*

H4: *The tool is sufficient for creating and organising all of the business owner's advertisements.*

H5: *The tool saves the business owner time.*

H6: *The tool can be used by any website to create and arrange advertisement domains.*

H7: *New staff can understand and use this tool with minimal training.*

H8: *The domain model home is useful and easy to use.*

H9: *Registration is useful and easy to use.*

H10: *Login and Logout are useful and easy to use.*

H11: *The creation functions are useful and easy to use.*

These hypotheses were tested by surveying selected businesses and analysing their responses, as described below.

6.3.2.Evaluation Setup

Initially, the business owners were informed about the system as a whole and the idea of adaptive advertising in general was explained. At the end of this presentation, each business owner was asked to use the tool and then to fill in a four-part questionnaire (the domain model questionnaire is in Appendix C). The first part collected the participant’s demographic information. The second part consisted of general questions about tool usability and the extent to which the business owners agreed that the tool is important for their work and would make their work easier. Likert scale [98] questions were used in the third part to obtain feedback on the tool's features and functions. A five-point Likert scale was used. Respondents were asked to choose from five answers evaluating the tool's usefulness and ease of use, with 1 being 'not useful at all' or 'very hard to use', and 5 being 'very useful' or 'very easy to use', respectively. The last part of this questionnaire consisted of open questions designed to obtain any further comments the owners may have had.

6.3.3.Results

Responses were obtained from businesses in a number of industries, including communication, construction, consulting, media, online education, trading, training and transportation (see Table 6.1). A total of 42% of these businesses were classified as small, 25% as medium-sized and 33% as large (see Figure 6.3). 58% of the businesses were located in Saudi Arabia, and the remaining 42% in the United Kingdom (see Figure 6.4).

Table 6.1 Type of business

	Type	Frequency
Type of Business	Communication	3
	Constructing	1
	Consulting	2
	Media	1
	Online Education	1
	Trading	2
	Training	1
	Transportation	1
	Total	12

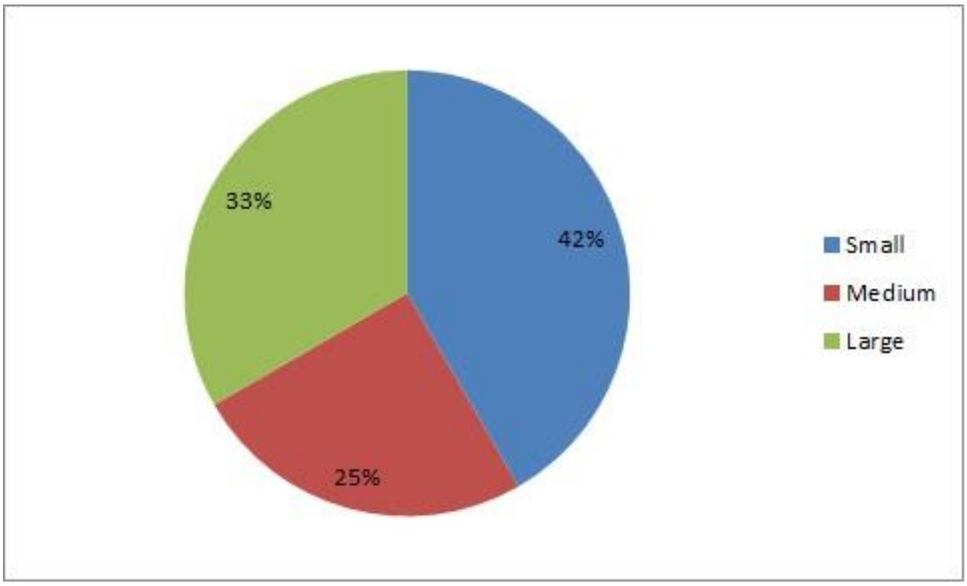

Figure 6.3 Size of Business

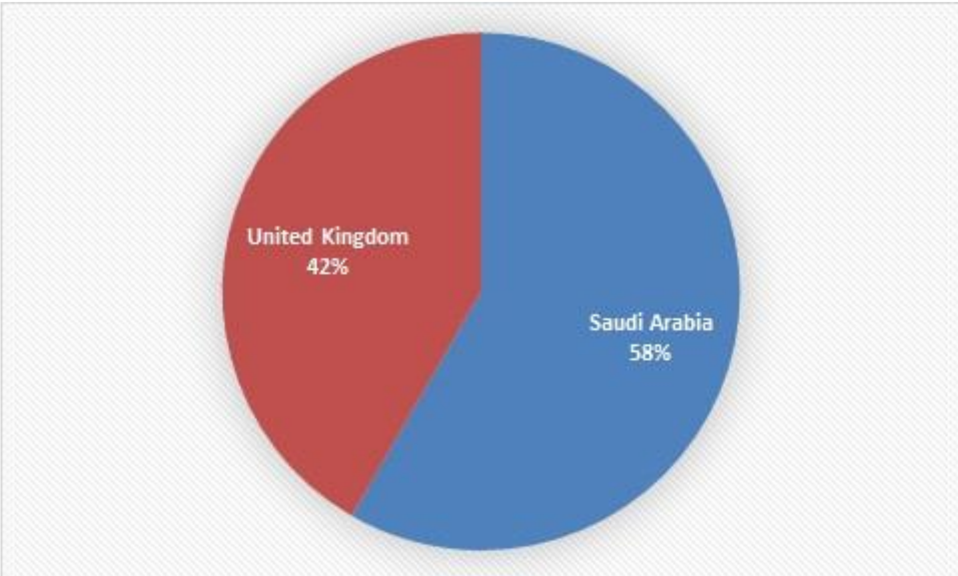

Figure 6.4 Country

As Table 6.2 shows, the first section of the survey posed a series of general questions about the functionality of the domain model tool, in order to become familiar with the overall response of businesses to the tool. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 6.5.

Table 6.2 General Questions of the AEADS Domain Model Tool

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	The tool is important for my business	4.42	4	.49	9.53	.0001	4.13	0	.0001	H1
2	The GUI of the tool is NOT attractive (swapped)	4.17	4	.55	7	.0001	3.78	6	.0001	H2
3	This tool makes our work easier	4.42	4	.49	9.53	.0001	4.13	0	.0001	H3
4	This tool is NOT enough to create and organise all of your advertisements (swapped)	4.42	4	.49	9.53	.0001	4.13	0	.0001	H4
5	This tool must be used by any websites to create and arrange any advertisements domains	4.17	4	.68	5.63	.0002	3.44	12	.0006	H6
6	This tool is NOT saving time (swapped)	4.75	5	.43	13.40	.0001	4.13	0	.0001	H5
7	A new member of staff can understand and use this tool with minimal training	4.76	5	.47	5.63	.0002	3.44	12	.0006	H7

The general questions section included seven questions which alternated between a positive and negative tone, in order to eliminate any bias that could be introduced by the questionnaire [22]. For the interpretation in Table 6.2, the negative questions were swapped over to be interpreted on the same scale as the positive ones (by applying to all data the formula $6-x$, where x was the actual answer). As Table 6.2 shows, the key question within this section was whether the tool was able to create and organise all of a business's advertisements, as this is an important consideration for businesses. According to the questionnaire's findings, the majority of respondents believed the tool was able to create and organise all of their business's advertisements. Furthermore, most participants felt that the tool was important for their business. These results support hypotheses H4 (the tool is sufficient for creating and organising all of our advertisements) and H1 (the tool is important for our business). It was clear that businesses liked the idea of authoring their advertisements using this lightweight tool, which helped them to organise their advertisements on their webpages easily.

The questionnaire results also support hypotheses H5 and H6, with the vast majority of participants stating that the tool would save time and could be used to create and arrange advertisement domains for any website, which is also important for businesses. The results of the questionnaire also show that a majority of respondents felt that new staff would be able to understand and use this tool with minimal training. This finding supports hypothesis H7.

This section of the questionnaire revealed that the company representatives involved in this study were extremely satisfied with the domain model tool. Furthermore, all participants felt that the tool performed well and that it was reliable. These findings support both hypotheses H3 and H11.

Whilst business satisfaction can still be considered high for the authoring element of the system interface, it received the lowest level of satisfaction. Despite this, it scored above 4, which supports hypothesis H2 (the GUI of the tool is attractive). However, some participants felt that the interface was not as attractive as it could be and were less satisfied with this element of the system. It is noted that business owners are looking towards the overall improvement of the tool's interface. They stated that the GUI should be developed and improved upon. They noted that one way of implementing such improvements would be to choose alternative colours, as colour plays an essential role in the advertisement of products.

The participants classified the questions in the general questions part of the domain model as either agree or strongly agree, as shown in Table 6.2. Their mean score is 4.17-4.76, and the standard deviation is 0.43-0.68.

A parametric paired T-test for all businesses was performed to compare the average score for all domain model questions with the neutral response. The T-value is 23.14, and the probability is 0.0001 < 0.05 (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all businesses, the Z-Score is 5.67. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 0. The distribution is approximately normal because of U-value.

These results show that the domain model was appreciated by businesses in the test sample, and that the positive difference is statistically significant when compared to a neutral response of 3.

As mentioned earlier, the next section of the questionnaire included the use of a Likert scale, in order to help respondents express their opinions regarding the usefulness of the domain model tool. Table *6.3* below outlines the participants' responses to the questions within this section. This section of the questionnaire involved evaluating the usefulness of the domain model tool's features and functions. The findings denote that businesses were very pleased. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 6.5.

Table 6.3 Usefulness of the AEADS Domain Model Tool

No.	Features and Functions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	Domain Model - Home	4.17	4	.55	7	.0001	3.78	6	.0002	H8
2	Registration	4.67	5	.47	11.73	.0001	4.13	0	.0001	H9
3	Login	4.58	5	.49	10.65	.0001	4.13	0	.0001	H10
4	Creation Functions	4.67	5	.47	11.73	.0001	4.13	0	.0001	H11
5	Logout	4.58	5	.49	10.65	.0001	4.13	0	.0001	H10
6	Registration Process	4.92	5	.28	23	.0001	4.13	0	.0001	H9
7	Sufficient Data	4.08	4	.76	4.73	.0006	3.09	18	.002	H4
8	Reset Information	4.33	4	.62	7.09	.0001	3.78	6	.0002	H9
9	Submit Information	4.42	4	.49	9.53	.0001	4.13	0	.0001	H9
10	Creating Account	4.92	5	.278	23	.0001	4.13	0	.0001	H9
11	Login Process	4.83	5	.37	16.32	.0001	4.13	0	.0001	H10
12	Reset Password	4.67	5	.47	11.73	.0001	4.13	0	.0001	H9
13	Adding Category - Subcategory	4.67	5	.47	11.73	.0001	4.13	0	.0001	H11
14	Removing Category - Subcategory	4.58	5	.49	10.65	.0001	4.13	0	.0001	H11
15	Adding Advertisement inside subcategory	4.67	5	.47	11.73	.0001	4.03	0	.0001	H11
16	Adding Advertisements Name	4.67	5	.47	11.73	.0001	4.13	0	.0001	H11
17	Adding Advertisements Description	4.5	4.5	.50	9.95	.0001	4.13	0	.0001	H11
18	Adding Advertisements file name	4.58	5	.49	10.65	.0001	4.13	0	.0001	H11
19	Saving the Tree into XML	4.75	5	.60	9.75	.0001	3.78	6	.0002	H11
20	Load the XML file (Domain Model) as tree	4.67	5	.62	8.86	.0001	3.78	6	.0002	H11

Overall, the domain model tool received good ratings, with every component receiving a rating of 4 or more. These figures suggest that the participants believed the tool to be very useful. This argument is also supported by the mean values of 4.08-4.92 and the standard deviation values of 0.28-0.76.

Hypothesis H9 predicted that registration would be useful and easy to use. Hypothesis H10 predicted that login and logout would be useful and easy to use. Hypothesis H11 predicted that the creation functions would be useful and easy to use. These three hypotheses were supported, since the business owners agreed that they found these three functions very useful.

Moreover, the creation features and functions, including adding categories and subcategories, removing categories and subcategories, adding advertisements inside subcategories, and adding an advert's name, description, and file name received scores of at least 4.5. This outcome suggests that these features and functions are useful, which supports hypotheses H4 and H11.

Meanwhile the reset information of the profile and domain model homepage received ratings of 4 or more, which supports hypotheses H8 and H9. These were the least important functions of the domain model tool, according to the participants. The lack of emphasis on these particular functions may have been because the implementation of the GUI was incomplete. This issue is further discussed in the qualitative answer section 6.3.4. Consequently, they felt that these functions are not useful enough. However, the ratings of all the features and functions of the domain model are representative of high satisfaction levels amongst participants. Businesses involved in this study believed that the features and functions of the domain model tool were useful or very useful. These findings support hypothesis H11.

The average for all the domain model features and functions in term of usefulness is of 4.60. When compared with the neutral response of 3, this shows a difference of 1.60. A parametric paired T-test was performed for all participants and their average scores for all domain features and function usefulness were compared with the neutral response. The T-value is 45.11, and the probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all businesses, the Z-Score is 5.93. The p-value is 0.0001. The results are clearly significant at $p \leq 0.05$. Additionally, the U-value is 0. The distribution is approximately normal because of U-value.

This result shows that the domain usefulness of features and functions were appreciated by the businesses in the test sample, and that the positive difference is statistically significant when compared to a neutral response of 3.

Table *6.4* below outlines the participant's perspectives of the domain model tool with regards to its ease of use. According to the data analysis, the findings reveal that the efficiency of the domain model tool is very good, with participants stating that they found using the tool to be either 'easy to use' or 'very easy to use'. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 6.5.

Table 6.4 Ease of Use of the AEADS Domain Model Tool

No.	Features and Functions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	Domain Model - Home	4.75	5	.43	13.40	.0001	4.13	0	.0001	H8
2	Registration	5	5	0	23	.0001	4.13	0	.0001	H9
3	Login	5	5	0	23	.0001	4.13	0	.0001	H10
4	Creation Functions	4.92	5	.28	23	.0001	4.13	0	.0001	H11
5	Logout	4.92	5	.28	23	.0001	4.13	0	.0001	H10
6	Registration Process	5	5	0	23	.0001	4.13	0	.0001	H9
7	Sufficient Data	4.58	5	.76	6.92	.0001	3.44	12	.0006	H4
8	Reset Information	4.75	5	.43	13.40	.0001	4.13	0	.0001	H9
9	Submit Information	4.5	4.5	.50	9.95	.0001	4.13	0	.0001	H9
10	Creating Account	4.83	5	.37	16.32	.0001	4.13	0	.0001	H9
11	Login Process	4.92	5	.28	23	.0001	4.13	0	.0001	H10
12	Reset Password	4.75	5	.43	13.40	.0001	4.13	0	.0001	H9
13	Adding Category - Subcategory	4.5	4.5	.50	9.95	.0001	4.13	0	.0001	H11
14	Removing Category - Subcategory	4.5	4.5	.50	9.95	.0001	4.13	0	.0001	H11
15	Adding Advertisement inside subcategory	4.67	5	.47	11.73	.0001	4.13	0	.0001	H11
16	Adding Advertisements Name	4.67	5	.47	11.73	.0001	4.13	0	.0001	H11
17	Adding Advertisements Description	4.58	5	.49	10.65	.0001	4.13	0	.0001	H11
18	Adding Advertisements file name	4.58	5	.49	10.65	.0001	4.13	0	.0001	H11
19	Saving the Tree into XML	4.58	5	.49	10.65	.0001	4.13	0	.0001	H11
20	Load the XML file (Domain Model) as tree	4.25	4	.72	5.74	.0001	3.44	12	.0002	H11

According to the data analysis, the participants felt that the system had good usability and accessibility. This suggestion is supported by the mean values of 4.25-5 and standard deviation of .00-.76. In addition, subsequent data analysis showed that the registration, login and registration process functions were highly rated by the businesses. This supports hypotheses H9 and H10.

Moreover, the creation features and functions including adding and removing categories and subcategories, adding advertisements inside subcategories and adding advertisements name, description, and file name received scores of at least 4.5. This finding shows that these features and functions are easy to use, which supports hypotheses H4 and H11.

Whilst some features received slightly lower scores, overall satisfaction remained good. For instance, a score of 4.25 was achieved with regards to loading the XML file (domain model) as a tree. This was the least highly rated system element, as it takes some time to be loaded. Nonetheless, this score is still high enough (over 4) to indicate the ease of use of this feature.

The suggestion that the domain model tool would be easy to use was proposed through hypothesis H11, which is further supported by these results.

The average for all the domain model features and functions in terms of ease of use is 4.71. When compared with the neutral response of 3, this shows a difference of 1.71.

A parametric paired T-test was performed for all businesses and their average score for the ease of use of all domain features and functions was compared with the neutral response. The T-value is 54.25, and the probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all businesses, the Z-Score is 5.43. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 24. The distribution is approximately normal because of U-value.

These results show that the domain ease of use of features and functions were appreciated by the businesses in the test sample, and that the positive difference is statistically significant when compared to a neutral response of 3.

Table 6.5 below shows the aggregated hypotheses for all questions, to better illustrate how the features explored directly support the hypotheses. The scores are constructed by averaging all answers about all the features that correspond to one particular hypothesis, both from a functionality and usability point of view. In this way, the support for all hypotheses by the business owner respondents is clearly illustrated.

Table 6.5 Aggregated Hypotheses of the AEADS Domain Model Tool

No.	Hypothesis	Average for all questions							
		Mean	Median	SD	T-test		Mann-Whitney		
					T-value	P-value	Z-score	U-value	P-value
1	H1	4.42	4	.49	9.53	.0001	4.13	0	.0001
2	H2	4.17	4	.55	7	.0001	3.78	6	.0001
3	H3	4.42	4	.49	9.53	.0001	4.13	0	.0001
4	H4	4.36	4	.67	7.06	.0003	3.55	10	.0009
5	H5	4.75	5	.43	13.40	.0001	4.13	0	.0001
6	H6	4.17	4	.68	5.63	.0002	3.44	12	.0006
7	H7	4.76	5	.47	5.63	.0002	3.44	12	.0006
8	H8	4.46	4.5	.49	10.20	.0001	3.96	3	.0002
9	H9	4.73	4.77	.40	15.43	.0001	4.10	.5	.0001
10	H10	4.81	5	.27	17.77	.0001	4.13	0	.0001
11	H11	4.63	4.86	.50	11.16	.0001	4.05	1.33	.0001

6.3.4.Qualitative Answers

From a review of the open-ended questions (which are questions requiring more than one word answers and which allow participants to elaborate on their thoughts and views) it is noted that business owners are looking towards the overall improvement of the tool’s interface, as it received the lowest level of satisfaction (still above 4) by businesses in the quantitative results. They stated that the GUI should be developed and improved upon. They noted that one way of implementing such improvements would be to choose alternative colours, as colour plays an essential role in the advertisement of products. Furthermore, the business owners stated their wish to be able to restructure and edit the instructions on the initial page. Additionally, the participants expressed worries pertaining to any problems or issues that may arise throughout the process of classification or uploading the advertisement from the hard disk. As an example of this, one particular participant queried whether there was a specific category within the web tool that focused on support and could help businesses if problems arise. However, all domain model tool features and functions received a high level of satisfaction by most of the business owners and they agreed that the tool features and functions very useful and easy to use.

They also pointed to a particular problem they had encountered during the classification process. Specifically, they stated that in the event of an error being made during the process of classification, or when they wish to make an addition to the subgroups, it is necessary that they delete certain items before adding the desired subgroup, after which they must then re-add any items they had deleted prior to this action. It was noted by this business owner that this wastes a significant amount of time. These answers and responses, the details involved and the fact that the business owners were able to elaborate on their ideas were very valuable and useful when it comes to further developing and enhancing the domain model tool. As the questions were open-ended rather than closed, the participants in this study were able to add additional comments, thoughts and ideas that were in some way removed from the questionnaire's more structured elements.

As a result of this particular freedom of expression, the business owners were able to focus on certain issues and matters that were not immediately evident to this project's researcher. The benefits of allowing participants to elaborate through the use of open-ended questions, and thereby highlight various issues and draw attention towards specific insights, is that new and fresh ideas may be stimulated, which aid in the further development of the tool under review. It consequently was possible to make certain changes and modifications to the domain model, for the purposes of allowing it to reach its potential. One particular example of this is the suggestion that a facility of support should be incorporated with a view towards improving the user experience. This has been implemented in the second version of the system, as further described in Chapter 9, section 9.2.1.

6.4. Comparison with other Domain Models and Discussion

Closely related fields are that of authoring of adaptive hypermedia. It is easier than ever to author adaptive hypermedia, as researchers continue to add tools that introduce and facilitate the adaptation process [41]. Adaptive hypermedia systems [23] represent an opportunity to increase personalisation and supply users with reports on matters within specific areas of interest. For the business domain, this technology helps customers by improving the efficiency and accuracy with which information is delivered [23]. Adaptation occurs when links to other websites or content are altered for the individual, in order to create a more tailored experience. The main types of adaptation are ‘navigational’ and ‘presentational’ [131]. An authoring system is a computer-based system used to create adaptive web content [44]. Most authoring systems used for adaptive hypermedia use separate tools when creating domain model (DMs), goal and constraints models (GMs), user models (UMs), adaptation models (AMs) and presentation models (PMs) [50].

Along with user models, domain models are considered to be one of the main parts of adaptive hypermedia. They are used to describe and categorise all the information content and knowledge accessible in hypermedia. In general, domain models in hypermedia systems are structured either as hierarchical authoring models, or graphical models [25] that represent pieces of knowledge. Boyle and Encarnacion [19] present a hypertext document that automatically adapts to the ability level of the reader. It uses a simplified form of the domain model without any links between concepts. In contrast, Cristea et al. [42] presented a domain model which contains a hierarchy of concepts, along with details of the attributes and relationships between these concepts. In addition, Chen et al. [40] introduces an adaptive web content delivery system, which uses as the domain web contents from the Internet. With respect to the domain model in advertising adaptation systems, the domain model must represent the available advertisements. In addition, these advertisements must be categorised and divided into groups and subgroups.

In the following, four popular domain model creation tools are discussed. A brief comparison between these tools and the AEADS domain model tool will then be made. These tools are the domain model representations in MOT [49, 61], ADE [127], AdRosa [88], and the MyAd [4] systems. The selection of these tools is based on the similarity of the approach between AEADS and these systems, as there is a plethora of adaptive systems proposing a variety of domain models to choose from. These systems vary in terms of the destination they were designed for. The MOT and ADE systems were designed to adapt courses in the education field, while AdRosa and MyAd were designed for adaptation in the advertisement field.

Based on the LAOS Adaptation framework [50], MOT [49, 61] was designed to be an educational adaptive hypermedia system at Eindhoven University of Technology. The domain model in MOT contains a hierarchy of concepts and sub-concepts associated with concepts. A collection of attributes was associated to all concepts to represent related data for these concepts. MOT also uses the XML representation to store the domain model to be suitable for the web. The goal model in MOT may complement the domain model, since it contains the structured lesson level representations, which repeat some of the information in the domain model, and add additional metadata.

Similarly to the MOT [49, 61] system, the ADE system [127] is designed based on LAOS [50]. It concentrates on the separation of concerns, since it separates content from the adaptation requirements, from the presentation context, and from the user model. The domain model in ADE is composed of a concept/attribute hierarchical structure, which builds individual pages in the goal model.

The entities of domain in the AdRosa system [88] are advertisements. The domain model represents how to organise these advertisements, and categorises the advertising domain into groups (conceptual spaces) based on the advertiser's website, such as advertisements for travel, sports, and so on. If page A on the publisher's website is about sports, then AdRosa will assign it to the sports conceptual space in the domain of advertisements.

In the MyAds system [4], the domain model is part of the Data Collection Model, which contains different information about company products and user data from different sources. The product crawler is the tool that is used to construct the domain model. This tool brings products from e-commerce websites with the following metadata: price, image, description and the Amazon.com URL. The ads generator engine is connected to a product crawler, to arrange the ads in the database.

The MOT and ADE systems concentrate on adaption in the education fields. Consequently, their domain models must contain lessons. MOT focusses on personalisation for individuals, while ADE also applies social interaction. However, the AEADS system is unlike these systems, as it targets adaptation in the e-advertising field, which requires different domains and consequently a different domain model structure. In contrast, the AdRosa and MyAds systems target the e-advertising field, similar to the AEADS system. The AdRosa and MyAds systems retrieve the domain model from the advertiser's website and the e-commerce website, respectively. This is somewhat consistent with the research in this thesis, since the domain model in the AEADS system is owned by the website owner, and enriched with the AEADS system functionality. However, the enrichment needs to happen in the AEADS system extension, and it needs to be added manually. In the case of the MyAds system, all of the advertisements will be saved in a database. This contradicts the portability, which is one of the priorities of this research.

The domain model exists in all adaptation systems, since it is considered the centre of these systems. All these adaptation systems try to adapt the entities and the relationships that exist in the domain model structure. The entities in e-advertisement adaptations are the advertisements, associated with some attributes to describe them.

The domain model tool of the AEADS system is described in this Chapter. This tool has a simple structure that can give businesses an easy way to manage the advertisements on their websites. The results obtained from the experiments show that the domain model tool is easy to use and can be understood easily by new staff. It can also be concluded that the authors can save time by using this tool. Finally, based on the qualitative data gathered, the domain model tool needs to be further improved. This is done via the second iteration of the domain model, which is presented in Chapter 9, section 9.2.1.

6.5. Conclusions

An adaptive system can help businesses to increase their revenue, by enabling them to send the appropriate advertisements to the appropriate customers at the right time. The domain model (DM) tool, which is the first part of the AEADS system, was introduced in this Chapter. The first tool of the AEADS system has been implemented, in order to allow businesses to organise their advertisements in groups and subgroups, and to attach any necessary information (metadata) to these advertisements, which makes their work easier and saves their time. The information attached to each advertisement covers the name, location on storage media, and a description about the advertisement, to be used later in the delivery part of the AEADS system.

Furthermore, the contents and structure of many domain model tools were compared with the introduced domain model tool in the AEADS system. The comparison was made with domain models from MOT, ADE, AdRosa, and MyAds systems, and revealed that it is necessary to construct a new domain model for the AEADS system.

The features and functions of this tool have been tested. Furthermore, the tool has been evaluated by 12 business owners, who were positive towards all of the features and functions of the domain model tool and who scored them between 4 and 5 on a Likert scale, in terms of effectiveness (*usefulness*) and efficiency (*ease of use*) (with 1 being not useful all and not easy to use and 5 being very useful and easy to use). Additionally, all businesses agreed that the tool would be important for their business and would make their work easier in terms of organising advertisements. Moreover, they strongly agreed that the domain model tool could save them time, and that new staff would be able to understand and use it with minimal training. The overall results show that the domain model was appreciated by businesses in the test sample, and that the positive difference is statistically significant, when compared to a neutral response of 3.

Finally, the open-ended question section of the questionnaire showed that some of the business owners had some suggestions for the domain model tool, which have been addressed in the second version that is discussed in Chapter 9, section 9.2.1. Two important suggestions were to simplify the classification process, which would allow businesses to add subgroups and move the items from group to subgroup easily, with no need to delete the items before adding the desired subgroup, and to add browsing commands to the domain model tool, which would ensure that all advertisement file names could be inserted correctly by businesses.

Overall, it can be concluded that the introduced domain model tool can reduce the author's burden in the creation of the domain, by using the domain's structure and flexible interface, which can make the domain model more effective and productive.

In summary, the research discussed in this Chapter has implemented various objectives and research questions, as follows (the implemented parts are underlined): the first part of the research objective **O4:** "<u>*Based on the outcome from O3, implement tools for the theoretical model, to support the creation of adaptive advertising by website owners*</u>". In addition, for the evaluation part, this Chapter has implemented the first part of the research objective **O6:** "<u>*Evaluate each design and implementation step, both technically and, where appropriate, with real businesses*</u> *and internet users*". The procedure of analysing these objectives is outlined and the outcomes have helped to answer the second part of the research question **R2:** "*How can we create a model for lightweight adaptive advertising and <u>design the corresponding system</u> that can be integrated with most websites?*". The first part of this research question has been answered in Chapter 5 previously, by proposing a new model for adaptive advertising. It is also partly answered in this Chapter, through the implementation of the domain model tool of the overall AEADS system. Furthermore, the process of investigating the objectives above are outlined and the outcomes support answering the research question **R3:** "<u>*How can we support website owners in the creation of adaptive advertising, in order to be able to efficiently add adaptive advertising in a lightweight manner to their website*</u>*?*". The answer of this research question has began in this Chapter, through the implementation and evaluation of the domain model. The follow-up implementation and evaluation of the AEADS system based on the LAAI model is discussed in the Chapters 7, 8, and 9, where the remaining parts of research questions **R2** and **R3** are further answered.

Chapter 7

Adaptation Model for Lightweight Adaptive Advertising

7.1. Introduction

This Chapter will partially address research objectives **O4:** "*Based on the outcome from O3, implement tools for the theoretical model, to support the creation of adaptive advertising by website owners*", and **O6:** "*Evaluate each design and implementation step, both technically and, where appropriate, with real businesses and internet users*". This Chapter will discuss the implementation and evaluation of the second model of the AEADS system. This supports the answer to the last part of the research question **R2:** "*How can we create a model for lightweight adaptive advertising and design the corresponding system that can be integrated with most websites?*". Moreover, it partially supports answering the research question **R3:** "*How can we support website owners in the creation of adaptive advertising, in order to be able to efficiently add adaptive advertising in a lightweight manner to their website?*". For all objectives and research questions above, parts not covered by the current Chapter are further addressed by Chapters 6 and 8, and are revisited as a whole in Chapter 9.

Most adaptive hypermedia systems for the education field and its related fields use the definition of *adaptation rules* that are contained in the *adaptation model (AM)*. These rules represent the behaviour of the adaptive hypermedia systems at runtime. These adaptation rules will lead the strategy of the adaptation process in adaptive systems. An *adaptation strategy* is the plan or method that is designed to achieve the goal of change being carried out on a system to fit a given situation or purpose in a given period of time [37]. For example, in the educational field, the author may assign rules to the system to hide a concept based on the experience of the user. Moreover, in the field of advertisement adaptation, the author can insert rules to show, extensively, advertisements of a specified type, in accordance with a specified user behaviour.

The understanding of the natural relationship between advertisements and users will therefore help to develop an adaptation strategy that would correctly suit the needs, problems or issues facing the advertising adaptation system. Based on the LAAI model, the rest of this Chapter will show the details of the adaptation model in the AEADS system that contain and control the adaptation rules and strategies. This tool can be designed and built by thoroughly analysing and understanding how the trends are emerging, the attitudes, beliefs, behaviours, and market sentiments.

In this thesis, the adaptation model is one of the components as described in Chapter 5, section 5.4.

The Chapter is structured as follows. The next section contains the description of the design and implementation of the adaptation model (AM), in an actual system, AEADS. This is followed by a comparison with other adaptation models. Next, the adaptation model evaluation, including the presentation of a quantitative and qualitative evaluation, is followed by a discussion. The final version of the adaptation model is not evaluated separately, but as a component of the whole system, in Chapter 9, section 9.4. The Chapter ends with a conclusion.

7.2. Design and Implementation of the Adaptation Model (AM)

The *adaptation model (AM)* is a crucial component of personalisation, and also traditionally the most difficult one to implement and use [27]. For e-advertising purposes, it has been opted for a straightforward rule-based model, describing *adaptation rules*. The *adaptation model (AM)* in the AEADS system is constructed by the author and has a link with the inference engine in the delivery model, as illustrated in Figure 7.1 (as explained in Chapter 5, section 5.4). It defines rules and strategies to be applied by the inference engine. The adaptation model is built as an overlay model [36, 63] of the domain model. I.e., for each domain model entity – advertisement – adaptation rules and/or strategies are assigned. For flexibility and efficiency, the author can exclude some domain model entities from this, so that it can be general and available for most users. For e-advertising purposes, it has been opted for a straightforward rule-based model, describing adaptation rules.

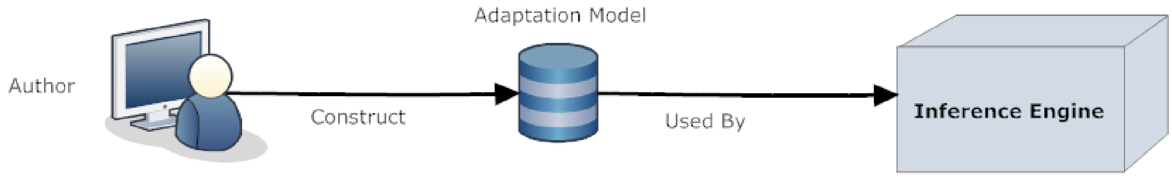

Figure 7.1 Adaptation Model (AM)

The adaptation model tool is the second tool of the AEADS authoring package for adaptive e-advertising delivery, and illustrates the adaptation model proposed, as well as the simple approach to authoring of relatively complex adaptation rules. The tool is aimed at proof of concept, and can be extended, based on the same adaptation model, to a different (or extended) set of desired general and behaviour rules, depending on the needs of the business.

The adaptation model (AM) identifies two types of relevant rules, which are proposed as part of this thesis (as described by [118], as well as in Chapter 5): *general rules* and *behaviour rules*. General rules include typical rules, e.g., based on age, gender, device type and bandwidth – user features. These features in the general rules will provide the start for building the first prototype of the adaptation model tool. This part of the AM tool is illustrated in Figure 7.2, where the four features, *device type*, *bandwidth*, *gender*, and *age*, are listed. Each feature and their assigned values are presented in one row, to allow to the author to choose the appropriate values for a specified advertisement, based on the author's view. The interface is very simple, as the aim is to make it easy to use for the author: the author needs only to highlight an advertisement, check the feature and then choose the appropriate value for this feature. The author can choose one or more features, according to their view.

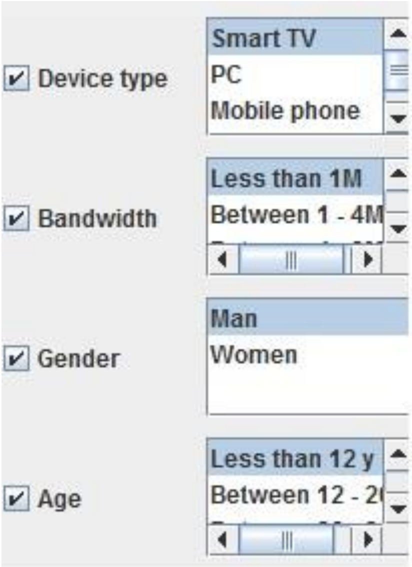

Figure 7.2 General Rules

Next, behaviour rules representing predefined strategies in the first prototype have to be selected. These are also fixed and limited, to keep things simple. Instead of opting for complicated authoring systems, such as, e.g., based on the LAG language [45], where authors have to specify their own adaptation strategy programs, and thus have (at least some basic) programming skills, this approach ensures adaptive flexibility, whilst keeping the choices extremely simple. These strategies support the adaptation based on user actions: *view*, *click*, *not clicked* actions. Four predefined strategies are added to the adaptation model, as illustrated in Figure 7.3. For example, the first strategy is applied to an advertisement, to determine that after a specified number of clicks, determined by the author, another specified number of advertisements, also determined by the author, will be recommended to appear to the user. These advertisements will belong to the same subgroup of advertisements as the currently displayed advertisement. In addition, the author can show an advertisement, based on the number of clicks on other advertisements, as in the strategy number four.

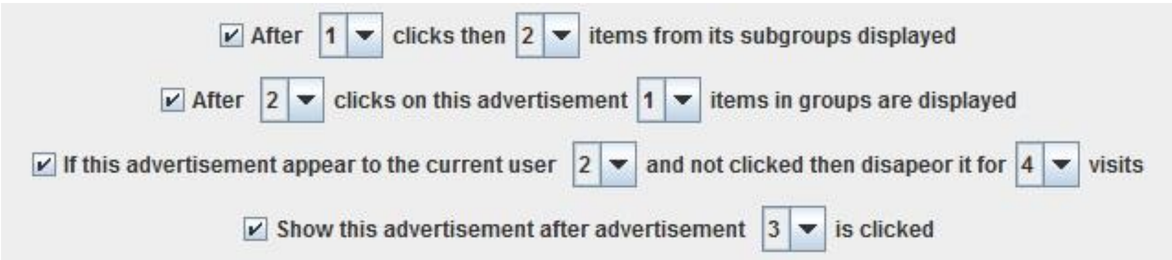

Figure 7.3 Behaviour Rules

Finally, the author can apply one rule – general or behaviour – or combine multiple rules – general or behaviour – for an advertisement. Thus, rules are explicitly connected to advertisements, and determine the degree of adaptation (or personalisation) which that advert can be involved in. Furthermore, the author can change and delete the rules of an advertisement easily, by simply unchecking the checkbox. All these rules that apply on advertisements in the domain are saved in an XML file, as illustrated in Figure 7.4. The XML structure for the general and behaviour rules is simple and allows the inference engine to exploit information easily. As the figure illustrates, the advertisement is listed in the XML file by its ID and assigned some general rules or behaviour rules. Using XML files should enhance the portability, easy processing and generalisation of the system, as described in [114].


```xml
<Rules>
	<General>
		<Item id="MedicalAndLegalAndSocialSciences1421663642903">
			<Gender>Women</Gender>
			<DeviceType/>
			<Age>
			<Between firstNumber="15" secondNumber="20"/>
			</Age>
			<Bandwidth>
			<Between firstNumber="" secondNumber=""/>
			</Bandwidth>
		</Item>
		<Item id="MedicalAndLegalAndSocialSciences1421663762256">
			<Gender>Man</Gender>
			<DeviceType>PC</DeviceType>
			<Age>
			<Between firstNumber="" secondNumber=""/>
			</Age>
			<Bandwidth>
			<Between firstNumber="" secondNumber=""/>
			</Bandwidth>
		</Item>
	</General>
	<Behaviour>
		<Item id="MedicalAndLegalAndSocialSciences1421663642903">
			<subgroup>
			<click>2</click>
			<show>1</show>
			</subgroup>
			<group>
			<click/>
			<show/>
			</group>
			<notclicked>
			<appear/>
			<disappear/>
			</notclicked>
			<showAfterclick>MedicalAndLegalAndSocialSciences1421663762256</showAfterclick>
		</Item>
	</Behaviour>
</Rules>
```


Figure 7.4 XML Sample of Adaptive Model Rules

7.3. Comparison with other Adaptation Models

Many ways of modelling adaptation specifications have been previously proposed. In this section, four popular adaptation model creation tools will be compared with the AEADS adaptation model tool, as introduced in the previous section. These tools are adaptation models in the PEAL [62], ADE [127], AdRosa [88], and MyAds [4] systems. The selection of these tools is based on the similarity of the approach between AEADS and these systems, as there is a plethora of adaptive systems proposing a variety of adaptation models to choose from. In the first part, a summary for each tool will be given, and then a comparison will be made, and explained, between these tools and the new tool introduced.

The PEAL system [62], working together with the MOT system [49, 61], in the MOT package, has been built based on the LAOS framework [50], and implements the adaptation model in this framework. PEAL implements all three levels of the LAG model: direct adaptation rules, adaptation language and adaptation strategies. Direct adaptation rules are the basis for adaptation, while the adaptation language increases system efficiency to support, for example, repetitive actions, and, generally speaking, fine-grain adaptation instructions.

The ADE [127] system has been built based on the LAOS framework [50], similarly to the PEAL-MOT system. The adaptation model of the LAOS framework is represented by a strategy database and strategy interpreter. The strategy database stores adaptation strategies in ADE, to support the separation of the LAOS concepts – in this case, to separate adaptation specification from content description. The strategy interpreter should interpret the strategy from the strategy database to run the strategy on the content.

The AdRosa [88] system uses data-mining techniques to extract knowledge from the webpage content and historical user sessions, as well as the current behaviour of the online user. Its method of adapting a web banner combines in one personalised framework several useful factors of advertising, such as an advertising policy. The advertising policy that is established by the advertiser and another policy that is set up separately by the publisher for each advertisement represent the adaptation strategies that must be applied for advertisements. Advertising policy may contain information about emission limits, and priority. The advertisers can specify an emission limit of one advertisement per user during a single user session. In addition, the publishers can apply some priority features for each advertisement.

In the MyAds [4] system, the Personalisation and Decision Making Engine and the Product Search Engine are located on the server side, to represent the adaptation model. This system is based on a new framework that attempts to update the structure of the LAOS [50] adaptation framework, to support adaptation in the advertisement field. The Personalisation and Decision Making Engine match the user to the appropriate product.

As illustrated previously herein, the PEAL-MOT and ADE systems target the adaptation in the education field. In addition to the authoring of the required adaptation rules and strategies, some experience is necessary to write and control them. Although the LAG language is simple, it requires some effort to learn how to write code with this structure. In addition, any syntax error cannot be discovered easily, which places an additional burden on the author. On the other hand, the AdRosa and MyAds systems target the e-advertising fields, similar to the AEADS system presented in this thesis. The adaptation policy in the AdRosa system is limited and reflects two opinions: those of the advertiser and publisher, as mentioned above, which may decrease the efficiency of the system. The MyAds system does not let authors specify the storage of adaptation rules and strategies, how these are updated in the system and also how to interact with the Personalisation and Decision Making Engine. Moreover, the concept of these two systems, AdRosa and MyAds, are different from the AEADS system concepts, since they concentrate on collecting advertisements from advertisers across the web and organising these advertisements according to certain criteria. In contrast, the AEADS system concentrates on advertisements located on the author’s website, which result in the rules and policy of adaptation being processed only from the author’s viewpoint.

7.4. Evaluation

As this model and its implementation are aimed at adaptive advertising for businesses, it was crucial to evaluate it firstly with business owners.

The adaptation model tool was presented for evaluation to eleven business owners, who were selected from a variety of company types. As these were the experts in their field, a quantitative study was less important than a qualitative study, based on focussed interviews. The experiment lasted about an hour for each business owner, based on the natural flow of the interactions and discussion. The results have been published in [114].

7.4.1. Hypotheses

The following hypotheses have been defined, to evaluate the adaptation approach, as described above and instantiated by the adaptation model (AM), from a business owner's perspective.

H1: *The tool is important for the business owner's business.*

H2: *The tool is easy to use.*

H3: *General Rules are useful and easy to use (e.g., age, gender, etc.).*

H4: *Behaviour Rules are useful and easy to use.*

H5: *Applying rules on items or advertisements is useful and easy to use.*

H6: *Combining multiple rules on items or advertisements is useful and easy to use.*

H7: *Changing rules for items or advertisements is useful and easy to use.*

H8: *Deletion rules for items or advertisements are useful and easy to use.*

These hypotheses have been tested, as said, by surveying a set of selected business owners and analysing their answers, as further described below.

7.4.2. Evaluation Setup

A questionnaire has been created for businesses to evaluate the tool, based on the hypotheses above, in terms of *effectiveness* (usefulness) and *efficiency* (ease of use).

Eleven business proprietors, chosen from a wide range of industries, were asked to use the adaptation model tool, according to the following guidelines.

Initially, they were given a general overview of the system and were also introduced to the concept of adaptive advertising. Following this, each participant was asked to use the tool and evaluate it. The questionnaire was provided at this stage to facilitate the appraisal process. The questionnaire was composed of three sections (the domain model questionnaire is in Appendix D). The first section related to demographic data. The second section incorporated a Likert scale [98], to allow participants to provide a comprehensive evaluation of the tool's functionality and utilities. In this survey, the Likert scale provided five response options to participants and they were required to select from these, when assessing the tool: number one on the scale represented *not useful at all* or *very difficult to use*, while five represented *very useful* or *very easy to use*. The final section of the questionnaire contained a series of open-ended questions that were designed to elicit additional feedback on the tool from the business owners.

7.4.3.Results

Participants in this experiment were chosen from a variety of industries, namely media, transportation, consultation, retail, telecommunications, construction and web-based education services (Table 7.1). From the total of the businesses involved, 46% were SMEs, 27% medium and 27% were large companies (Figure 7.5). Furthermore, 55% were based in Saudi Arabia while 45% were based in the UK (Figure 7.6). In such a way, an as representative spread as possible for the initial case study was targeted.

Table 7.1 Type of Business

	Type	Frequency
Type of Business	Communication	2
	Constructing	1
	Consulting	2
	Media	1
	Online Education	1
	Trading	2
	Training	1
	Transportation	1
	Total	**11**

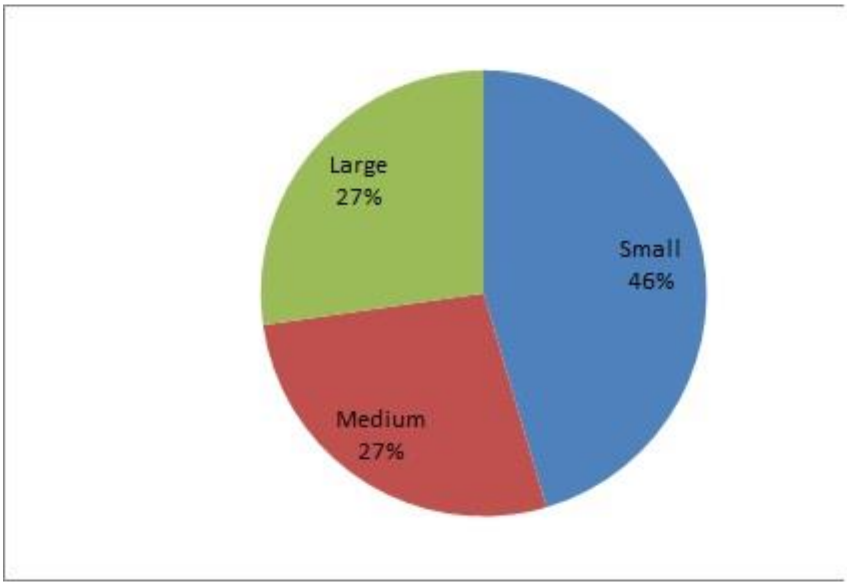

Figure 7.5 Size of Business

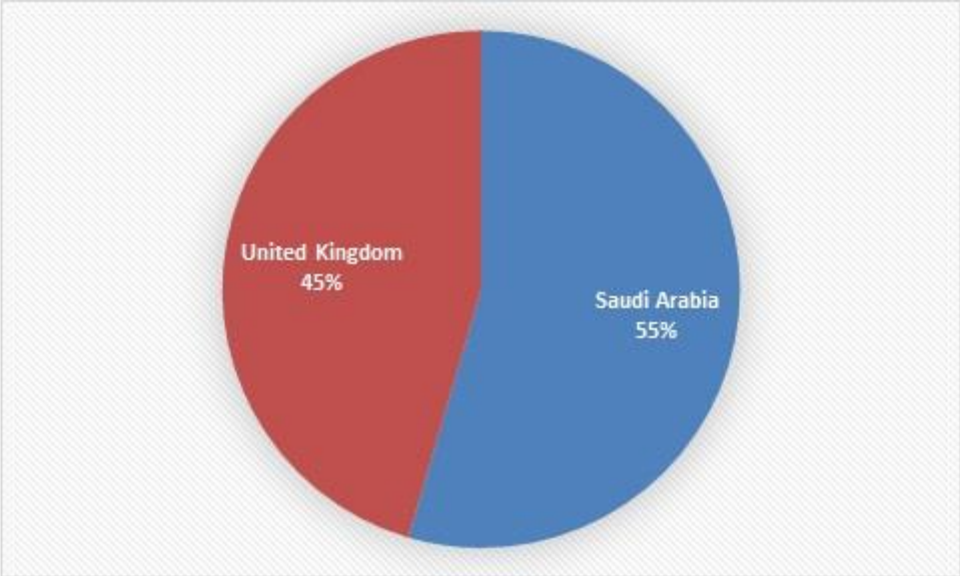

Figure 7.6 Country

This section of the questionnaire requested that respondents evaluate the usefulness of the adaptation model tool features and functions. The findings from this section of the questionnaire denote that businesses were very pleased with the tool's features and functions. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 7.4.

Table 7.2 Usefulness of the AEADS Adaptation Model Tool

No.	Features and Functions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	Whole Tool	4.73	5	.45	12.26	.0001	3.94	0	.0001	H1
2	Having a rule on age	4.64	5	.48	10.76	.0001	3.94	0	.0001	H3
3	Having a rule on gender	4.64	5	.48	10.76	.0001	3.94	0	.0001	H3
4	Having a rule on device type	4.91	5	.29	21	.0001	3.94	0	.0001	H3
5	Having a rule on bandwidth	4.73	5	.45	12.26	.0001	3.94	0	.0001	H3
6	After (1,2,3,4) clicks then (1,2,3,4) items from its subgroups are displayed	4.64	5	.48	10.76	.0001	3.94	0	.0001	H4
7	After (1,2,3,4) clicks on this advertisement then (1,2,3,4) items in groups are displayed	4.82	5	.39	14.91	.0001	3.94	0	.0001	H4
8	If this advertisement appears to the current user (1,2,3,4) and is not clicked then let disappear it for (1,2,3,4) visits	4.64	5	.48	10.76	.0001	3.94	0	.0001	H4
9	Show this advertisement after advertisement (1,2,3,4) is clicked	4.18	4	.58	6.50	.0001	3.58	5.5	.0003	H4
10	Applying rule on item	4.91	5	.29	21	.0001	3.94	0	.0001	H5
11	Combining multiple rules on item	4.91	5	.29	21	.0001	3.94	0	.0001	H6
12	Changing rules for an item	4.55	5	.50	9.81	.0001	3.94	0	.0001	H7
13	Delete rules for an item	4.64	5	.48	10.76	.0001	3.94	0	.0001	H8

Overall, the rating of the adaptation model tool was good, with every tool component receiving a rating of 4 or more. These figures suggest that the participants involved in testing the system for the purposes of this study believed the tool's usefulness to be high. This argument is also supported by the mean values of 4.18-4.91 and the standard deviation values of 0.29-0.58.

Dealing with the tool's functions is one of the most important aspects for businesses, and includes such actions as: applying rule on item, combining multiple rules on item, changing rules for an item, and deleting rules for an item. Thus, according to the participants' answers, all these functions are useful or very useful, which supports hypotheses H5, H6, H7, and H8 regarding the usefulness aspect. Additionally, hypotheses H3 and H4 have been supported by participants, as they stated that general and behaviour rules are useful or very useful, with scores of at least 4, which is also important for businesses.

Moreover, out of the 13 features, the 'rule on device type' received the highest score, together with the rule 'apply rule on item' and 'combine rules on item'. They thus clearly liked the fact that rules are able to be applied to individual advertisements, and that multiple rules can be applied at the same type. The first feature considered one of the best, the one applying adaptation to device type, may be better understood if one considers the drive in now-a-days society to have ubiquitous access to the Internet via multiple devices, with a preponderance of smart mobile phones, iPads, etc. This means in terms of any new system that compatibility to devices is a must. Overall, this outcome suggests that these features and functions are most useful, which strongly supports hypotheses H3, H5, and H6 regarding the usefulness aspect.

On the lower end of the scale, the features which scored the lowest were 'if this advertisement appears to the current user (1,2,3,4) and is not clicked then it disappears for (1,2,3,4) visits' and 'modify rules for (the current) item'. The possible motive for this is that business owners may not see a strong reason for an advertisement to disappear (they may be wary of it) and they don't see a strong need to modify rules that have been created. Therefore, they felt that these functions might not always be needed. However, both of these features still received a score of at least 4, which indicates that they were still regarded as useful, which supports the usefulness aspect in hypotheses H4 and H7. These findings offer support to hypothesis H1, as all businesses involved in this study believe that the adaptation model tool features and functions are useful or very useful.

The average for all the adaptation model features and functions in term of usefulness is 4.69. When compared with the neutral response (of 3), this shows a difference of 1.69.

Performing a parametric paired T-test for all businesses, comparing their average score for all adaptation features and functions usefulness with the neutral response, the T-value is of 46.79, and the probability is of $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all businesses, the Z-Score is 12.15. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 0. The distribution is approximately normal because of the U-value.

Table 7.3, below, outlines the participants' perspectives of the adaptation model tool with regards to its ease of use. According to the data analysis, the findings of this section reveal that the efficiency of the adaptation model tool is very good, with participants stating that they found the tool to be 'easy to use' to 'very easy to use'. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 7.4.

Table 7.3 Ease of Use of the AEADS Adaptation Model Tool

No.	Features and Functions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	Whole Tool	4.91	5	.29	21	.0001	3.94	0	.0001	H2
2	Having a rule on age	4.82	5	.39	14.91	.0001	3.94	0	.0001	H3
3	Having a rule on gender	4.73	5	.45	12.26	.0001	3.94	0	.0001	H3
4	Having a rule on device type	4.82	5	.39	14.91	.0001	3.94	0	.0001	H3
5	Having a rule on bandwidth	4.55	5	.50	9.81	.0001	3.94	0	.0001	H3
6	After (1,2,3,4) clicks then (1,2,3,4) items from its subgroups are displayed	4.73	5	.45	12.26	.0001	3.94	0	.0001	H4
7	After (1,2,3,4) clicks on this advertisement then (1,2,3,4) items in groups are displayed	4.82	5	.39	14.91	.0001	3.94	0	.0001	H4
8	If this advertisement appears to the current user (1,2,3,4) and is not clicked then let disappear it for (1,2,3,4) visits	4.73	5	.45	12.26	.0001	3.94	0	.0001	H4
9	Show this advertisement after advertisement (1,2,3,4) is clicked	4.36	4	.48	8.96	.0001	3.94	0	.0001	H4
10	Applying rule on item	4.82	5	.39	14.91	.0001	3.94	0	.0001	H5
11	Combining multiple rules on item	4.82	5	.39	14.91	.0001	3.94	0	.0001	H6
12	Changing rules for item	4.55	5	.50	9.81	.0001	3.94	0	.0001	H7
13	Delete rules for item	4.91	5	.29	21	.0001	3.94	0	.0001	H8

According to the data analysis, the participants involved in testing the adaptation model tool felt that the tool had a good usability and accessibility. This suggestion is supported by the mean values of 4.36-4.91 and standard deviation of .29-.50.

Furthermore, subsequent data analysis showed that the 'whole tool' and the 'remove rules for item' elements were rated 5 by all participants, which strongly supports hypotheses H2, and H8.

Moreover, hypotheses H3, which is that general rules are useful and easy to use (e.g., age, gender, etc.), and H4, which is that behaviour rules are useful and easy to use, are supported, as most of the businesses are impressed with these features, which score at least 4. Likewise, businesses find that all functions of the tools are easy to use with minimal effort and time. The answers of the participants are also high and support hypotheses H5, H6, H7, and H8, in the ease of use aspects.

Whilst the lowest rated element was 'show this advertisement after advertisement (1,2,3,4) is clicked', this feature still received a score of 4 or higher. This implies that this element is still easy to use, which supports hypothesis H3 in the ease of use aspect.

Overall, these research findings suggest that the adaptation model tool is easy to use, which supports hypothesis H2.

The average for all the adaptation model features and functions in term of ease of use is 4.73. When compared with the neutral response (of 3), this shows a difference of 1.73.

Performing a parametric paired T-test for all businesses, comparing their average score for all adaptation features and functions ease of use with the neutral response, the T-value is 41.91, and the probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all businesses, the Z-Score is 5.67. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 0. The distribution is approximately normal because of the U-value.

Table 7.4 below shows the aggregated hypotheses for all questions, to better illustrate how the features explored directly support the hypotheses. The scores are constructed by averaging all answers about all the features that correspond to one particular hypothesis, both from a functionality and usability point of view. In this way, the support for all hypotheses by the business owner respondents is clearly illustrated.

Table 7.4 Aggregated Hypotheses for the AEADS Adaptation Model Implementation

No.	Hypothesis	Average for all questions							
		Mean	Median	SD	T-test		Mann-Whitney		
					T-value	P-value	Z-score	U-value	P-value
1	H1	4.73	5	.45	12.26	.0001	3.94	0	.0001
2	H2	4.91	5	.29	21	.0001	3.94	0	.0001
3	H3	4.73	5	.43	13.33	.0001	3.94	0	.0001
4	H4	4.62	4.75	.46	11.42	.0001	3.90	.69	.0001
5	H5	4.87	5	.34	17.96	.0001	3.94	0	.0001
6	H6	4.87	5	.34	17.96	.0001	3.94	0	.0001
7	H7	4.55	5	.50	9.81	.0001	3.94	0	.0001
8	H8	4.78	5	.39	15.88	.0001	3.94	0	.0001

7.4.4. Qualitative Answers and Discussion

The final section of the questionnaire asked participants to provide free feedback on the adaptation model tool and was designed to obtain an appraisal of the tool as a whole and also to determine if there were any aspects of the tool that should be eliminated or developed further. This qualitative research approach is invaluable in the early design phase, as any issues with accessibility, user interface or functionality can be rectified at an early stage, in order to enhance the overall performance of the model. Moreover, the whole experiment being of a focussed interview nature, the qualitative answers give further insight into the perceptions of the business owners of the whole approach in general, and the tool in particular. In terms of responses, several important points were made to suggest how to improve the tool and increase the likelihood of businesses incorporating it as part of their business model. Firstly, several participants requested that the application developers ‘make it easy for business owners’. This supports the initial assumption that business owners need extremely simple tools, if they are ever to consider using them for authoring of adaptive advertising. In fact, this particular business owner further told the interviewee that business owners are typically very busy, and any complexity should be avoided, as they can only invest a small amount of time in learning to use such tools. Secondly, several participants mentioned that the design of the tool can be improved. Again, more insight would be required in order to determine which design elements need work. The business owners mentioned that the interface should be improved, but were not specific about it. Further research needed to be conducted, to develop a more user-friendly interface design. From the start, the expectation was that this would be dependent on the business and business owner, and that a smooth merger with their own website look and feel would possibly be the best approach. In other words, there is no universal solution, but each solution would need to be customised for a particular business. The interface of the authoring tools is a minor issue and, due to time limitation, there will not be any further improvements in the second version of the AEADS system.

Several participants made queries about the functionality and, for instance, asked ‘how will you know the device type?’. This would be achieved by detecting the use of a mobile or non-mobile browser via the website configuration (as had been already implemented in this version of the system). This query suggests that the developers may want to provide more in-depth operational information to their clients, so that they are aware of how the processes are implemented and how they are affected by the use of different devices. One participant stated that there was ‘no reason to divide rules into two types, while another asserted that they would like to be able to ‘divide rules, based on products’. This again shows a diversity in perspectives, as each business has unique requirements. However, a possible way to deal with such issues would have been to extend the adaptation to implement a product-dependent rule, as many companies would require a different set of rules, based on their own products and their target demographic.

In fact, many participants stated that they would like to be able to apply their own customised rules using the system, or have a broader set of rules at their disposal. One participant requested a rule that would show another variation of the same product, when a user clicked on it more than twice. This would prove effective in adaptive advertising, as many hesitant customers may be swayed by the provision of more options (even simple ones, such as colour). Furthermore, one participant requested a unique set of rules for different product categories; for example, different rules could be chosen in the sale of books as opposed to shoes. Also in terms of product type, one participant proposed the availability of rules applicable to the sale of services. These rules could be applied in a similar way to those already devised and show a range of related services when a user visits more than twice.

In addition, one participant would like the option to apply a different set of rules depending on who is accessing the website, the company or a customer. Another participant requested the addition of a colour rule, whereas a different business owner believes that a rule based on nationality could prove useful. Another owner stated that a rule on education level or profession would also be well received. A different business owner asked to apply rules depending on the customers' search behaviour. This was developed in the second version of the user model, as discussed in Chapter 9, section 9.2.3.

The extensions above would facilitate a more advanced application of the adaptive advertising process, even potentially moving from the adaptation strategies to the adaptation language approach. This, however, would be more complex for business owners to apply, and thus the benefits need to be carefully evaluated against the costs. This was taken further in the follow-up implementation, where rules were opened up, to allow new rules to be specified directly by the authors, as is described in Chapter 9, section 9.2.2.

In terms of system features, three participants made suggestions on improving the range of services provided. One recommended the provision of a feature that would enable them to apply a specified set of rules to a group of specified products. This feature would streamline the implementation process, as many products would undoubtedly share a similar set of rules. This has been proposed before in adaptation language research [133], which shows that, case-by-case, it is implementable, but that a generic authoring method that is also easily usable would still have to be found. Another participant recommended that the system should allow them to apply a selection of rules to an advertisement. A different business owner expressed the need for a strategy that would allow them to target their customers more effectively, by narrowing in on demographics. This request might be inspired by the current way in which Facebook [52] and other social networking sites are allowing businesses to create and semi-customise advertisements by selecting a number of demographic parameters, such as age group, nationality group, gender and knowledge. Addition of such rules is relatively straightforward, but it depends a lot on the type of data about their customers that they have access to. A different line of research undertaken under the same umbrella has proposed to extract such user-related information from social networks [118], or to have a different way of allowing business customers to provide the personal data that they are comfortable in sharing with the business. This is not detailed further in this Chapter, which focuses on the authoring of the adaptation model, its first set of tools and their evaluation, but it is part of the Chapter 8, describing the user modelling aspects of the overall research question.

7.5. Conclusion

In conclusion, this work is based on the belief that an adaptive model tool would allow businesses to increase their sales potential, by facilitating the accurate targeting of advertisements, based on a series of predefined demographic attributes and rules. This tool of the AEADS system has been implemented, to allow businesses to understand how they can control the adaptation process, by creating, adding and removing rules for advertisements in the domain model. The adaptation model tool divides the rules for the author into *general*, relating to user characteristics, and *behaviour rules*, relating to user actions and behaviour. This division allows the AEADS system to enhance the process of adaptation of the delivery part, by facilitating authoring and ensuring that authors would create advertisement adaptation that is reasonable. Additionally, an extension of these rules can be developed easily, if requested by the business owners.

It was also shown that business owners wish to direct their advertising campaigns at specific consumer groups, as this can enable them to quickly and effectively assign a series of rules based on their target market. As discussed, the first version of the tool and its features and usability have been evaluated, both theoretically and by established businesses, and the overall initial outcome has been positive. A comparison of the adaptation model tool of the AEADS system, with similar tools, has been conducted. The comparison is applied with adaptation model tools from the PEAL-MOT, ADE, AdRosa, and MyAds systems. The comparison reveals that constructing the adaptation model in the AEADS system is necessary, as discussed in section 7.3 in this Chapter.

However, it is clear that there are aspects that require further development, and especially specific customisation for each business, as the feedback section provided a range of suggestions that could be used to enhance the overall functionality and usefulness of the tool. Thus, a new version of the adaptation model tool is introduced and presented in Chapter 9, section 9.2.2, based on the evaluation results. Customisation for the general rules is additionally introduced in this new version, based on the (business) author's view and needs. Overall, it can be concluded, based on the evaluation of the first version of the adaptation model tool, that the introduced adaptation model tool can reduce the authors' burden in the creation of adaptation rules and strategies. A simple interface on the adaptation model tool allows the author to add features and their values or remove features easily. As said, the second version of the adaptation model is presented in Chapter 9, section 9.2.2.

In summary, the research discussed in this Chapter has implemented various objectives and research questions, as follows (the implemented parts are underlined): the second part of the research objective **O4:** "*Based on the outcome from O3, <u>implement tools for the theoretical model, to support the creation of adaptive advertising by website owners</u>*". In addition, for the evaluation part, this Chapter has implemented the research objective **O6:** "*<u>Evaluate each design and implementation step, both technically and, where appropriate, with real businesses</u> and internet users*". The procedures for analysing these objectives are outlined and the outcomes have helped to answer the second part of the research question **R2:** "*How can we create a model for lightweight adaptive advertising and <u>design the corresponding system</u> that can be integrated with most websites?*". The first part of this research question has been answered previously in Chapter 5, by proposing a new model for adaptive advertising, and in Chapter 6, by implementing and evaluating the domain model (DM). It is also partly answered in this Chapter, through the implementation of the adaptation model tool of the overall AEADS system. Furthermore, the processes of investigating the objectives above are outlined and the outcomes have supported answering research question **R3:** "*How can we support website owners in the creation of adaptive advertising, in order to be able to efficiently add adaptive advertising in a lightweight manner to their website?*". The answer to this research question is continued in this Chapter through the implementation and evaluation of the adaptation model (AM). The further implementation and evaluation of the AEADS system based on the LAAI model is discussed in the Chapters 8 and 9, where the remaining parts of research questions **R2** and **R3** are further answered.

Chapter 8

User Model for Lightweight Adaptive Advertising

8.1. Introduction

This Chapter will address research objectives **O4:** "*Based on the outcome from O3, implement tools for the theoretical model, to support the creation of adaptive advertising by website owners*", and **O6:** "*Evaluate each design and implementation step, both technically and, where appropriate, with real businesses and internet users*". This Chapter will discuss the implementation and evaluation of the AEADS system's user model (UM). This supports the answer of the final part of the research question **R2:** "*How can we create a model for lightweight adaptive advertising and design the corresponding system that can be integrated with most websites?*". Moreover, it partially supports answering the research question **R3:** "*How can we support website owners in the creation of adaptive advertising, in order to be able to efficiently add adaptive advertising in a lightweight manner to their website?*". For all objectives and research questions above, the remaining parts are addressed by Chapters 6 and 7, and are revisited as a whole in Chapter 9.

Adaptive hypermedia systems allow for personalisation, and thereby can improve the efficiency and accuracy of information distribution [23]. The process is comprised of three main major task types: acquisition, representation and secondary inference, and production [91]. The *acquisition tasks* identify information regarding users' characteristics, computer usage and environment, in order to construct an initial model of the user. The *representation and secondary inference tasks* infer and express the content of the user model and make assumptions about them, such as their behaviours and the environment. The *production tasks* generate the adaptation of the contents and structure of the system, to meet the users' needs.

A user model is a basic component in any personalised system, and is a representation of user data that is stored for any adaptive changes regarding the system's behaviour. All adaptive hypermedia frameworks and models have a user model as one of their components. For instance, in AHAM [53], the user model contains concepts with attributes for storing user preferences, while in LAOS [50] the user model is even more complex, as explained in Chapter 3.

Social networks are good sources of user information [59], from which user behaviour and characteristics to personalise advertising can be retrieved. Social networks have become a part of all of our lives, and the number of people using social networking sites is increasing rapidly every year. These social networks reflect and record the social practices, behaviour, preferences, and concerns of their users. The various forms of social networks vary, from those in which users actively participate in content creation and production, to those that share content.

Facebook is one of the most popular social networking sites and, in December 2015, has had more than 1.55 billion monthly active global users [138]. Users can create personal profiles, add other users as friends, send messages, as well as post status updates and comments to other users' friends' "walls". Users can chat together, discuss their holidays and experiences, and upload photos and videos that their friends can comment on and "like" [76]. Today, users of social networking sites such as Facebook rely on them for communication, and many users prefer them to texting or calling by phone. For these reasons, Facebook has been used as the first social media data-gathering source for the first version of the system, as described in this Chapter. Follow-up versions (future work), however, will look into other sources, as explained in Chapter 10, section 10.5.

Fortunately for implementers, basic user data in Facebook, such as name, gender — and pictures — can be accessed by third-party sites without the user's permission. Therefore, gender, for instance, can be used in the adaptive recommendation of advertisements, by recommending male products to men, and female products to women. As previously stipulated, one can only access higher-level user data, by acquiring permission from the users themselves, and the user's privacy policy settings can be updated via third-party sites.

In this thesis, the user model is one of the components of the LAAI model, as described in Chapter 5, section 5.5.

This Chapter is structured as follows: the next section contains the description of the design and implementation of the user model (UM), in an actual system, AEADS. This is followed by the user model evaluation, including quantitative and qualitative evaluations, and analysing tracked data. Next, a comparison with other user models and discussion is presented. The final version of the user model is not evaluated separately, but as a component of the whole, in Chapter 9, section 9.4. The Chapter ends with a conclusion.

8.2. Design and Implementation of the User Model (UM)

The main functions of modelling a user's profile are *acquisition*, *representation* and *secondary inference*. In order to execute the initial step, the acquisition process, many methods exist, with regard to each class of user data. These include user data (characteristics acquisition methods), usage data (behaviour acquisition methods, environment data acquisition methods, and behaviour data acquisition methods). The user (customer) modelling tool in the AEADS system has been designed to be simple — that is, to possess only a few user model features and have an XML data structure — the latter so that it is *lightweight*, and that it can be integrated with any potential website user model. All of the data concerning the user model is thus stored within XML files. Storing all of the data in a lightweight fashion (XML) facilitates the integration into any commercial webpage, as XML allows for pipeline processing and provides independence to any other website processing [48, 144].

Two types of data are stored in the AEADS system's user model with regard to basic users (as proposed in this research and described in Chapter 5): *environmental data* and *behavioural data*. Based on hypothesis H1 (as expounded upon below, in section 8.3.1), and based on previous popular user models [4, 50, 53, 127], an initial *minimal set* of necessary dimensions for an advertising user model are defined, that include: 'age', 'gender', 'bandwidth', 'device type', 'number of clicks on advertisements', 'education level', 'education type', and 'hobbies'. Thus, the first step of the user model has been implemented: the acquisition and representation of basic data. These data can be retrieved through both *implicit* and *explicit* means. Users can login into the system via two methods: register (Figure 8.1; explicit data retrieval) and Facebook login (Figure 8.2). By logging in via the latter, the user model can automatically be populated (implicitly) with the necessary information for the adaptation of advertisements. Social data, collated by the use of the social login, permits the retrieval of sufficient user information and inference from specific to general cases, and can be retrieved with the use of social network authorisation, and authentication APIs. Some data may be obtained automatically, so that part of the burden can be removed from the system component, thereby enhancing generalisation and making the integration process easier. The specific device being used, for instance, can be determined automatically at user login. Finally, all users can update their information on their profile page.

The basic user information is arranged in an XML file, with attributes such as 'ID', 'name', 'password', 'email', 'age', 'gender', 'location', 'device used', and 'software used'. All basic data are stored in the `users.xml` file (Figure 8.3), in an attribute-value pair format. This is a simple, flat file, storing information about each user known to the system, similar to other user modelling approaches coming from other areas, e.g. the education area, with the well-known AHA! system [20].

Figure 8.1 User Registration

Figure 8.2 User Login

```
- <User>
    <userId>1095288034</userId>
    <userName>aqaffas</userName>
    <password>n/a</password>
    <email>aqaffas@hotmail.com</email>
    <age>kids</age>
    <gender>man</gender>
    <loginNumber>6</loginNumber>
    <totalClick>1</totalClick>
    <hobbies>Reading</hobbies>
    <educationLevel>postgraduate</educationLevel>
    <educationType>None</educationType>
    <bandWidth>2M</bandWidth>
    <softwareUsed>Mozilla/5.0 (Windows NT 6.1; rv:28.0) Gecko/20100101 Firefox/28.0</softwareUsed>
    <location>NamedFacebookType[id=106076586099038 metadata=null name=Coventry, United Kingdom type=null]</location>
    <deviceUsed>Computer</deviceUsed>
  </User>
</Users>
```


Figure 8.3 `users.xml`: User Model XML file sample

Conversely, a user's behavioural data needs to be acquired through tracking the user's actions on the site. These user's actions are added to the `user_item.xml` file, such as the *number of clicks on advertisement per user*, as well as the *number of times each advertisement is shown for each user*. The nature of the data collected is based firstly and foremostly on the principle of simplicity, of storing information-rich, but simple data, which can help in the adaptation process, without being too cumbersome for the advertisements provider or the customer. Secondly, the data collected are based on prior research [49, 88]. Figure 8.4 illustrates the structure of simple the `user_item.xml` file, each item entity containing the user's ID, and the advertisement's ID, followed by the number of clicks and the number of shows for this advertisement, regarding the user in question. All of this information is then stored. These values can be monitored and delivered to the user model, by using the *modifier engine* in the *delivery model (DM)* (according to the LAAI model, as described in Chapter 5). The number of clicks and shows will be used to fire and apply *behaviour rules* within the adaptation model. In addition, *plan recognition* [126] — the task of inferring the plan of an intelligent agent from observing the agent's actions or their effects — is subsequently be used and then applied in the AEADS system by using these data.

Additionally, a new XML file named `users_items_sequence.xml` (Figure 8.5) tracks every user’s advertisements selection sequence, although only the last ten selections are stored within the file. This decision is made for research purposes, and the number can be changed, depending on the needs of the business owner. As it is, this means that the priority is given to recent activity, and that the system ‘forgets’ (some of) the prior activities in it — note, however, that items clicked are stored separately, and not ’forgotten’, only the sequence of events is. The file is then used to predict users’ actions for current and similar users, as well as any more prediction in the future work.


```
- <UserItems>
  - <Item>
        <User_Id>1397838625271</User_Id>
        <Item_ID>LCD1393709718958</Item_ID>
        <NumberOfClicked>2</NumberOfClicked>
        <NumberOfShow>2</NumberOfShow>
    </Item>
  - <Item>
        <User_Id>1397838625271</User_Id>
        <Item_ID>AdvertRoot1393709791989</Item_ID>
        <NumberOfClicked>4</NumberOfClicked>
        <NumberOfShow>4</NumberOfShow>
    </Item>
  - <Item>
        <User_Id>1397838625271</User_Id>
        <Item_ID>LCD1393709721749</Item_ID>
        <NumberOfClicked>2</NumberOfClicked>
        <NumberOfShow>2</NumberOfShow>
    </Item>
  - <Item>
        <User_Id>1095288034</User_Id>
        <Item_ID>LCD1393709718958</Item_ID>
        <NumberOfClicked>1</NumberOfClicked>
        <NumberOfShow>1</NumberOfShow>
    </Item>
  </UserItems>
```


Figure 8.4 `User Item.XML` file

```
- <User_Sequences>
    - <Sequence>
        <User_Id>1418549743211</User_Id>
        <LastTenClicks>magazines1421668537619;
                       BusinessAndFinanceAndLaw1421665759956;
                       magazines1421668561058;
                       ComputerScience1421667998553;
                       magazines1421668535795;
                       BusinessAndFinanceAndLaw1421665765796;
                       magazines1421668535795;
                       AudioBooks1421664762350;
                       magazines1421668546883;
                       AudioBooks1421664751343</LastTenClicks>
      </Sequence>
    - <Sequence>
        <User_Id>1413114561396</User_Id>
        <LastTenClicks>MedicalAndLegalAndSocialSciences1421664018348;
                       ComputerScience1421668258200;
                       BusinessAndFinanceAndLaw1421665769020;
                       BusinessAndFinanceAndLaw1421665764268;
                       AudioBooks1421664764142;
                       magazines1421668549171;
                       BusinessAndFinanceAndLaw1421665393794;
                       AudioBooks1421664751343;
                       MedicalAndLegalAndSocialSciences1421663762256;
                       magazines142166853579</LastTenClicks>
      </Sequence>
    - <Sequence>
    <User_Id>1431804571426</User_Id>
    <LastTenClicks>MedicalAndLegalAndSocialSciences1421664003310;
                   MedicalAndLegalAndSocialSciences1421664012452;
                   MedicalAndLegalAndSocialSciences1421664003310;
                   MedicalAndLegalAndSocialSciences1421663762256;
                   MedicalAndLegalAndSocialSciences1421664003310;
                   Null; MedicalAndLegalAndSocialSciences1421664003310;
                   AudioBooks1421664754911;
                   AudioBooks1421664751343;
                   AudioBooks1421664754911</LastTenClicks>
    </Sequence>
</User_Sequences>
```


Figure 8.5 `User Item Sequence.XML` file

Furthermore, for advertising adaptations, the simple and straightforward *stereotype technique* [13] was used, as it is able to make inferences, based on limited observations. The way it functions is as follows. Each user is assigned to a group (stereotype), according to the type of features available on the website (a website owner arranges his advertisements into groups and subgroups), after which the system then determines the activation conditions for applying the stereotype to a user. For example, if the user model shows that the user is interested in computers and televisions, the system then activates the stereotype 'technology' from the usage data; i.e., if, according to the data, the user has purchased at least two electronic items or computers, then the stereotype 'technology' can be activated. The general rule in the adaptation model applies the stereotype, and is utilised against the user's characteristics, in order to assign a group of advertisements to every user.

8.3. Evaluation

8.3.1. Hypotheses

The following hypotheses have been defined to evaluate the user model tool, from an Internet users' perspective.

H0a: *The user model (UM) concept for advertising (as illustrated by the UM tool) is useful for constructing a user model for recommendation of advertisements.*

H0b: *The UM concept for advertising (as illustrated by the UM tool) is easy to use for constructing a user model for recommendation of advertisements.*

H0x are the basic hypotheses, which were tested directly via the questionnaire method. More specific hypotheses, as defined below, were also tested via the questionnaire method:

H1: *The attributes of the proposed UM are useful for recommending advertisements (username, password, email, age, gender, education level, education type, hobbies, bandwidth, location, device type, number of clicks on advertisements and software used).*

H2: *The data in the user model are useful for the advertisements delivery engine decision.*

H3: *Automatically generating user model data (location, device type, and software used) is useful.*

H4: *Social networks used as a source for user data are useful data source for recommending advertisements.*

H5a: *The input and output mechanisms of the user model tool are useful.*

H5b: *The input and output mechanisms of the user model tool are easy to use.*

H6a: *The stereotypes for users with respect to advertisements recommendation are useful.*

H6b: *The stereotypes for users with respect to advertisements recommendation are easy to use.*

H7a: *It is useful to integrate the user model creation tool in any JSP website.*

H7b: *It is easy to integrate the user model creation tool in any JSP website.*

H8: *Website administrators can understand, use, and update the stereotypes.*

These hypotheses were evaluated by surveying a sample group of Internet users and analysing their answers, as further described below.

8.3.2. Evaluation Setup

First, the respondents were introduced to the user model tool and given a general overview of adaptive advertising. Subsequently, participants were instructed to use the tool and thereby assess its effectiveness. In order to guide the evaluation process, a three-part questionnaire was provided at this point in the study. The first section collects data on the personal details of each user. The second part presents a number of questions to be answered using a five-point Likert scale [98], in order to encourage users to rate the effectiveness of the system in terms of its functionality and application. The Likert scale features responses were ranging from 'not at all useful' or 'very difficult' to 'very useful' or 'very easy to use'. A series of qualitative questions were posed in the final section, so that respondents could speak freely about their experiences when using the user model tool (the user model questionnaire is in Appendix E). The results of these results have been published in two papers [116, 117].

8.3.3. Results

Overall, 134 survey questionnaires, out of the 305 questionnaires distributed, were completed and returned. The reason as to why less than half of the questionnaires distributed were completed and returned may have been due to the fact that, prior to the survey, participants were informed that the questionnaires were not compulsory, and that their academic activities and outcomes would not be affected in the least, should they fail to do so. Whilst this has resulted in fewer answers than initially targeted, on the other hand, the answers that were collected were more likely to be from participants who actually paid attention and were involved in the study. The majority of participants who completed the questionnaire were aged 18-24 years (61.2%), whereas most of the rest of the participants who completed the questionnaire were aged 25-34 years (38.1%). Furthermore, the proportion of male participants was 70.9%, while the proportion of female participants was 29.1%. Moreover, results reveals that, with regard to the level of education, the majority of the participants held a bachelor’s degree, although a small percentage of participants (11.2%) held postgraduate educational credentials. Due to these participant statistics, the research data may have been biased in favour of well-educated young adults. However, this does not make the data erroneous, as the demographic used in the study is one that shapes both current and future demand, and therefore should be prioritised by web developers. More discussions about the appropriateness of the sampling process are in section 8.3 and Chapter 2.

Participants were asked to evaluate the various features and functions of the user model tool. A Likert scale between 1-5 was used (where 1 was representing low usefulness, and 5 representing high usefulness), to collect their responses. The results of this section are presented in Table 8.1. From a glance it can be seen that the general consensus was that participants responded well to the tool and were satisfied with its functionality. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 8.4.

Table 8.1: Usefulness for the Features of the AEADS User Model Tool

No.	Features and Functions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	Whole User model Tool	4.57	5	.50	36.48	.0001	14.15	0	.0001	H0a
2	User Registration Process	4.57	5	.50	40.24	.0001	14.15	0	.0001	H5a
3	Login Process	4.57	5	.50	36.73	.0001	14.15	0	.0001	H5a
4	Facebook Login Process	4.60	5	.49	37.55	.0001	14.15	0	.0001	H4
5	Submitting Information	4.57	5	.50	36.73	.0001	14.15	0	.0001	H5a
6	Updating User Profile	4.57	5	.50	36.48	.0001	14.15	0	.0001	H5a
7	Saving Information in XML as Export Format	4.69	5	.47	41.93	.0001	14.15	0	.0001	H5a, H7a
8	Facebook User Profile Import	4.56	4.5	.51	33.45	.0001	14.04	67	.0001	H4
9	Match User Characteristic with Stereotype	4.47	4	.50	33.97	.0001	14.15	0	.0001	H6a, H8
10	Adding own Stereotype	4.53	5	.50	37.55	.0001	14.15	0	.0001	H6a, H8
11	Modifying existing Stereotype	4.47	4	.50	33.97	.0001	14.15	0	.0001	H6a,H8
12	Deleting Stereotype	4.53	5	.50	36.73	.0001	14.15	0	.0001	H6a, H8

Most participants gave the features a rating of no less than four, with a standard deviation of 0.47-0.51 and mean value of 4.47-4.69. Medians were very high, mostly 5, with only 1 response at 4.5 and two at 4. This suggests that the tool's features were considered by the participants to be useful in practice. Subsequently, the user model tool can be classified as 'useful', because all scores were clearly greater than three. Additionally, the Cronbach's Alpha score is $0.91 \in [\geq 0.9]$, meaning that the reliability of the questionnaire was excellent [51]. These finding support and validate hypothesis H0a (targeted specifically by question 1 in Table 8.1, as well as indirectly targeted by the reset of the questions), which states that the user model (UM) concept for advertising (as illustrated by the UM tool) is useful for constructing a user model for recommendation of advertisements (see also Table 8.4).

Despite this generally positive reception from participants, some features of the model proved to be more popular than others. In particular, ‘Saving Information in XML as Export Format’ and the ‘Facebook Login Process’ were the features with the highest level of overall popularity, thereby validating hypotheses H4 and H5a (see also Table 8.4). In the open-ended questions, participants expressed their satisfaction with the Facebook login feature, something that a majority of web-authoring applications have incorporated. The considerable usefulness of such a feature resides in the fact that it not only supports more effective user model integration with regard to other web-based systems, but also makes the model more functional and easy to use, since users can gain access to a range of different applications, by entering their identification details a single time.

Consequently, hypothesis H7a is also validated by these results, highlighting not only the usefulness of the input and output mechanisms of the user model tool, but also the usefulness of the integration of the user model creation tool in any JSP website, by using XML files (see also Table 8.4). Furthermore, in the open-ended questions, the data storage in XML rather than storage of data with the use of a database was questioned by one participant, which raised awareness about the necessity to provide a clear explanation as to the manner in which the transfer of XML data between various programmes can be easily achieved [132]. This has been done with the AEADS system that was integrated with an online bookstore for evaluation purpose, as can be seen in Chapter 9, section 9.4.

However, the features ‘Match User Characteristic with Stereotype’ and ‘Modifying existing Stereotype’ were seen to be, whilst still positively evaluated, as the least popular features. This may have been due to the fact that the intended function of these features was not clearly understood by the participants. However, this feature has been incorporated with the AEADS system for authoring purposes to be used by business owners during authoring processes. In addition, this feature is evaluated in the overall system evaluation, as discussed in Chapter 9, section 9.4.3. Nevertheless, as said, the less popular features are still considered very useful, because all of them received a score higher than four, which supports hypotheses H6a and H8 (see also Table 8.4).

The average for all the user model features in term of usefulness is of 4.56 which, when compared to the neutral response (of 3), shows a difference of 1.56.

Performing a parametric paired T-test for all users compares their average score regarding the usefulness of all user features. The T-value's neutral response, was 126.69, and its probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all users, the Z-Score is 17.30, and the p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 0. The distribution is approximately normal because of the U-value.

These results shows that the user model features in terms of usefulness are appreciated by the users in the test sample, and that the (quite large) positive difference, when compared to a neutral response of three, is statistically significant.

Participants were also separately asked to evaluate the various attributes of the user model tool, by also using a Likert scale to indicate their responses. The results of this evaluation can be seen presented in Table 8.2, with the general agreement being that participants responded well to the user modelling tool and were satisfied with its functionality. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 8.4.

Table 8.2: Usefulness for the UM Attributes of the AEADS User Model Tool

No.	Attributes	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	Location	4.57	5	.49	36.73	.0001	14.15	0	.0001	H1, H2
2	Device Type	4.51	5	.50	35.15	.0001	14.15	0	.0001	H1, H2
3	Software Used on Device	4.58	5	.49	36.99	.0001	14.15	0	.0001	H1, H2
4	Username	4.51	5	.50	34.77	.0001	14.15	0	.0001	H1, H2
5	Passwords	4.57	5	.49	36.73	.0001	14.15	0	.0001	H1, H2
6	Email	4.56	5	.50	36.23	.0001	14.15	0	.0001	H1, H2
7	Age	4.58	5	.49	36.99	.0001	14.15	0	.0001	H1, H2
8	Gender	4.5	4.5	.50	34.60	.0001	14.15	0	.0001	H1, H2
9	Education Level	4.68	5	.47	41.48	.0001	15.49	0	.0001	H1, H2
10	Education Type	4.58	5	.49	36.99	.0001	14.15	0	.0001	H1, H2
11	Hobbies	4.58	5	.49	36.99	.0001	14.18	0	.0001	H1, H2
12	Bandwidth	4.60	5	.49	37.84	.0001	14.15	0	.0001	H1, H2
13	Retrieve the Location Automatically	4.54	5	.50	35.77	.0001	14.15	0	.0001	H3
14	Retrieve the Device Type Automatically	4.56	5	.51	35.18	.0001	14.04	67	.0001	H3
15	Retrieve the Software Used Automatically	4.46	4	.50	33.70	.0001	14.15	0	.0001	H3
16	Retrieve the Number of Shows for Each User	4.57	5	.49	36.48	.0001	14.15	0	.0001	H2
17	Retrieve the Number of Clicks for Each User	4.51	5	.50	34.96	.0001	14.15	0	.0001	H2
18	Retrieve the Last 10 Sequence of Clicks for Each User	4.46	4	.50	33.70	.0001	14.15	0	.0001	H2

There was a general consensus amongst the participants with regards to the idea that, in order to select suitable advertisements compatible to users' profiles and preferences, every user model attribute proposed should be collected. The participants classified the attributes of the user model as either ‘useful’ or ‘very useful’, which is confirmed by their mean score of 4.46-4.68 and the standard deviation of 0.47-0.51. Additionally, Cronbach’s Alpha score is 0.92 $\in$ [$\geq$ 0.9], meaning that the reliability of the questionnaire was excellent [51].

Two of the user model’s attributes, ‘Education Level’ and ‘Bandwidth’ were seen to be more useful than the others. Both of these attributes received extremely high ratings. Therefore, to a certain degree, hypotheses H1 and H2 are partially confirmed by these results, as these hypotheses argue in favour of the attributes’ utility, regarding the proposed user model for advertisement suggestion (see also Table 8.4). However, especially the popularity of the first attribute may be related to the sample population’s characteristics, and the fact that they were students. It is questionable if the same priorities would be appearing for an older population sample. Thus, these results need interpreted with care. Moreover, the manual calculation and input of bandwidth was reported by some participants during the open ended questions as being confusing and unclear. Consequently, in order to ensure superior monitoring for all users, bandwidth restrictions should be taken into account automatically. Automatic retrieval of bandwidth has been fixed in the second version of the user model, as shown in Chapter 9, section 9.2.3.

Conversely, two attributes were associated with notably low scores, namely; ‘Retrieve Software Used Automatically’ and ‘Retrieve the Last 10 Sequences of Clicks for Each User’. Despite the fact that each of these attributes received lower scores, they still secured scores higher than four. Furthermore, one potential explanation as to why these attributes were unpopular among the participants may be the fact that the participants became anxious with regard to their activities and behaviour that was being monitored. As a result, such attributes were not deemed to be of paramount importance, although their utility was nevertheless acknowledged. Thus, hypotheses H2 (computed from all user model attributes) and H3 (computed from the generated user model attributes: 13-16 in Table 8.2) are validated by these results (see also Table 8.4).

The average score for all of these user model attributes was of 4.55. When compared with the neutral response (of 3), this shows a (large) difference of 1.55.

Performing a parametric paired T-test for all users, and comparing the average score for all user attributes with a neutral response, the T-value is 149.37, and the probability is $0.0001 < 0.05$, the significance threshold most commonly used in significance research.

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a non-parametric Mann-Whitney test for all users, the Z-Score is 17.30 and the p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 0. The distribution is approximately normal because of the U-value.

This result shows that the user model attributes are appreciated by the users within the test sample, and that the positive difference, when compared to a neutral response of three, is statistically significant.

After evaluating the usefulness of the tool, as well as of its individual features, an evaluation of the usability of the tool and its features was performed, as follows. The results were also collected on a Likert scale between 1-5, with 1 meaning not usable, and 5 meaning very usable. As indicated in Table 8.3 (see below), the majority of users found the user model tool ‘easy’ or ‘very easy’ to use. This indicates that the tool, in general, has a high degree of usability and that all of its features and functions can be utilised without the need for specialised training or advanced knowledge. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 8.4.

Table 8.3: Ease of Use for the Features of the AEADS User Model Tool

No.	Features and Functions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	Whole User model Tool	4.53	5	.50	35.35	.0001	14.12	0	.0001	H0b
2	User Registration Process	4.57	5	.49	36.73	.0001	14.15	0	.0001	H5b
3	Login Process	4.57	5	.50	28.12	.0001	13.94	134	.0001	H5b
4	Facebook Login Process	4.57	5	.50	36.48	.0001	14.15	0	.0001	H4
5	Submitting Information	4.55	5	.50	36	.0001	14.12	0	.0001	H5b
6	Updating User Profile	4.63	5	.48	38.79	.0001	14.15	0	.0001	H5b
7	Saving Information in XML as Export Format	4.51	5	.50	34.77	.0001	14.15	0	.0001	H5b, H7b
8	Facebook User Profile Import	4.53	5	.50	35.35	.0001	14.15	0	.0001	H4
9	Match User Characteristic with Stereotype	4.52	5	.50	35.15	.0001	14.15	0	.0001	H6b, H8
10	Adding own Stereotype	4.50	4.5	.50	33.70	.0001	13.97	134	.0001	H6b, H8
11	Modifying existing Stereotype	4.46	4	.50	33.70	.0001	14.15	0	.0001	H6b, H8
12	Deleting Stereotype	4.55	5	.50	33.70	.0001	14.15	0	.0001	H6b, H8

The results obtained from the survey questionnaire also revealed the fact that the participants were of the opinion that no feature of the proposed user model presented any difficulty of use. This was confirmed by the mean scores, which fell between 4.46-4.63 for this dimension, as well as by the standard deviation, which was between 0.48-0.50. Furthermore, with regard to ease-of-use, the Cronbach's Alpha is 0.90, meaning that the level of reliability is excellent [51]. These results support the high-level hypothesis H0b, in that they indicate the model is easy to use.

One of the most important and novel things within this research is the integration between AEADS and other websites. On the basis of the results obtained, it can be seen that users were very impressed with its features, as it received an average score of 4.51 for the ‘Saving Information in XML as Export Format’ feature, for use in a delivery engine, thereby facilitating the integration of the user model creation tool in any JSP website. According to these results, hypothesis H7b has been supported and validated, as can be seen in the study’s qualitative answers.

Furthermore, the findings of the data analysis indicate that some features were better received by participants than others. Therefore, the features of the ‘User Registration Process’ and ‘Updating User Profile’ enjoyed highly-favourable responses from the participants, which validate H5b in so far as affirming that both input and output mechanisms of the user model tool are easy to use (see also Table 8.4). It is clear that the user profile function has been implemented well in a lightweight manner, as participants felt that the user profile is easy to use.

Conversely, the features of ‘Adding own Stereotype’ and ‘Modifying existing Stereotype’ were less favourably received by participants from a usability point of view, matching their responses to the usefulness of the same features. It must be noted that, despite being less well-received by participants, the two latter features still scored above four, which means that they are not difficult to use. Thus, these features still received high usability marks, confirming thus hypothesis H6b, which propounds the argument that advertisement recommendations were suitable and posed no obstacle with regard to their use. Overall, the user model tool’s ease-of-use (H0b) is supported by the analysis results of the survey data. H7b, that states that it is easy to integrate the user model creation tool in any JSP website, is also supported by the results of question 7 (see also Table 8.4).

The average for all the user model features in terms of ease of use was of 4.54, which shows a difference of 1.54, when compared to the neutral response (of three).

A parametric paired T-test for all users was then performed. This, involved the comparison of the users’ average score for ease-of-use regarding the user model features, with a neutral response. The T-value was seen to be 123.91, and the probability was $0.0001 < 0.05$ (the significance threshold most commonly-used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a parametric Mann-Whitney test for all users, the Z-Score was 17.30, and the p-value was 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 0. The distribution is approximately normal because of the U-value.

These results show that the user model features in terms of ease-of-use were appreciated by the users of the study's test sample, and that the positive difference, when compared to a neutral response of three, is statistically significant.

Table 8.4 below shows the aggregated hypotheses for all questions, to better illustrate how the features explored directly support the hypotheses. The scores are constructed by averaging all answers about all the features that correspond to one particular hypothesis, all from a functionality and usability point of view. In this way, the support for all hypotheses by the Internet user respondents is clearly illustrated.

Table 8.4 Aggregated Hypotheses of the AEADS User Model Tool

No.	Hypothesis	Average for all questions							
		Mean	Median	SD	T-test		Mann-Whitney		
					T-value	P-value	Z-score	U-value	P-value
1	H0a	4.57	5	.50	36.48	.0001	14.15	0	.0001
2	H0b	4.53	5	.50	35.35	.0001	14.12	0	.0001
3	H1	4.57	4.96	.49	36.79	.0001	14.26	0	.0001
4	H2	4.56	4.90	.49	36.44	.0001	14.24	0	.0001
5	H3	4.52	4.67	.50	34.88	.0001	14.11	22.33	.0001
6	H4	4.57	4.88	.50	35.70	.0001	14.12	16.75	.0001
8	H5a	4.60	5	.49	38.42	.0001	14.15	0	.0001
9	H5b	4.57	5	.49	34.88	.0001	14.10	26.8	.0001
10	H6a	4.50	4.5	.50	35.56	.0001	14.15	0	.0001
11	H6b	4.51	4.63	.50	34.06	.0001	14.11	33.5	.0001
12	H7a	4.69	5	.47	41.93	.0001	14.15	0	.0001
13	H7b	4.51	5	.50	34.77	.0001	14.15	0	.0001
14	H8	4.50	4.56	.50	34.81	.0001	14.13	16.75	.0001

8.3.4. Analysing User Tracking Data

As discussed in section 8.2, the AEADS user model includes two methods of login: register (*explicit* data retrieval) and Facebook login (*implicit* data retrieval). During the evaluation phase, when tracking the user's actions, it emerged that most of the users have logged in into the AEADS system using their Facebook account, as shown in Figure 8.6. This is in line with the results from the questionnaires, where most users agreed that logging in using a Facebook account is useful and easy to use. In the quantitative data analysis, the Facebook login process was the feature with the highest level of overall popularity. Moreover, in the open-ended questions, participants again expressed their satisfaction with the Facebook login feature, something that a majority of web-authoring applications have incorporated. The considerable usefulness of such a feature resides in the fact that it not only supports more effective user model integration with regard to other web-based systems, but also makes the model more functional and easy to use, since users can gain access to a range of different applications, by entering their identification details a single time.

Figure 8.6 Users Login to the AEADS System

Furthermore, in the webpage were included a number of personalised advertisements, based on users profiles. Their evaluation has been conducted related to the implementation of the delivery model, which has been used to deliver personalised advertisements to Internet users. During the evaluation processes, the number of clicks is increased with the increased time of system use. This information can reflect the users' predilections regarding the system's use, as time progresses. An assumption can therefore be made that advertisements can be matched better to users, after longer-term tracking of the users' action is applied, as illustrated in Figure 8.7. This is related to the well-known cold-start problem [121] in any system relying on user data. Overall, the data collected from users' tracking within the user model supports the possibility that such a system attracts users to view advertisements, as the advertisements are personalised based on their characteristics and preferences.

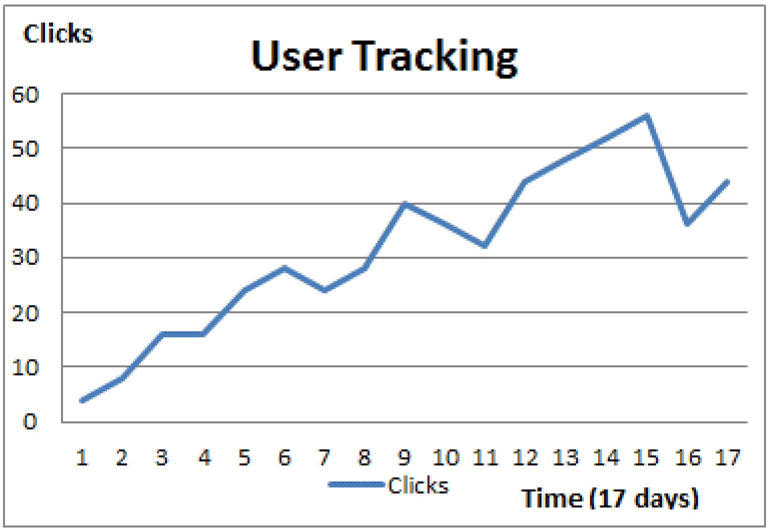

Figure 8.7 Clicks progress against time

In the following, the data collected from the actual use of the AEADS user model with Internet users are analysed. The users' tracking data shows that the advertisements in the category books have a higher rate of clicks, as shown in Figure 8.8. Businesses categorise advertisements in the first level of adaptation based on user characteristics. According to the dominant characteristics of most participants, namely; the 18-24 year-old age group, and a bachelor's degree level of education, the book group became the most highly clicked on by participants. Moreover, the advertisements that have been presented to them were based on their characteristics.

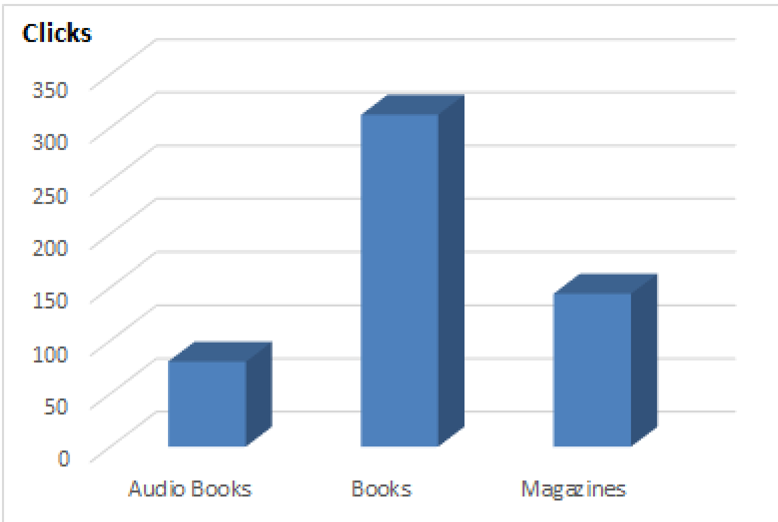

Figure 8.8 Number of clicks for different groups

Sub-categories were also tracked, such as sub-groups for the books category, the most popular of which are computer science books, as shown in Figure 8.9. Most of the participants were studying some courses of computer science, therefore most of their clicks were on the computer science books subcategory. Furthermore, as said, the advertisements that have been presented to them were based on their characteristics.

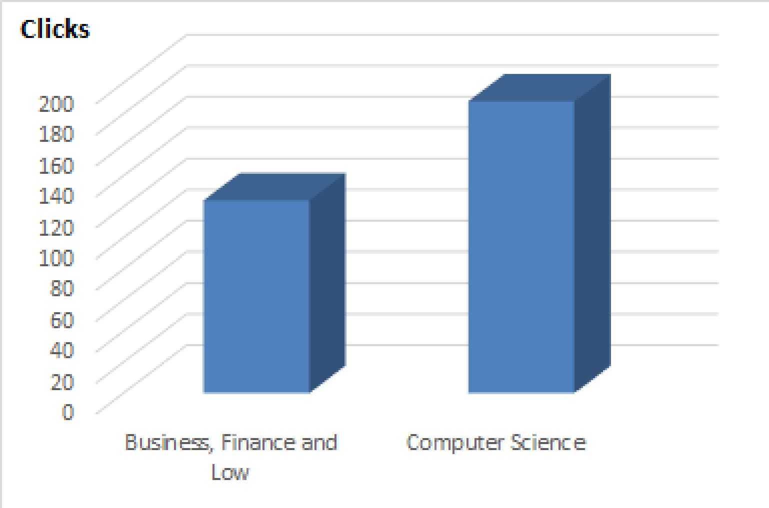

Figure 8.9 Number of clicks for books sub-groups

Thus, in the data analysed above, computer science books will be mostly recommended to the users, by showing them advertisements about these topics. Additionally, to a somewhat less frequent degree, business, advertisements about finance and law books will be shown to users. Other, generic advertisements on popular books, will also be shown, with lesser frequency, to the users. Finally, some advertisements on magazines and a few on audio books will appear from time to time.

8.3.5. Qualitative Answers and Discussion

In addition to the questions designed to shed light on the participants' views with regard to the various features and functions of the user model tool, the survey questionnaire also included a section in which the participants were requested to provide free feedback about the tool. This was intended to help the participants identify those dimensions that required improvement. Feedback such as this was considered to be an essential part of the study, even if sparse, as not all participants filled in these free-text boxes, due to the fact that it assisted in the resolution of any emerging problems with the system, thereby allowing the addition of increased performance of the user model to the tool in the next iteration. Thus, important insights and recommendations were derived from the feedback provided by participants. Indeed, the expansion of the scope of targeted campaigns could be achieved through the diversification of the spectrum of hobbies and leisure activities supplied by the tool in the form of features, as suggested by a number of participants. It should be noted that the attributes can be changed by businesses using the stereotype technique. Meanwhile, other participants expressed their satisfaction with the Facebook login feature, something that a majority of web-authoring applications have incorporated. This feature also received a high score of usefulness from the participants in the quantitative answers, as can be seen in section 8.3.3. The considerable usefulness of such a feature resides in the fact that it not only supports more effective user model integration with regard to other web-based systems, but also makes the model more functional and easy to use, since users can gain access to a range of different applications, by entering their identification details a single time. To some degree, these findings are in line with hypothesis H4, which maintains that advertisement recommendations can draw on the user data source, as supplied by social networking platforms. An additional suggestion of relevance that was made by one participant was that the model tool should not specify age in letters but rather by numbers. Conversely, no remarks as to the potential improvements that could be brought to the tool were made by a number of participants, although participants did express their agreement that such research is necessary and significant, especially because online marketing systems and tactics are being continually innovated and transformed. As said above, the attributes can be changed by businesses, using the stereotype technique. Meanwhile, the manual calculation and input of bandwidth was reported by some participants as confusing and unclear. Nevertheless, the bandwidth attribute was seen by the participants to be more useful than the others in the quantitative responses. Still, in order to ensure superior monitoring for all users, bandwidth restrictions should be taken into account automatically. Automatic retrieval of bandwidth has been introduced in the second version of the user model, as shown in Chapter 9, section 9.2.3. During the evaluation processes, one participant was asking if they could stop repeating the presented advertisements that they would not like to see. The advertisements were presented based on adaptation rules that the business owners applied on advertisements and users could not stop them. However, the social data feature implemented in the second version of the user model, addresses this issue, as it allows users to ‘like’ or ‘stop’ an advertisement. More discussion about this feature is presented in Chapter 9, section 9.2.3.

In addition, data storage in XML rather than storage of data with the use of a database was questioned by one participant, which raised awareness about the necessity to provide a clear explanation as to the manner in which the transfer of XML data between various programmes can be easily achieved [132]. This has been done with the AEADS system that was integrated with an online bookstore for evaluation purpose, as can be seen in Chapter 9, section 9.4. Nevertheless, this feature received a high score of usefulness by participants in the quantitative answers, as can be seen in section 8.3.3. Free feedback further confirmed that the system could be easily run by all users, regardless of the level of their system knowledge.

The feedback provided by one participant addressed the fact that the creation of more comprehensive and detailed user profiles, as well as the identification of particular target groups of users, required the collection of a greater number of demographic data. Similarly, a different participant recommended that the tool should be diversified, by the introduction of a larger range of dimensions, as well as the formulation of more clear-cut rules, with the intention of devising marketing strategies of greater efficiency. It should be noted that the AEADS system collects only the data that are needed to personalise the advertisement. However, despite the fact that all the feedback provided by the participants was relevant and helpful, care should be exercised when taking these recommendations on board, due to the fact that the aim was the creation of a user model characterised by flexibility, ease-of-use, applicability, and transferability. Careful implementation of the suggestions is essential, as previous experience with adaptive hypermedia has proven that confusion and lack of clarity may be exacerbated rather than diminished through the addition or more features.

Based on the findings of this study, it can be argued that, by relying on a range of pre-established demographic characteristics and rules, the proposed user model tool could be employed to increase and enhance the precision of advertisement targeting, thereby potentially boosting business sales and profitability. Adaptive advertising systems could be made more portable by the AEADS user model, which can be compatible with wide range of websites. Thus, concerning the ease of incorporation with regard to the user model tool in any JSP website, hypotheses H7a and H7b hold true. Furthermore, the tool could not only help existing systems to expand, but also provide the flexibility needed by businesses, in order to achieve advertisement customisation, while eliminating the need for current model revamping. Additionally, the model could potentially allow websites to request a method which may be found within a particular location within those websites, whilst simultaneously organising and amending all the advertisements on a specific page — with the help of a single code and in conformance with established adaptation rules [134] — while also concurrently maintaining a record of those advertisements shown and accessed by users.

8.4. Comparison with other User Models and Discussion

As stated in the hypotheses above, the user model structure that has been introduced is considered to be suitable for advertisements by this study's participants, who agreed that it can be constructed and utilised in a simple manner. The most popular features of the model were: portability, and therefore its lightweight structure with regard to data representation, in terms of export facility in XML; the multi-system login facility; and connection with social networks, via the introduction of the social networks login. More significantly, users thought that those user characteristics collected by the proposed user model positively affected the selection of appropriate advertisements with regard to them, the users. Moreover, the additional user model information obtained by tracking the users positively affects and enhances the delivery of appropriate advertisements as can be seen in section 8.3.4.

A number of systems have been proposed to facilitate adaptation, including the following examples from different fields: MOT [49, 61], ADE [127], AdRosa [88], and MyAds [4, 5]. A full discussion of all these systems is presented in Chapter 3.

The four user models listed above will now be compared with the one proposed in this study. Selection of these tools is based on the similarity in approach between AEADS and these systems, as there is a plethora of adaptive systems proposing a variety of user models to choose from. In the first part of this discussion, a summary of each tool will be presented, followed by a comparison between the existing and new tool advocated here.

The user model within the MOT [49, 61] system has a number of initial values and essential attributes specific to the target user. Out of these, commonly used variables include interests, level of knowledge, and learning style, among others. These are the variables that describe the user, either generically, or as an overlay over the domain model, and the presentation can take additionally into account the physical environment and the properties of the content presentation, and provide output for different platforms and display devices, including HTML, XTML, laptops, and phones.

Another example of an adaptive system is ADE [127], a generic adaptive delivery system which supports a rich user model but which only runs in-session. Nevertheless, this system is often used to address user model parameters including the number of times a user has visited a concept, the active time spent by each user on a page, and clicks on links. The ADE user model is non-persistent between sessions, and so was not applied here, as this was considered essential to the business case.

AdRosa [88] is an adaptive system that automatically personalises web banners for users. To reduce user input, and at the same time, respect their privacy, AdRosa integrates web usage and content-mining techniques, employing similarities between individuals to dynamically reflect the interests of each user. Thus, data are assimilated without cooperation from the user, and identification is not necessary within this system. AdRosa also possesses a simple user model, dependant on the categorisation of web banners for groups, and is based on the similarities between various individuals in-session.

The user model in the MyAds system [4, 5] contains information concerning buyers and their viewing history; in other words, it tracks advertisements viewed by users, and is initialised via a registration process, or Facebook login, and is updated via a user's actions in order to correlate specific advertisements. Thus, users are able to declare their specific interests to the MyAds system by labelling advertisement categories from one to ten, annotate subsequent recommendations, and specifying whether, or not, they are interested in buying specific items. As such, the MyAds system is the closest to the AEADS system.

It is worth noting that the MOT and ADE systems are predominantly designed for educational adaptations, and thus adapt to courses in line with the characteristics and behaviours of users, while the AdRosa and MyAds systems are targeted to adapt to advertisements. In addition, in terms of deployment, the MOT, ADE, and MyAds systems are run as standalone, which is inappropriate for the paradigm of this research study, as integration is needed for businesses to enhance their websites with AEADS features.

In further comparisons, the size of the user model also plays an important role in determining the efficiency and accuracy of any adaptation system. In this respect, the AdRosa system possesses a very light user model, as preserving privacy is viewed as the main goal. Because of this, however, the structure of the user model means that AdRosa is unable to provide enough, or sufficiently accurate advertisements to web users, as a variety of data needs to be both monitored and stored. Using data-mining techniques, knowledge is extracted to reduce both user input and data storage, but the minimisation of available user data, to respect privacy, limits the accuracy of the results and any development of the adaptive system. Indeed, the user model in this system relates to short-term interests, as it uses the fixed, static characteristics of the users. In contrast, user models in the ADE, MyAds, MOT, and AEADS systems support short-term and long-term interests, as their permanency of data support allow them to predict for both timescales. Similarly, the attributes of the AEADS user model consist of a flexible and changeable list that can be modified, based on the preferences of the business owner.

In addition, any social data interaction within the user model can be stored in the social data component of the AEADS system; for example, ‘like’ and ‘stop’ data are stored by this system to provide accurate information. The MOT, ADE, AdRosa, and MyAds systems do not support such data collection, while just social network login is supported by MyAds.

Summarising, all the functions of the user model (encapsulated within the AEADS user model) are distinct from storage and are located within the delivery section of the AEADS system. This separation has the effect of increasing the portability and should allow easy extension of the system, without affecting it overall. Indeed, the AEADS system can deal with users both with, and without identification, as it employs two algorithms for each of type, as discussed in Chapter 5, section 5.5. When users are unidentified, the system will start by randomly showing all advertisements and then start to monitor clicks, thus dealing with this cold-start issue as well as permitting gradual adaptation to a user's preferences. A comparison of the different adaptive systems discussed in this section is summarised in Table 8.5, below.

Table 8.5 User Model in Different Systems

System	**Purpose**	**UM Size**	**UM Initialisation**	**UM Structure**
AEADS	Advertisement	Short-Term Long-Term	Social Login, Registration, Automatically	4 components represent levels of information
MOT	Courses	Short-Term Long-Term	Registration	(variable-value) in storage
ADE	Courses	Short-Term Long-Term	Registration	(variable-value) in storage
AdRosa	Advertisement	Short-Term	Automatically	vectors in storage
MyAds	Advertisement	Short-Term Long-Term	Social Login, Registration	2 components represent users and companies

8.5. Conclusion

A lightweight user-modelling approach has been proposed within this research. This approach may assist Internet users to register to web-based e-commerce systems, and thereby assist companies to target their audience more directly, by tailoring their marketing campaigns towards specific consumer demographics and focusing their advertisements on those users who satisfy predetermined range of criteria. Based on theoretical considerations and practical testing outcomes, a minimum set of user model dimensions have been validated. The evaluation results indicate that the initial functionality and usability of the small prototype system is promising. However, further modifications for the system are made, which are based on those suggestions offered by the study's survey respondents. The user modelling tool has been refined further, by taking into account user feedback and creating a lightweight adaptive system that is more customisable and based on the needs and preferences of the Internet users, as resulting from the case study. The second version of the user model tool is presented in Chapter 9, section 9.2.3.

In order to make the adaptation process easier and reusable, the design of the user model in AEADS is attained by separating it into four components. The user's data are arranged into three components: *user data*, *behaviour data*, and *social data*. This type of construction and the permanency of data support allows the system to predict the desired advertisements that should be relevant to users both in the long- and short-term, for future sessions based on business rules. The *future advertisements* represents the fourth component that contains advertisements that will be shown in the future, at the next login, to each user.

A comparison has been conducted between the user model of the AEADS system, with user models from the MOT, ADE, AdRosa, and MyAds systems. Based on this comparison, the user model in the AEADS system has been shown to have some commonalities, but also some different features. As such, this exercise shows that a separate user model construction was necessary for AEADS, and previous user models could not be used *as-is*.

The second version of the user model development, which adds the social input data and future adverts' components to the user model, is also described in Chapter 9, section 9.2.3. These two components try to enhance the efficiency of the AEADS system, by introducing a real image about a user's behaviour and maintain the appropriate advertisements for the next session. As the adaptation rules creation tool was updated in the second version, the general rules also became more flexible and their number was able to be increased or decreased, as is further shown in Chapter 9, section 9.2.2. Overall, the user model must be sufficiently flexible, to obtain and store flexible general rules data. Therefore, a simple tool was required, in order to create the code that acquired general rules data for integration into the businesses website.

In summary, the research discussed in this Chapter has implemented various objectives and research questions, as follows (the implemented parts are underlined): the UM part of the research objective

O4: "*Based on the outcome from O3, implement tools for the theoretical model, to support the creation of adaptive advertising by website owners*". Additionally, with regard to the evaluation, this Chapter has implemented the research objective **O6:** "*Evaluate each design and implementation step, both technically and, where appropriate, with real businesses and internet users*". The procedure of analysing these objectives has been outlined and the outcomes have helped to answer the research question **R2:** "*How can we create a model for lightweight adaptive advertising and design the corresponding system that can be integrated with most websites?*". This research question has been partly answered in Chapter 5, by proposing a new model for adaptive advertising, and in Chapter 6 and Chapter 7, by implementing and evaluating the domain model (DM) and adaptation model (AM), respectively. Furthermore, the research question has also been partially answered in this Chapter, through the implementation of the user model tool of the overall AEADS system. Furthermore, the process of investigating the objectives has been outlined and the outcomes have supported an answer to research question **R3:** "*How can we support website owners in the creation of adaptive advertising, in order to be able to efficiently add adaptive advertising in a lightweight manner to their website?*". The answer of this research question is continued in this Chapter through the implementation and evaluation of the user model (UM). Further implementation and evaluation of the delivery model (DM) of the AEADS system based on the LAAI model, shall be discussed in the following Chapter (Chapter 9), wherein the research questions **R2** and **R3** are answered in full.

Chapter 9

Delivery Model for Lightweight Adaptive Advertising

9.1. Introduction

This Chapter addresses research objectives **O5:** "*Implement a delivery engine that resides on the businesses' own websites, to support delivering personalised advertisements to the users*", and **O6:** "*Evaluate each design and implementation step, both technically and, where appropriate, with real businesses and internet users*". This Chapter will describe the implementation of the second iteration of the authoring toolset (domain model (DM), adaptation model (AM), user model (UM)) of the AEADS system, which has been discussed previously in Chapters 6, 7, and 8. In addition, this Chapter will discuss the implementation and evaluation of the delivery model (DM) of the AEADS system. This supports the final answer to the research question **R2:** "*How can we create a model for lightweight adaptive advertising and design the corresponding system that can be integrated with most websites?*". Moreover, it supports the final answer to the research question **R3:** "*How can we support website owners in the creation of adaptive advertising, in order to be able to efficiently add adaptive advertising in a lightweight manner to their website?*". The above research questions have been previously partially answered in Chapters 6, 7, and 8.

Providing suitable content and products for different users meets the needs of both businesses and customers. It increases the profit of businesses and allows greater customer satisfaction. The adaptation process attempts to match content and products to the general profiles of targeted customers, without modifying the structure. There has been a rise in the growth of e-commerce and web applications in recent years [2, 5, 88], and thus the improvement of the delivery systems is important, as a way of matching such growth in e-commerce and web applications. Delivering adaptation courses to match users' experiences is the first field in which this concept is applied [32]. The delivery systems are used to offer solutions, by showing the appropriate part of the course for each user. Generally, the content of the delivery framework depends on the monitoring, decision and adaptation modules [146].

E-commerce has given customers the power to choose from a variety of options offered by different companies, and thus competition has greatly emerged in terms of pricing of the commodities and their qualities, among other competitive factors [113]. Delivering adaptive advertising will support this process by both maximising the profits of businesses and increasing customer satisfaction. This forms a major factor that is considered a way of winning customers over by being dependable and answering to their needs.

In this thesis, the delivery model is one of the components ensuring that the end-user receives the appropriate information, as described in Chapter 5, section 5.6.

The current Chapter is structured as follows. The next section contains the description of the implementation of the second iteration of the authoring toolset (domain model (DM), adaptation model (AM), user model (UM)) of the AEADS system. This is followed by the description of the design and implementation of the delivery model (DM), in an actual system, AEADS. Subsequently, an evaluation of the delivery model with business owners and Internet users, including quantitative and qualitative evaluations, and analysing tracked data, is presented. Next, a comparison with other delivery models and a discussion are presented, following which the second iteration of the delivery model is demonstrated, which is built based on evaluation results. All of the tools included in the AEADS system are evaluated as a whole in this evaluation. The current Chapter finishes with a conclusion.

9.2. The Second Iteration of the Authoring of Adaptive E-Advertising

The second iteration of the AEADS authoring tools, including the domain model (DM), the adaptation model (AM) and the user model (UM), was implemented based on the evaluations obtained from both business owners and Internet users. A full discussion of these evaluations was presented in the previous Chapters (6, 7, and 8). In addition, the second iteration of these tools is evaluated in the final evaluation, as can be seen in section 9.4 below.

9.2.1. The Second Iteration of the Domain Model (DM)

Three points can be raised based on the evaluation results that are presented in Chapter 6, section 6.3. Firstly, a *container for the authoring tools* may be required, to make the access for all tools easier and also, as there is no need to use each tool separately. The idea of this container has been proposed by me, in order to simplify the authoring process. Moreover, some of the business owners were worried about potential problems arising. For instance, one participant asked, “Is there a support category within this web tool to help the users if they face a problem?”. In the first iteration (explained in Chapter 6), the authors controlled their advertisements using separate tools for each of the models, including the domain model. In contrast, as a result of considering these issues, in the second iteration, an application was created that becomes a container that contains all authoring tools: the *domain model (DM)* and the *adaptation model (AM)*. In addition, it includes two help tools (the help tool supports the tool that provides the main functionality). The first tool helps to modify the general rules within the adaptation model, as is further explained in section 9.2.2, below. The second help tool permits businesses to add various plan libraries to the system, as further explained in section 9.6. Note that this container contains a menu and a toolbar to run all the authoring and help tools, as can be seen in Figure 9.1.

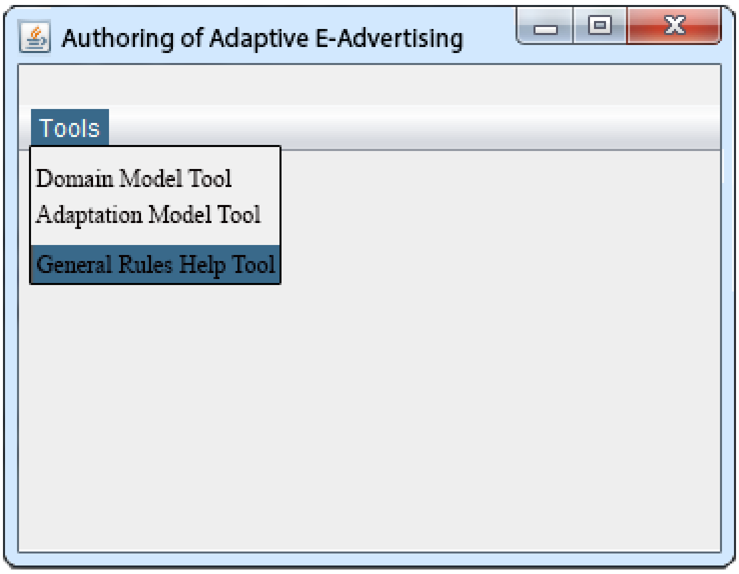

Figure 9.1 Application Menu

Secondly, a new feature has been added to the first tool’s user interface, the creation of a domain model, based on the evaluation obtained from business owners (presented in Chapter 6, section 6.3).

The facility that enables a business owner to easily add a domain has also been implemented and this is explained below. A *browse command* has been added, to obtain the name of the file that contains the advertisements from the hard disk, as shown in Figure 9.2. Since there was no guarantee of the correctness of the file name that could be manually written by the author in the first iteration of this tool, the file name in the second iteration is to be filled-in automatically, via the browse command. The correct name, after browsing, can be inserted in the 'HardDiskName' field, by using this command. This command will overcome an invalid file name when advertisements are displayed by the decision engine.

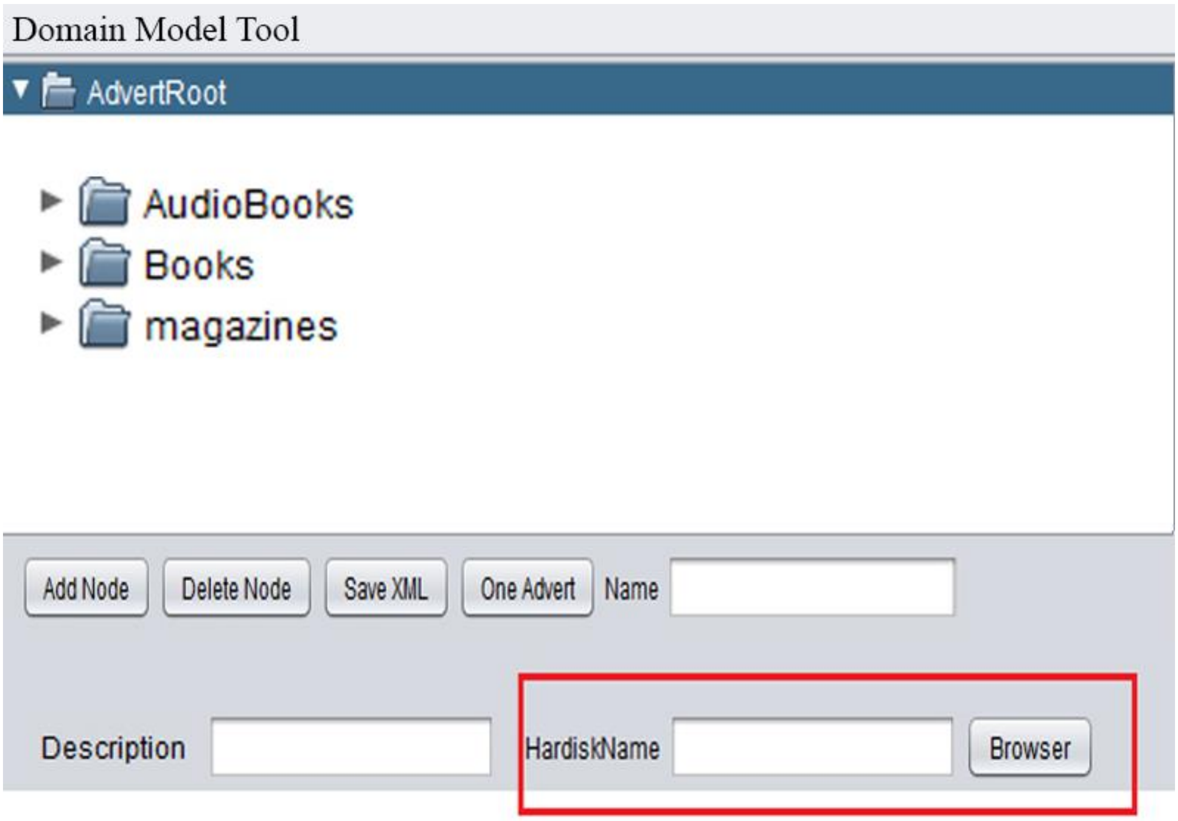

Figure 9.2 Second Version of the Domain Model Tool

Furthermore, some bugs in the first version were fixed and a solution was found for the second version, while some other simplifications of the classification process took place, as was reported by various businesses during the evaluation processes (discussed in Chapter 6, section 6.3). It was stated that if an error within the classification process is made, or if people wish to add to the subgroups, certain items must be deleted prior to the desired subgroup being added, after which any items that they had deleted before this action must be added again. Business owners took note of the fact that this process wasted a significant amount of time, so the process was improved.

9.2.2. The Second Iteration of the Adaptation Model (AM)

In the first version of the adaptation model (AM) tool that was introduced in Chapter 7, there were four fixed general rules (based on user model parameters such as *age*, *gender*, *bandwidth* and *device type*). These rules represent the features that this research considers to be most related to the adaptation of advertisements, as explained in Chapter 7, section 7.2. The rules aim to provide the adaptation process with more flexibility, in terms of allowing the author to be involved in determining the features that must be added to the general rules, as well as being involved in determining the values that will be assigned to each feature. In the second version of the implementation, as it became clear during the evaluation process (discussed in Chapter 7) that every business owner would like to apply a different set of adaptation rules to the advertisements, a new tool (a help tool that supports the tool that provides the main functionality) has been created, to help the author control the features that appear in the general rules and their values within the adaptation model tools. This help tool was created specifically to allow the author to add two types of values for each feature. The first type was created with regards to features that could take a range of *discrete values*. This allows the author to list values manually, in this case adding more than just the feature name, being also able to provide the range of values for the feature, as shown in Figure 9.3. For example, the author can add a *gender* feature and decide whether the value type of this feature is to be a discrete value. Thus, within this feature, an author could potentially add the values of *man* and *woman*.

The other types of features are those that can take interval values, named as *range values* here. To illustrate this, if the author adds the *age* feature with a range value type, the author can also add a range of values to this feature, as shown in Figure 9.4 (for ages between 10 and 16 years old).

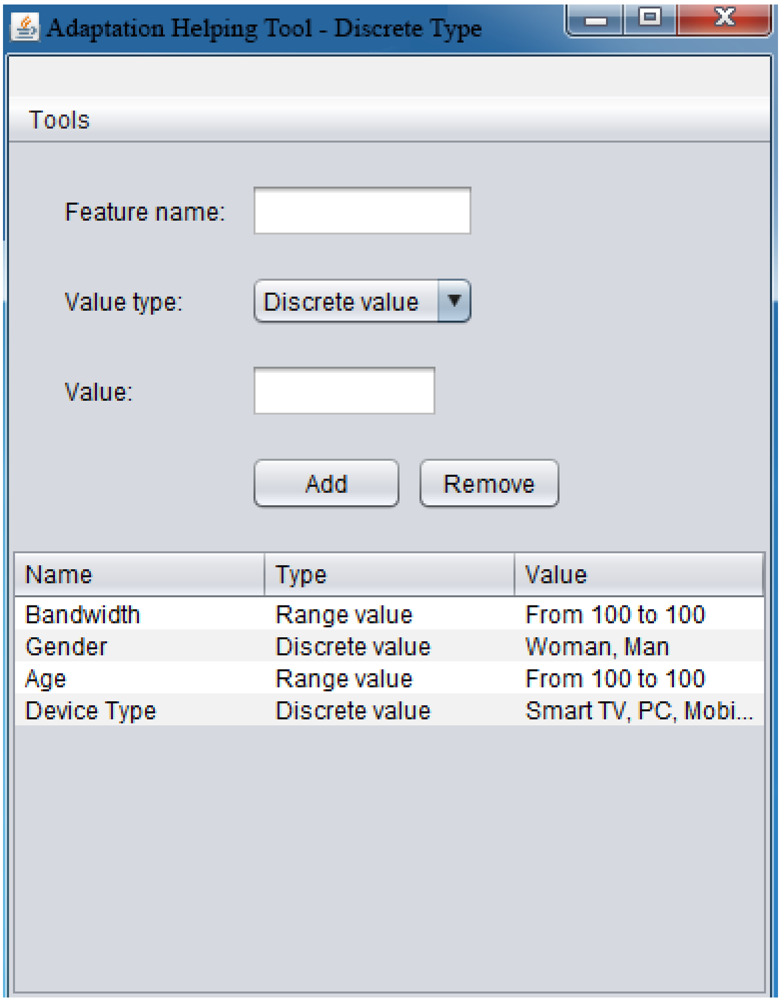

Figure 9.3 Adaptation Helping Tool - Discrete Type

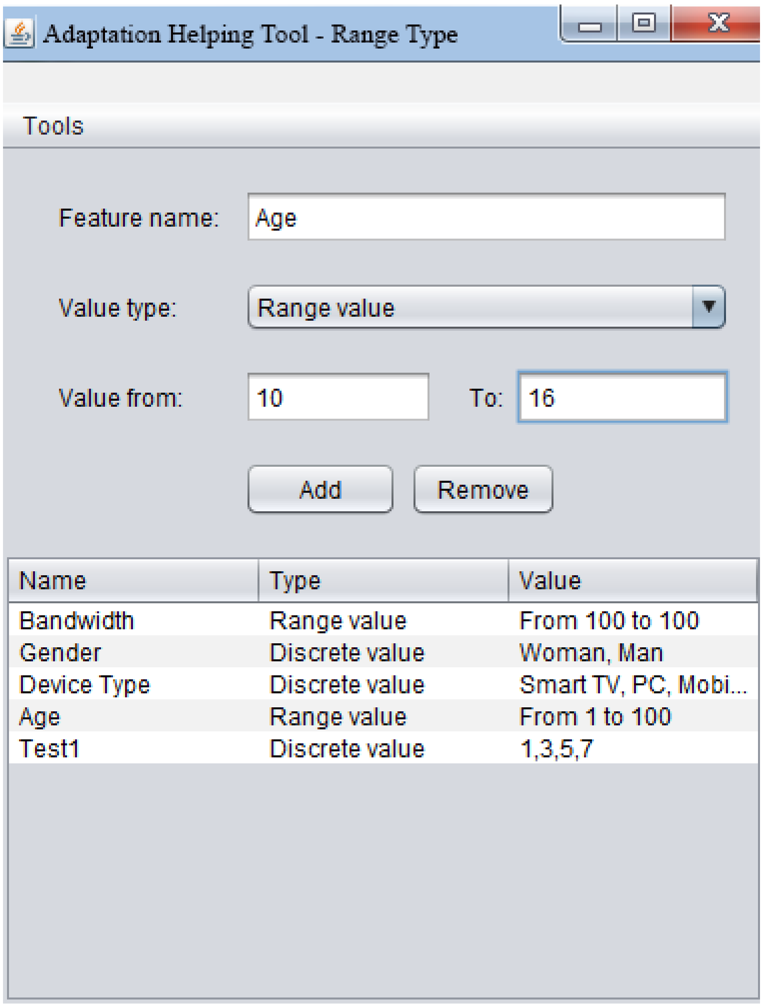

Figure 9.4 Adaptation Helping Tool - Range Type

This tool saves these features in a lightweight manner, as is the overall policy of the toolset, in an XML file, the `GeneralRules.XML` file. In addition, the registration process or automatic acquisition of data must be updated, to reflect these changes. The adaptation model tool also had to be updated, to reflect the modifications made by business owners choosing features for advertisements (items). As shown in Figure 9.5, the author can select (highlight) an advertisement that is obtained from the domain model, then can choose the feature from the features combobox – device type – and then assign a value, which is also a discrete value, shown in another combobox – smart TV, PC, mobile Phone, Tablet – before clicking the 'Add Feature' button. In addition, if the feature that is selected by the author has a range of values, as illustrated in Figure 9.6 – such as with the age feature – two list boxes will appear, allowing the author to decide on the range of values.

Moreover, when the author selects an advertisement, then the general rules assigned to this advertisement will be shown, as illustrated in Figure 9.6. Two lists are shown: one list is for the features and the other list is for the values that are assigned to this advertisement. The button for removing features is used to remove any feature that the author has previously assigned to an advertisement. Finally, the tool must prevent the author from adding an advertisement multiple times to a specified general rule with different values. This represents the additional validation functionality of the tool, which prohibits authors from introducing errors.

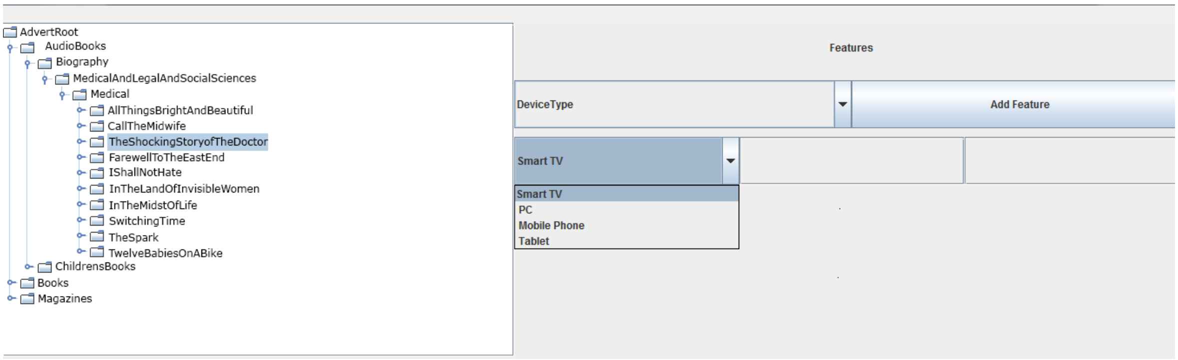

Figure 9.5 Second Version of the Adaptation Model: Selection of the Device Type

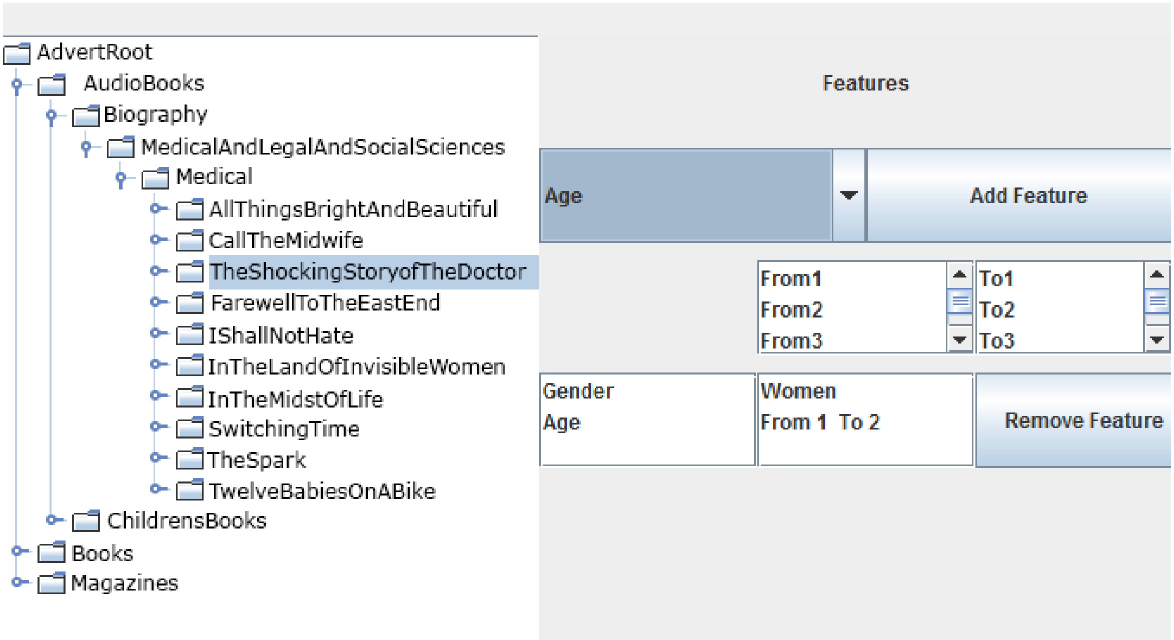

Figure 9.6 Second Version of the Adaptation Model: Selection of the Age

The *behaviour rules* section, which has been discussed in Chapter 7, does not differ within this version of AEADS, due to time and literature limitations. Any suggested extensions and further research into this section are dealt with in future work in Chapter 10, section 10.5.

9.2.3. The Second Iteration of the User Model (UM)

In the second version of the AEADS system that has been proposed and implemented by this research, based on the test and the evaluation of the user model, as discussed in Chapter 8, the *storage structure of the advertisement* was improved, including for the advertisements that were to be presented to the user in future, based on general rules, behavioural rules and plan recognition. Each advertisement is categorised against its reason for its generation. In the previous version (explained in Chapter 8), these advertisements are discarded when the user logs out and they are not saved for subsequent sessions. Thus, a new component that has been proposed, as a result of the work in this thesis, '*Future Adverts*', is added to the user model, in order to save these advertisements, so that they can be shown to the user the next time that they login. This component will maximise the efficiency and accuracy of the user model, as well as making the system more efficient overall. However, if the advertisement is not valid anymore, or the product becomes obsolete in the meantime, this advertisement will be deleted and advertisements will be shifted in the same queue, as is explained in the delivery model in section 9.3.2 below.

In addition, a new set of *social data* is added to the user model, as was proposed by Internet users during the evaluation process. This necessity derived during the session involving open-ended questions, when end users were asking for the advertisements to be hidden, as they did not want to view them any longer (as discussed in Chapter 8, section 8.3). This led to social data being overlaid [29, 36] over the advertisements, in order to allow the user to 'like' or 'stop' actions (among others) on any advertisements. This social data enables the delivery function to apply some action based on this data according to the rules, as chosen by the business owner, or else to be set as default by AEADS. For instance, if a user selects the 'stop' button for an advertisement, all advertisements within that specific advertisement's subcategory will be blocked. This social data are stored in a new component, known as *social data*, within the user model, to support social interaction. If advertisements are liked by many users, they can be recommended to new users, based on the similarity of the user profiles. This data are acquired from the user, by adding linked buttons under each advertisement, after which the user can click on those links to choose the data that is appropriate for them. Figure 9.7 shows two button-like links, ‘like’ and ‘stop’, under each advertisement, which increase the opportunities for users to be involved in the adaptation process.

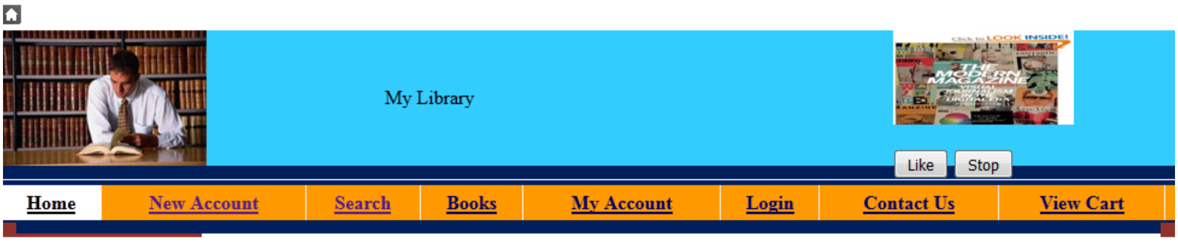

Figure 9.7 Social Data in the AEADS System

Moreover, when tracking the use of advertisements, besides the click and display processes, the *connection between the search processes and the resulting buying processes* had to be made explicit, to further facilitate recommendations based on search, that are likely to influence buying, by tracking and adapting to user behaviour. This feature was proposed by business owners during the evaluation of the adaptation model that was discussed in Chapter 7, section 7.4, as one of the business owners asked to apply certain rules depending on the customers’ search behaviour. By recording and storing a user’s searching and buying actions, the system is able to publish advertisements that relate to a specific user’s online activity. Furthermore, some bugs in the first version were fixed and a solution was found for the second version, while other simplifications were made, to boost the functionality, such as with the automatic retrieval of bandwidth, which came about due to a report made by a user during the evaluation processes (discussed in Chapter 8, section 8.3), which stated that he does not know anything about bandwidth, nor about its automatic retrieval. Finally, the components for social data and future adverts are arranged within the user model and connected to the modifier and inference engine within the delivery model, as seen depicted in Figure 9.8.

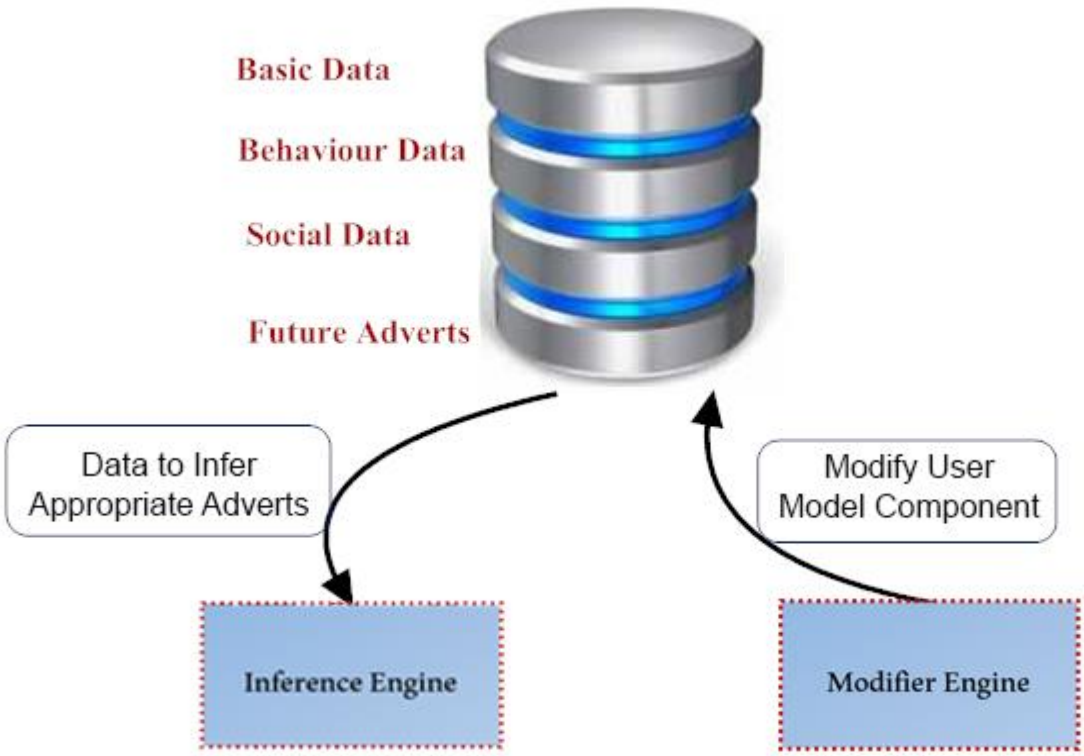

Figure 9.8 New Component in the UM

9.3. Delivering Adaptive E-Advertising

The *delivery model (DM)* (Figure 9.9) is resident on the same website server, in order to deliver advertisements to Internet users. This part parses the contents of the XML files and uses adaptation strategies to send appropriate advertisements to the respective users, based on a user model. It consists of three engines: *inference, decision* and *modifier* (as explained in Chapter 5, section 5.6). These three engines will be discussed in detail in the following sub-sections.

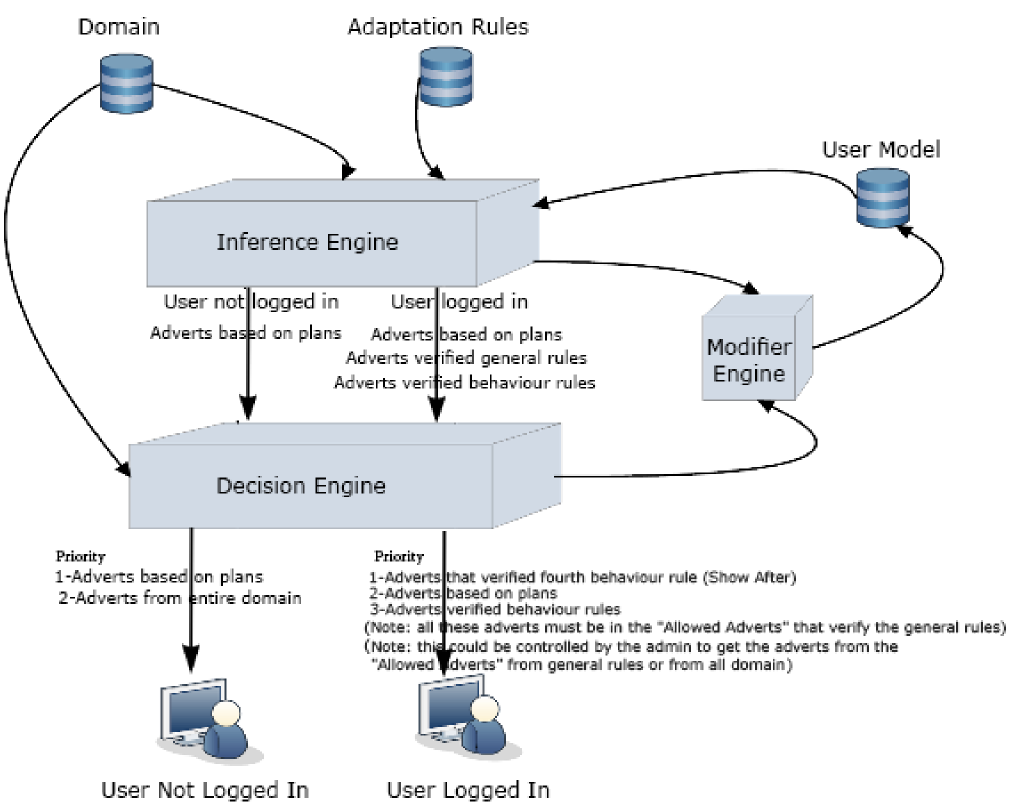

Figure 9.9 Delivery Engines of the AEADS System

9.3.1. The Inference Engine

The *inference engine* gathers data from the domain model, the adaptation model and the user model, to apply its processes to inferring multiple sequences of advertisements, which will be sent to the decision engine. Firstly, it checks whether or not the current user is logged in to the website. If the current user is not logged in, the inference engine only applies the *plan recognition* process. The plan recognition process will depend on the *plan libraries*, which the businesses create in the authoring part. The inference engine checks the clicked items and checks the plan libraries, to acquire a sequence of advertisements to be dispatched to the decision engine (as explained in Chapter 5, section 5.6).

Figure 9.10 illustrates this process, when the user clicks on an advertisement, the plan recognition process of the inference engine is initiated. The inference engine will match this clicked advertisement with the plan library, which exists in the authoring part, to choose one of them to be send to the decision engine. In addition, Figure 9.11 shows a sample of the XML file that contains the library of plans. Using XML files should enhance the portability, easy processing and generalisation of the system, as previously discussed. Each node represents an advertisement, and inside this node, an edge will be inserted with the advertisement ID referring to the linked advertisement. The simple structure of the XML file allows authors to easily add plans. In the second version, a small tool has been implemented in order to build these plans, which should help to simplify the process, as discussed in section 9.6, below.

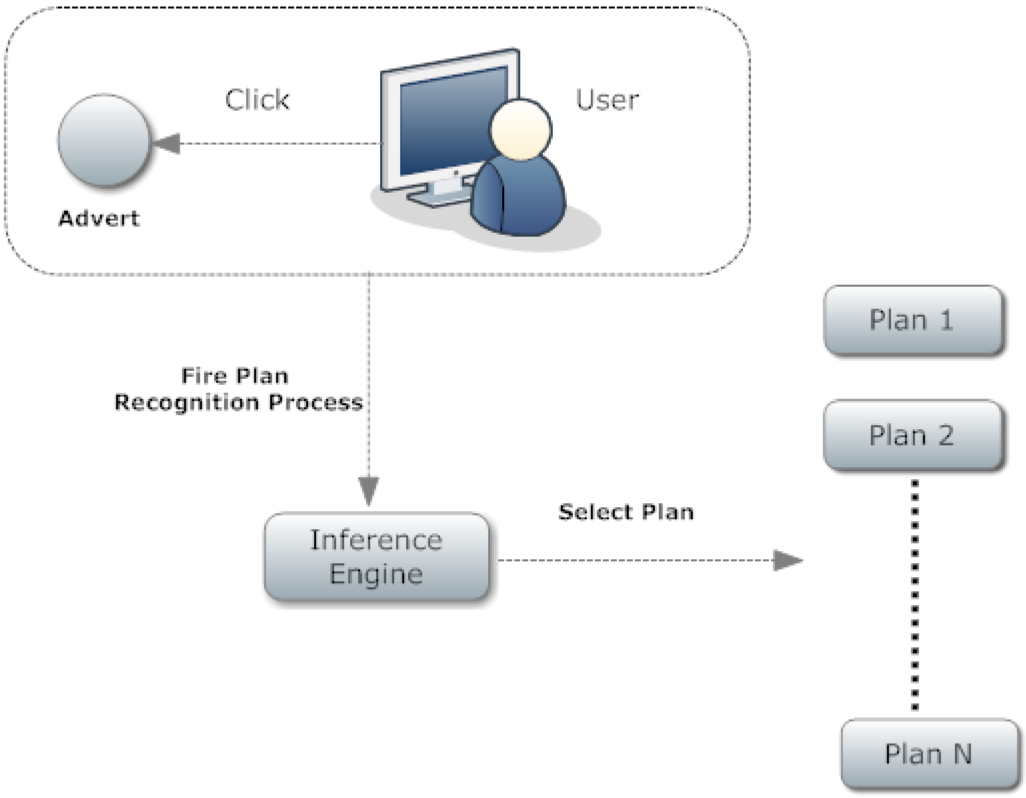

Figure 9.10 Plan Recognition in the Inference Engine

```
- <data>
  - <Node id="MedicalAndLegalAndSocialSciences1421663642903">
      <Edge to="MedicalAndLegalAndSocialSciences1421664003310"/>
    </Node>
  - <Node id="MedicalAndLegalAndSocialSciences1421663762256">
      <Edge to="MedicalAndLegalAndSocialSciences1421664003310"/>
    </Node>
  - <Node id="MedicalAndLegalAndSocialSciences1421663892926">
      <Edge to="MedicalAndLegalAndSocialSciences1421664003310"/>
    </Node>
  - <Node id="MedicalAndLegalAndSocialSciences1421664003310">
      <Edge to="AudioBooks1421664751343"/>
    </Node>
  - <Node id="MedicalAndLegalAndSocialSciences1421664010444">
      <Edge to="MedicalAndLegalAndSocialSciences1421664003310"/>
    </Node>
  - <Node id="MedicalAndLegalAndSocialSciences1421664012452">
      <Edge to="MedicalAndLegalAndSocialSciences1421664003310"/>
    </Node>
  - <Node id="MedicalAndLegalAndSocialSciences1421664014219">
      <Edge to="MedicalAndLegalAndSocialSciences1421664003310"/>
    </Node>
  - <Node id="MedicalAndLegalAndSocialSciences1421664016547">
      <Edge to="MedicalAndLegalAndSocialSciences1421664003310"/>
    </Node>
  - <Node id="MedicalAndLegalAndSocialSciences1421664018348">
      <Edge to="MedicalAndLegalAndSocialSciences1421664003310"/>
    </Node>
  - <Node id="MedicalAndLegalAndSocialSciences1421664020300">
      <Edge to="MedicalAndLegalAndSocialSciences1421664003310"/>
    </Node>
  - <Node id="AudioBooks1421664751343">
      <Edge to="AudioBooks1421664754911"/>
    </Node>
    <Node id="AudioBooks1421664753151"> </Node>
    <Node id="AudioBooks1421664754911"> </Node>
    <Node id="AudioBooks1421664756488"> </Node>
    <Node id="AudioBooks1421664758312"> </Node>
  - <Node id="AudioBooks1421664760071">
      <Edge to="AudioBooks1421664764142"/>
    </Node>
    <Node id="AudioBooks1421664762350"> </Node>
  - <Node id="AudioBooks1421664764142">
      <Edge to="BusinessAndFinanceAndLaw1421665391531"/>
    </Node>
    <Node id="AudioBooks1421664765878"> </Node>
    <Node id="AudioBooks1421664767710"> </Node>
  - <Node id="BusinessAndFinanceAndLaw1421665391531">
      <Edge to="Algorithms1421667406440"/>
    </Node>
    <Node id="BusinessAndFinanceAndLaw1421665393794"> </Node>
    <Node id="BusinessAndFinanceAndLaw1421665395850"> </Node>
    <Node id="BusinessAndFinanceAndLaw1421665397450"> </Node>
    <Node id="BusinessAndFinanceAndLaw1421665399554"> </Node>
    <Node id="BusinessAndFinanceAndLaw1421665407586"> </Node>
    <Node id="BusinessAndFinanceAndLaw1421665409578"> </Node>
    <Node id="BusinessAndFinanceAndLaw1421665411682"> </Node>
    <Node id="BusinessAndFinanceAndLaw1421665447553"> </Node>
    <Node id="BusinessAndFinanceAndLaw1421665450305"> </Node>
    <Node id="BusinessAndFinanceAndLaw1421665751430"> </Node>
    <Node id="BusinessAndFinanceAndLaw1421665754157"> </Node>
    <Node id="BusinessAndFinanceAndLaw1421665756357"> </Node>
```


Figure 9.11 Plan Library in XML file

On the other hand, if the current user is logged in, then the *general rules* will be applied, firstly by the inference engine, to assign a group of advertisements from the entire domain to the current user, according to features, such as gender and age, based on stereotypes created. This group of data that allowed for the current user will be directly sent to the modifier engine, to update the user model.

Furthermore, the *behaviour rules*, which represent adaptation strategies, are next applied. A sequence of advertisements is also retrieved and passed to the decision engine, based on these rules. As a non-logged-in user, the inference engine also applies the plan recognition process and passes it to the decision engine. Finally, all of these advertisements must apply the general rules applied in the first step. The inference engine processes are presented in Figure 9.12, below.

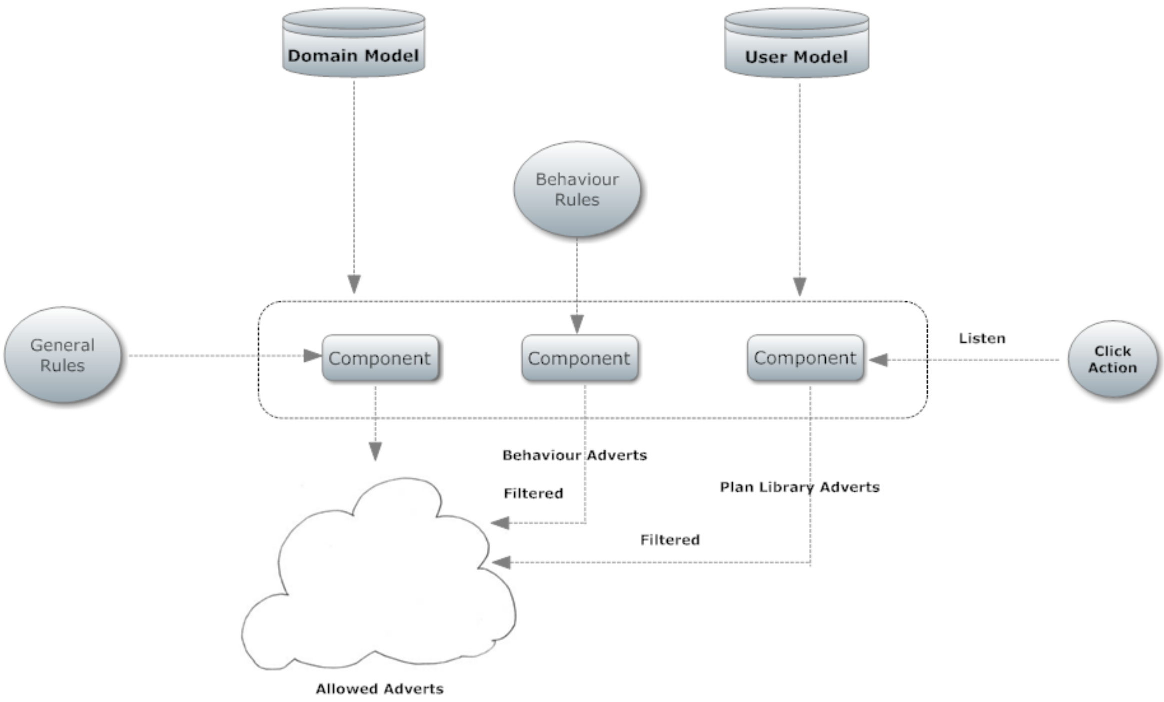

Figure 9.12 Inference Engine Process (User Logged In)

The inference engine reflects the changes within the user model component. It processes the new *social data* – ‘like’ and ‘stop’ – that have been added to the second version of the user model. The inference engine can stop an advertisement or an entire group of advertisements based on the requirements of the user. Based on the ‘like’ selection, the inference engine can display a selected advertisement with additional information, along with the appropriate group of advertisements the liked advert belonged to. In addition, the *searching and buying processes* initiated by the user are considered within the inference process, a feature which is implemented in the second version of the user model. Matching between search words and advertisement names or descriptions in the domain becomes one of the processes of the inference engine. The searching and buying behaviour of users will be stored in the user model and the inference engine will assign specific related advertisements based on this behaviour.

9.3.2. The Decision Engine

The *decision engine* is responsible for displaying advertisements to the current user. Firstly, a flexible method that allows businesses to put any number of advertisements anywhere they want, will be used by the decision engine. The businesses are only assigned the ID of the html element that contains the advertisement image with a fixed name 'Image_Universal_AdLocation'. As shown in Figure 9.13, the ID of the link that represents this advertisement will be assigned the name 'A_Universal_AdLocation' and this code is set to be repeated on all webpages. This method allows businesses to add any number of advertisements in any location on the webpage, as can be seen in Figure 9.14. Furthermore, the number and location of advertisements can vary from page to page, based on businesses views (as explained in Chapter 5, section 5.6).

```
<a href="AdvertsDetails.jsp" id="A_Universal_AdLocation">
<img src="" width="150" height="78" id="Image_Universal_AdLocation" />
</a>
```

Figure 9.13 Advertisements Location Determination Code

When a user loads a webpage, the decision engine searches for the IDs, which represent the advertisements, and changes their names, by giving them a number in increasing order. The decision engine then determines the number of advertisements, which will appear on the current webpage. This process is aimed at giving the system flexibility and usability, as businesses can insert the advertisements where they wish, as well as control the number of advertisements and the location of each advertisement on the webpage (Figure 9.14).

Figure 9.14 Advertisements on the Webpage

If the current user is not logged in (Figure 9.15), then the entire domain model and sequence of advertisements, from the inference engine yielded from the plan recognition process by any click by the user, will be available to display by the decision engine for the current user. Higher priority advertisements will be displayed first. The decision engine arranges the available advertisements, in the order as based on the following algorithm (as described in Chapter 5, section 5.6):

1. Display the advertisements from the plan recognition, firstly;
2. Randomly display advertisements from the entire domain, if the plan recognition advertisements is finished.

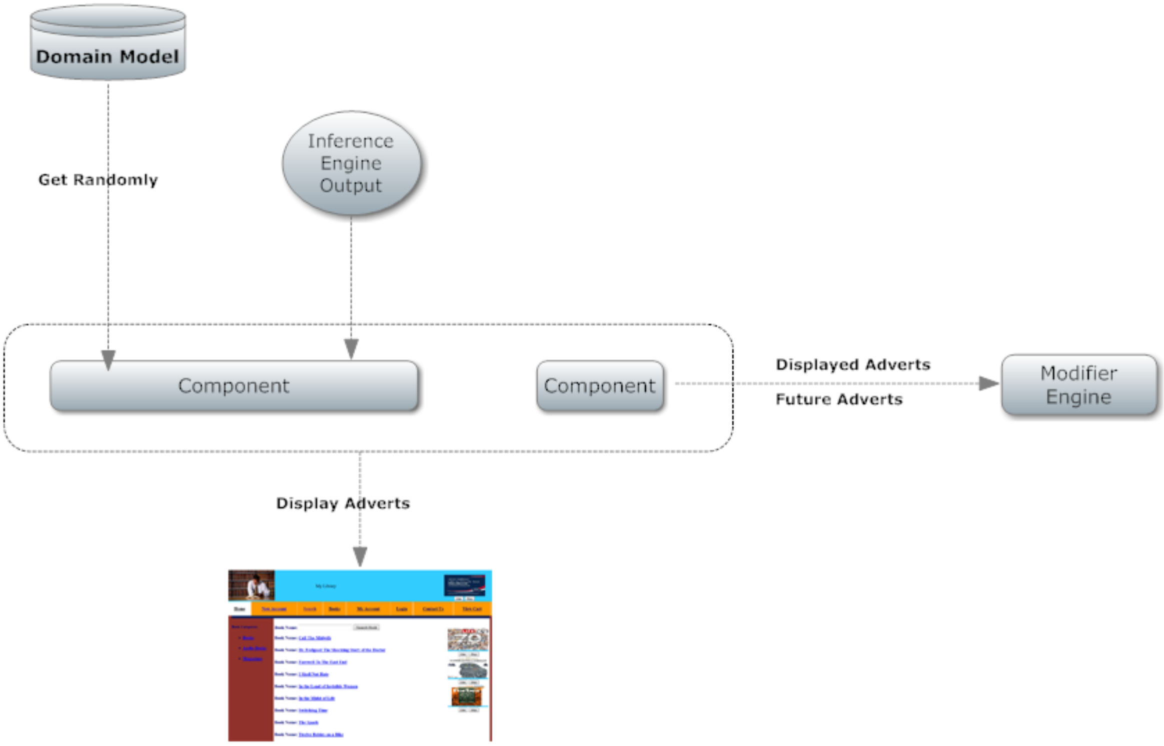

Figure 9.15 Decision Engine Process (User not Logged In)

On the other hand, if the current user is logged in, then a sequence of advertisements from the inference engine, which meet the behaviour rules, will be retrieved and sent to the decision engine. A sequence of advertisements based on plan recognition from the inference engine will be given to the decision engine. In this case, the decision engine arranges the available advertisements, based on the following algorithm:

1. The fourth behaviour rule, that is explained in Chapter 7, "Show After" has first priority, if it exists;

2. If there are advertisements from the plan recognition, display them; If the plan recognition advertisements are exhausted, display advertisements, which meet the other behavioural rules.

Moreover, as *searching*, *buying*, and *social data* storage and processing have been added to the second version of the user model, the advertisements sent to the decision engine from the inference engine will use these data, thus altering the decision priority for displaying advertisements. Finally, the remainder of the advertisements from the plan, behaviour and applying processes will be sent to the user model to be saved in the future advertisements component within the user model, to await the next login from the current user.

9.3.3. The Modifier Engine

The *modifier engine* acquires information from the inference and decision engines, to update the user model. The user model is updated based on certain events; for example, during the user's login, the modifier engine detects whether or not the device type and bandwidth have changed and it modifies these within the user model. If the user logs into the AEADS system using two devices at the same time, the last device used will be stored. When the decision engine delivers a number of advertisements to be shown on the current page, the modifier engine updates the user model, with the advertisements then shown to the current user. Furthermore, the *advertisements allowed* for the current user will be sent from the inference engine, according to specific features, such as gender and age, to the modifier engine, in order to update the user model and save these advertisements within the user model for the current user (as described in Chapter 5, section 5.6).

Furthermore, the modifier engine will save the remaining advertisements from the inference engine and those that the decision engine did not show on certain webpages, in the user model – *future advertisements component* – at the user's logout. Additionally, within the user model, the searching and buying processes of users are stored; the modifier engine is updated to store this new information. In the following section, the evaluation of the proposed second iteration of the AEADS authoring toolset as well as the delivery model tool are presented and then evaluated as a whole.

9.4. Evaluation

In order to test the AEADS system and obtain valuable feedback with regards to its *effectiveness* (usefulness), *efficiency* (ease of use) and *satisfaction*, as discussed in Chapter 2, section 2.5, the AEADS system was integrated with an online bookstore. This was an idea that was originally proposed by this study right at the beginning, as previous evaluations in this research had evaluated the tools separately. In order to evaluate the AEADS system, samples of businesses and Internet users were asked to utilise the system in its current format. An important point is that both the Internet users (the clients) and the business owners (the providers) were required to participate in the e-advertising domain research, to effectively evaluate both sides of the needs and interaction, unlike in prior research [5]. Business owners are using the AEADS system (authoring toolset) and the Internet users use the resulting (authored) website, which the delivery model tool resides on. The user modelling profile attributes of the AEADS system were integrated into online bookstores user profiles, as can be seen in Figure 9.16. In the figure, the 'name', 'user name', 'password' and 'email' attributes form the online bookstores user profile attributes, while the attributes 'age', 'gender', 'bandwidth', 'education level', 'education type' and 'hobbies' are the AEADS user modelling profile attributes. The user (customer) modelling tool in the AEADS system has been designed to be simple — that is, to possess only a few user model features and have an XML data structure — the latter so that it is *lightweight* and can be integrated with any potential website user model, as discussed in Chapter 8, section 8.2. In addition, Figure 9.17 shows that the AEADS system login page has been integrated to the online bookstores, which thus includes two methods of login: registering (explicit data retrieval) and Facebook login (implicit data retrieval), as discussed in Chapter 8, section 8.2.

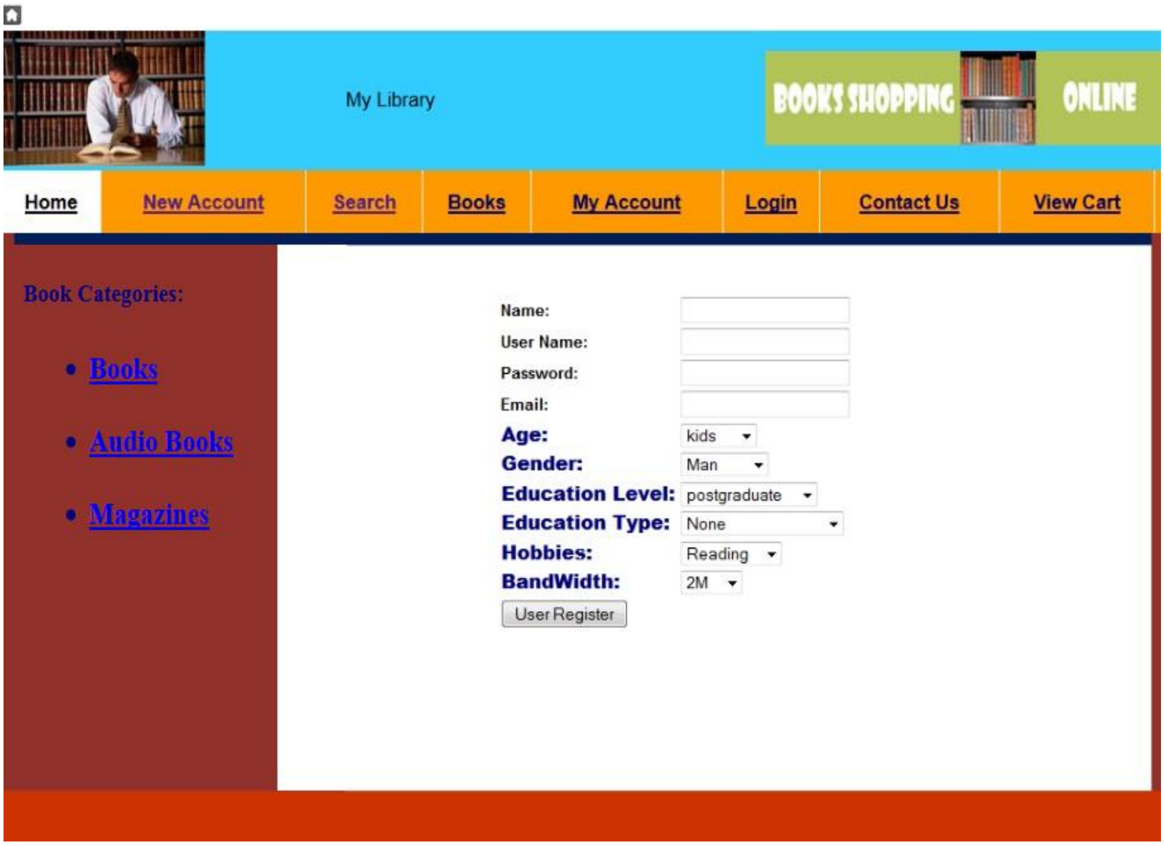

Figure 9.16 Book Store Registration

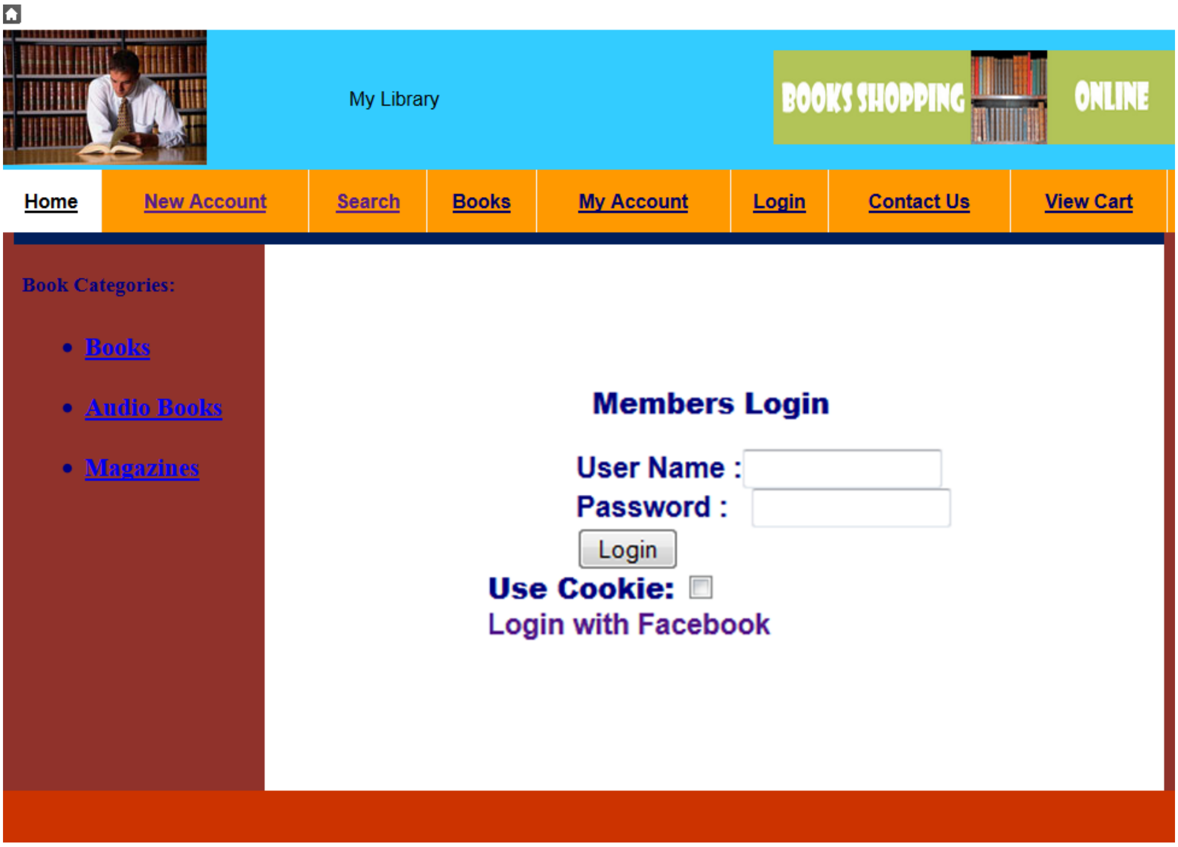

Figure 9.17 Book Store Login

Two evaluation processes were designed to evaluate the AEADS system and its main features and functions. The main aim of these surveys was to determine whether business owners and Internet users responded favourably to the new lightweight advertising delivery system and whether or not the new design facilitated them in adapting advertisements based on consumer feedback. Thus, 450 different Internet users were sent the user questionnaire, while the second evaluation for business owners was conducted with seventeen different business owners.

9.4.1. Hypotheses for Internet Users

The following hypotheses have been defined to evaluate the AEADS system, from an Internet users' perspective.

H0a: *The AEADS system and its functions are useful for adaptive advertising.*

H0b: *The AEADS system and its functions are easy to use for adaptive advertising.*

H0c: *The AEADS system and its functions are sufficient for adaptive advertising.*

H0d: *The AEADS system and its functions are desirable for adaptive advertising.*

H0x are the basic hypotheses, which were tested directly via the questionnaire method. More specific hypotheses, as defined below, were also tested via the questionnaire method.

H1: *The various functions in the AEADS system are well integrated.*

H2: *The AEADS system has a shallow learning curve.*

H3: *The AEADS system personalises advertisements better than regular e-business systems.*

H4: *The AEADS system is very easy to remember how to use, in comparison to other e-business systems.*

H5: *The AEADS system overcomes the privacy concerns.*

H6: *Users prefer to login via Facebook account rather than register.*

H7: *The collected data are enough and acceptable for users.*

H8: *The AEADS system interface is user-friendly.*

H9: *The AEADS system performance is adequate.*

H10: *The AEADS system reliability is achieved.*

H11: *The AEADS system increases the clicking behaviour on advertisements.*

These hypotheses were evaluated by surveying a sample group of Internet users and analysing their answers, as further described below.

9.4.2.Evaluation Setup for Internet Users

All 450 Internet users invited to participate in the testing process were required to use, assess and evaluate the AEADS system. This is a relatively good number of users for such a study, when compared with other studies in e-business, e-advertising, and e-learning [4, 128]. The discussion on the ideal number for such evaluations can be found in Chapter 2 on Methodology. This process involved a number of different stages, which will be outlined below.

The participants were first given a general overview of the AEADS system and the concept of adaptive advertising. The participants were then asked to use the system and evaluate its functionality. At this stage, a six-part survey was distributed, to facilitate the assessment process (the full system questionnaire can be found in Appendix F). The opening section of the questionnaire asked participants to provide a number of personal demographic details, such as age, gender, level of education, etc. The following section asked participants to answer a number of system usability scale (SUS) [22] questions in relation to the adaptive advertisements integrated within the company's webpage. The next step required users to answer a number of general questions, while the fifth section required them to offer more in-depth responses regarding the usability and functionality of the system. This section utilised a Likert scale [98] for responses, as participants were required to analyse and evaluate the effectiveness and applicability of the system. The Likert scale offered each participant five different response options to each statement presented in relation to the AEADS system. Numerical data are used to represent a certain feeling or opinion: for instance, 1 = 'not at all useful' / 'very difficult' / 'not at all sufficient' / 'not at all desirable'; whereas 5 = 'very useful' / 'very easy to use' / 'very sufficient' / 'very desirable'. The last section then asked a number of qualitative questions, which invited the participant to offer feedback and discuss their experience in testing the AEADS system. The results are presented in the next section.

9.4.3. Internet Users Evaluation Results

A total of 381 questionnaires were completed accurately and returned to the researcher: an impressive amount considering that only 450 questionnaires were distributed. The number of completed surveys is also impressive, considering the fact that students were assured that participation was voluntary and that opting out would have no impact on their academic performance. Whilst this has resulted in less answers than initially targeted, on the other hand, the answers that were collected were more likely to be from participants who actually paid attention and were involved in the study. Of those who responded to this questionnaire, almost two thirds were aged between 18 and 24 while a further 22.8% were aged between 25 and 34. This demographical data are presented in Figure 9.18. In terms of gender, over two thirds of those who took part in the survey were male, while only 27% were female (Figure 9.19). Finally, in terms of education level, the majority of participants held a

Bachelor's degree, while only 14.2% were pursuing a post-graduate qualification (Figure 9.20). This indicates that the data may be skewed towards younger, more well-educated males. Nonetheless, this demographic is the most crucial for web providers, as they are currently the most prolific Internet users, and likely to maintain a high rate of Internet usage in the future. It is therefore imperative that web providers meet the needs of this niche social group.

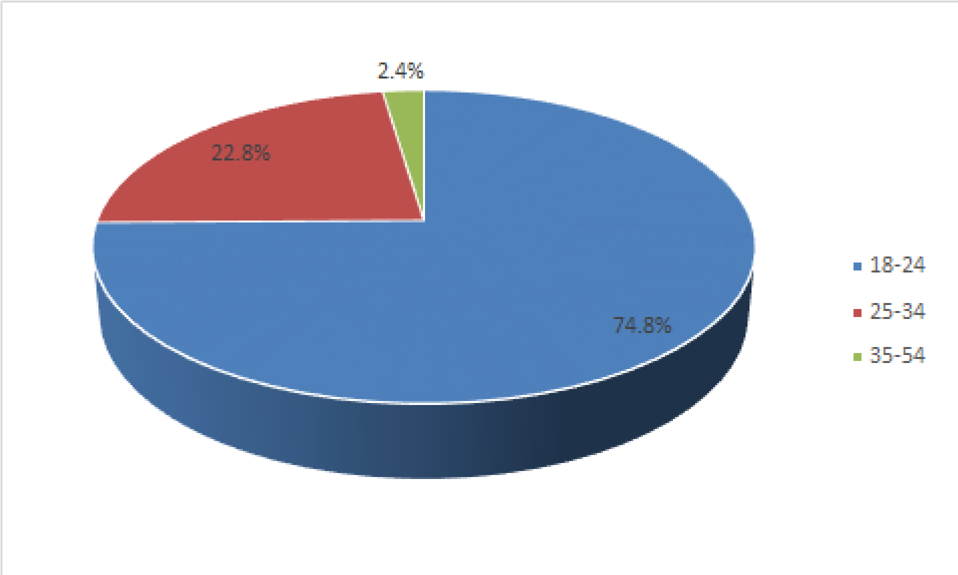

Figure 9.18 Age

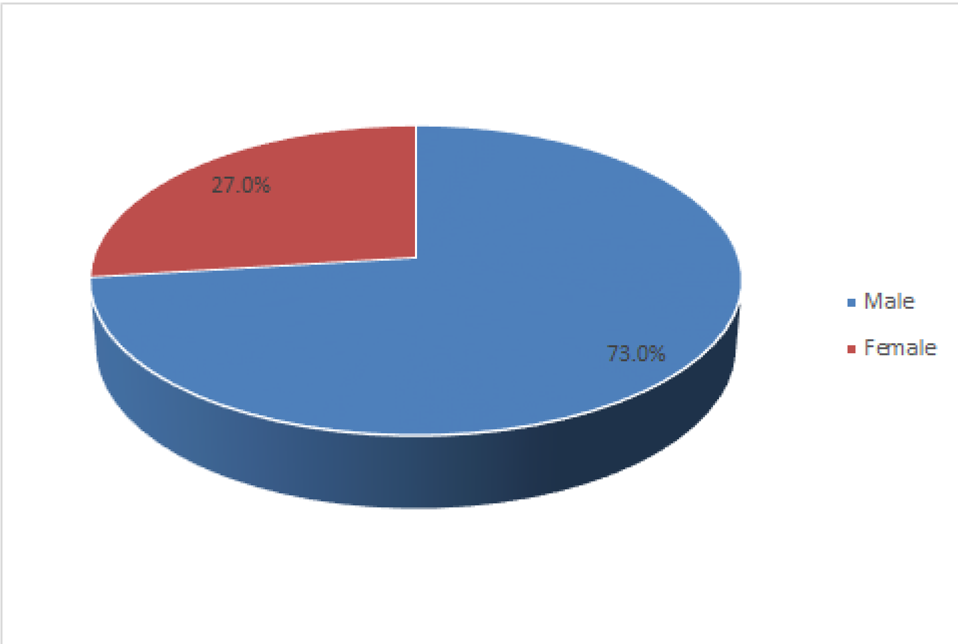

Figure 9.19 Gender

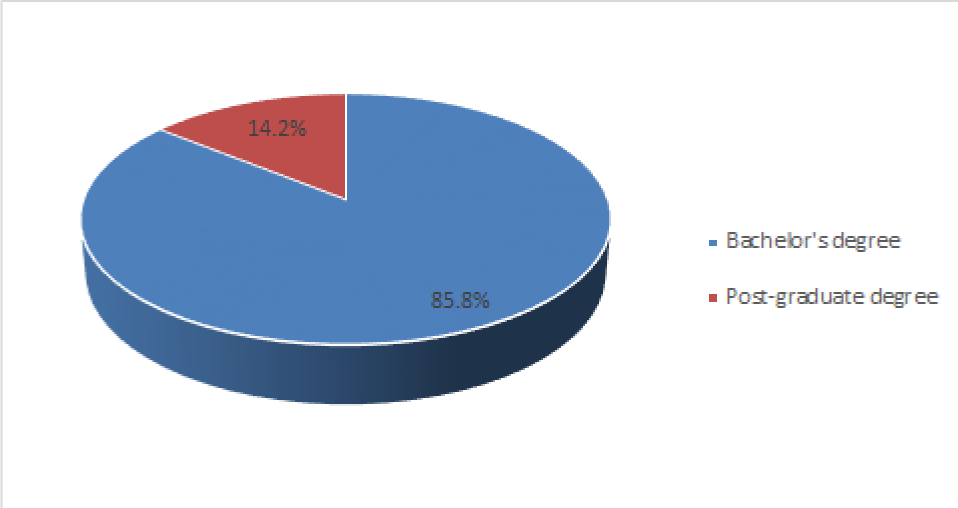

Figure 9.20 Education Level

In terms of the system usability scale (SUS) standard questions [10], ten questions were asked in the respective section. These questions frequently switched between a positive and negative tone, in order to prevent participants from unknowingly adopting a subjective attitude towards the AEADS system, as can be seen in Table 9.1. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.8.

Table 9.1 System Usability Scale (SUS) of the AEADS System

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	I think that I would like to use this system frequently	4.48	4	.51	40.41	.0001	17.21	100	.0001	H0b
2	I found the system unnecessarily complex	1.52	2	.59	34.21	.0001	16.35	1100	.0001	H0b
3	I thought the system was easy to use	4.84	5	.36	66.82	.0001	17.30	0	.0001	H0b
4	I think that I would need the support of a technical person to be able to use this system	1.55	2	.59	34.51	.0001	16.43	1000	.0001	H0b
5	I found the various functions in this system were well integrated	4.45	4	.50	40.83	.0001	17.30	0	.0001	H0b, H1
6	I thought there was too much inconsistency in this system	1.54	2	.60	35.53	.0001	16.43	1000	.0001	H0b
7	I would imagine that most people would learn to use this system very quickly	4.21	4	.46	36.23	.0001	16.87	500	.0001	H0b, H2
8	I found the system very cumbersome to use	1.56	2	.60	32.51	.0001	16.10	1400	.0001	H0b
9	I felt very confident using the system	4.13	5	.41	57.56	.0001	17.30	0	.0001	H0b
10	I needed to learn a lot of things before I could get going with this system	1.51	1	.57	36.17	.0001	16.52	900	.0001	H0b, H2

The majority of those questioned in the study agreed that the system is simple enough to be understood and used by the majority of Internet users, without any requirement of specialised training or advanced knowledge. They also considered the system well integrated, and stated that they would like to use the system on a frequent basis. In addition, they strongly agreed that the AEADS system is easy to use, with 96.9% and 95.6% stating that they felt very confident using the system. During the evaluation processes, most of the users understood how to use the system from the presentation given at the beginning of the evaluation processes. They were also confident when they used the system. Additionally, they further backed up these statements in the section for open-ended questions, which is described in section 9.4.5. Furthermore, the overall SUS score for AEADS is 87.70 out of 100. Thus, it can be assumed that the system is indeed valid and reliable. These findings support hypothesis H0b, which posits that the AEADS system is easy to use. The answers of Internet users with the negative questions mapped onto the positive domain, via the following formula (eq. (1)).

$$new\_question\_value = 6 - old\_question\_value \tag{1}$$

This mapping allows the direct comparison of all the question results, regardless if they were initially posed in a positive or negative manner.

Performing a parametric paired T-test for all users, comparing their average score for AEADS with the neutral response, the T-value is 126.67, and the probability is 0.0001 < .05 (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all users, the Z-Score is 17.21. The p-value is 0.0001. The result is clearly significant at $p \leq .05$. Additionally, the U-value is 100. The distribution is approximately normal because of the U-value.

This result shows that the AEADS system was appreciated by the users in the test sample, and that the positive difference, when compared to a neutral response of 3, is statistically significant.

The comparative analysis of AEADS with other e-business systems is presented in Table 9.2. This section of the questionnaire required users to answer six questions. The purpose of this section was to accumulate familiarity with the needs of each user, and to ensure that the AEADS system satisfied these needs, in order to achieve a competitive advantage over market competitors. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.8.

Table 9.2 Comparison of the AEADS with other e-business systems

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	I believe AEADS helps me to receive personalised advertisements more than a regular e-business system	4.76	5	.43	61.99	.0001	17.30	0	.0001	H3
2	I believe that, compared to another e-business system, AEADS is: - Much more difficult to use - More difficult to use - Neither easier nor more difficult to use - Easier to use - Much easier to use	4.53	5	.50	43.41	.0001	17.30	0	.0001	H0b
3	I believe that, compared to another e-business system, AEADS is: - Very Useless - Useless - Neither useful nor useless - Useful - Very useful	4.41	4	.50	40.26	.0001	17.30	0	.0001	H0a
4	I believe that, compared to another e-business system, the interaction with AEADS is: - Very hard to learn - Hard to learn - Neither easy nor hard to learn - Easy to learn - Very easy to learn	4.32	4	.51	35.65	.0001	16.78	600	.0001	H2
5	I believe that, compared to another e-business system, the interaction with AEADS is: - Very hard to remember how to use - Hard to remember how to use - Neither easy nor hard to remember how to use	4.33	4	.51	35.45	.0001	16.78	600	.0001	H4

	- Easy to remember how to use **- Very easy to remember how to use**									
6	**I am willing to disclose some of my personal data to gain personalisation benefits**	**4.72**	**5**	**.45**	**51.17**	**.0001**	**17.30**	**0**	**.0001**	**H5**

Of those questioned, 95.2% believed that AEADS helped them to receive personalised advertisements more effectively than a regular e-business system would allow. They mentioned that their experiences with Google advertisements had confused them when it came to finding the specific content they were looking for, especially when it came to downloading specific software online. This finding substantiates hypothesis H3. Furthermore, 94.4% of those questioned stated that they would be willing to disclose some of their personal data, in order to gain personalisation benefits, which supports hypothesis H5. Obviously, users liked the advertisements that were presented to them during the evaluation processes, as these advertisements were personalised based on their data obtained from the user profiles, along with their behaviour, which was monitored by the system, as is further discussed in section 9.4.4. Based on the results of this section, it was also concluded that 88.2% and 90.6% of those surveyed considered AEADS to be significantly more effective and easy-to-use than other e-business systems. Furthermore, hypothesis H2 is supported, as 86.4% claim that the AEADS system has a gentle learning curve. Overall, all the Internet users demonstrate a high degree of satisfaction with the system and believe that it operates more effectively in personalising advertisements, as indicated by mean values of between 4.32-4.76 and standard deviation values of .43-.51. In addition, the Cronbach's Alpha score is $0.97 \in [\geq 0.9]$, meaning that the reliability of the questionnaire is excellent [51].

The average for all the AEADS functionality, when comparing with other e-business systems, is of 4.51. When compared with the neutral response (3), this shows a difference of 1.51.

Performing a parametric paired T-test for all users, comparing their average score for all the AEADS comparing with other e-business systems, with the neutral response, the T-value is 128.16, and the probability is 0.0001 < 0.05 (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all users, the Z-Score is 17.30. The p-value is 0.0001. The result is clearly significant at $p \leq .05$. Additionally, the U-value is 0. The distribution is approximately normal because of the U-value.

This result shows that AEADS, when compared with other e-business systems, is appreciated by the users in the test sample, and that the positive difference, when compared to a neutral response of 3, is statistically significant.

As shown in Table 9.3, the fourth section of the survey posed a series of general questions about the functionality of the AEADS system, in order to become familiar with the overall response of Internet users to the system and its overall effectiveness. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.8.

Table 9.3 General Questions about the AEADS System

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	I prefer to login via Facebook account rather than register	4.29	4	.49	39.31	.0001	17.21	100	.0001	H6
2	The collected data are enough and acceptable	4.51	5	.50	42.46	.0001	17.30	0	.0001	H7
3	The system interface is user-friendly	3.98	4	.42	38.08	.0001	15.91	1600	.0001	H8
4	The system performance is adequate	4.40	4	.51	39.63	.0001	17.21	100	.0001	H9
5	The system reliability is achieved	4.36	4	.51	38.46	.0001	17.13	200	.0001	H10
6	Overall, are you satisfied with our service	4.35	4	.50	38.42	.0001	17.13	200	.0001	H0c
7	I would buy/ click more	4.67	5	.48	47.67	.0001	17.13	200	.0001	H11
8	I am not worry about my privacy	4.45	5	.58	38.68	.0001	16.61	800	.0001	H5
9	The information requested by the system is sufficient for the personalisation I need	4.41	4	.49	40.26	.0001	17.30	0	.0001	H7
10	The information requested by the system overcomes privacy concerns with me	4.80	5	.40	70.80	.0001	17.30	0	.0001	H5

As indicated in Table 9.3, this section focused primarily on the influence of the AEADS system in encouraging users to click sponsored links or make purchases on the basis of personalised advertisements. This section also focused on the degree to which participants were concerned about their online security and the safety of their personal information. Of those questioned, 93.5% stated that the system would encourage them to click more links and make more purchases, while 90.9% claimed that they were largely unconcerned about their privacy and online security. These findings support hypothesis H11, which posits that the AEADS system increases the clicking behaviour on advertisements. The data collected from users' tracking within the AEADS system supports the possibility that such a system attracts users to view advertisements, as the advertisements are personalised and thus based on their characteristics and preferences, as discussed in section 9.4.4. Furthermore, these findings also substantiate hypothesis H7, as 90.2% of participants felt that the system was justified in collecting private information and were willing to offer such data in exchange for a more effective adaptive advertising mechanism, as the AEADS system collects only the data that is needed to personalise the advertisement. In addition, 85.7% of the participants stated that they would login via Facebook, if they were to use this system regularly, which substantiates hypothesis H6, as these participants prefer to login into the system using their Facebook account, as discussed in section 9.4.4.

A significantly large proportion of participants (95.9%) strongly agreed that the information requested by the system overcome any privacy concerns. These findings particularly support hypothesis H5. Generally, the majority of users were extremely satisfied with the effectiveness of the system and believed that it performs exceptionally well. In addition, the majority of those questioned had faith in the reliability of the system. These findings support hypothesis H10. In addition, the Cronbach's Alpha score was $0.96 \in [\geq 0.9]$, meaning that the reliability of the questionnaire is excellent [51].

A comparatively low score was obtained in relation to the user interface of the system, as only 79.5% of those questioned considered the system interface to be user-friendly. However, this relatively low level of satisfaction could be attributable to the interface of the website on which the assessment was performed. Though the design of the website was beyond the researcher's control, the system nonetheless scored highly in terms of usability and ease of use. This finding supports hypothesis H8, which posits that the user interface of the AEADS system is user-friendly.

The average for the entire AEADS system is 4.14. When compared with the neutral response (3), this shows a difference of 1.14.

Performing a parametric paired T-test for all users, comparing their average score for AEADS with the neutral response, the T-value is 113.12, and the probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used to back up the results of the previous test. When performing a Mann-Whitney test for all users, the Z-Score is 17.30. The p-value is 0.0001. The result is clearly significant, at $p \leq 0.05$. The U-value is 0. The distribution is approximately normal because of the U-value.

This result shows that the AEADS system was appreciated by the users in the test sample, and that the positive difference, when compared to a neutral response of 3, is statistically significant.

Participants were next asked to evaluate the various features and functions of the AEADS system, using a Likert scale to indicate their responses. The results of this section are delineated in Table 9.4, and the general consensus is that the participants responded well to the system and were satisfied with its functionality. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.8.

Table 9.4 Usefulness of the AEADS System

No.	Features and Functions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	Registration process is useful	4.46	4	.54	37.31	.0001	16.87	500	.0001	H0a
2	Logging in using Facebook account is useful	4.33	4	.52	36.82	.0001	16.87	500	.0001	H0a
3	I can manage my profile	4.48	4	.52	39.37	.0001	17.04	300	.0001	H0a
4	Automatic extraction of device information (location, device type, device software, bandwidth) is useful	4.24	4	.46	38.27	.0001	16.95	400	.0001	H0a
5	I see the advertisements that are appropriate for me	4.69	5	.47	47.63	.0001	17.30	0	.0001	H0a
6	The personalised advertisements is acceptable for me	4.64	5	.48	46.07	.0001	17.30	0	.0001	H0a
7	I notice that the advertisements were personalised	4.47	4	.50	40.92	.0001	17.30	0	.0001	H0a
8	The system collects enough information from you	4.49	5	.54	38.29	.0001	16.87	500	.0001	H0a
9	Your behaviour on the website is tracked to give you suitable advertisements	4.60	5	.49	46.56	.0001	17.30	0	.0001	H0a

The main functions of the system were generally well-received by users, with more than 84.8% of participants stating that they found the various features extremely useful. The standard deviation values in this instance were between .46-.54 and a mean value of 4.24-4.69. Thus, the system can be considered ‘useful’ as a minimum score of three was attained in relation to all features. In addition, the Cronbach’s Alpha score is 0.90 $\in$ [$\geq$ 0.9], meaning that the reliability of the questionnaire is excellent [51].

In terms of which features proved the most popular with users, the majority of those questioned agreed that the advertisements shown were suitable, given their interests and preferences. In addition, the majority found the advertisements shown to be acceptable, and were satisfied that their behaviour on the website was monitored, in order to generate the most relevant advertisements. These findings substantiate hypothesis H0a, as the AEADS system and its functions is useful for adaptive advertising.

The least-liked features included ‘automatic extraction of device information (location, device type, device software, bandwidth) is useful’ and ‘logging in using a Facebook account is useful’. Nonetheless, as these features still scored above 4, they cannot be considered as disliked features. In fact, the lower score obtained by these features could be attributable to the user’s lack of understanding of the purpose of each feature. Another interpretation is that they might have been worried about the system extracting information without their knowledge (as in the extraction of the device information). Additionally, they might have been worried about the information that the system would have access to, if they were to login via their Facebook accounts. However, during the evaluation phase, when tracking the users’ actions, most of the users logged in to the AEADS system using their Facebook accounts, as discussed in section 9.4.4. Moreover, in the open-ended question section, one user questioned whether the system would continue to track their online activities once they had closed the webpage, as is further discussed in section 9.4.5. Nevertheless, as both rules achieved a minimum rate of 4, they can still be deemed useful. These findings substantiate hypothesis H0a, which posits that the AEADS system and its functions is useful for adaptive advertising.

The average for all the AEADS features in term of usefulness is of 4.49. When compared with the neutral response (3), this shows a difference of 1.49.

Performing a parametric paired T-test for all users, comparing their average score for the usefulness of all AEADS features, with the neutral response, the T-value is 123.46, and the probability is 0.0001 < 0.05 (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all users, the Z-Score is 16.87. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 500. The distribution is approximately normal because of the U-value.

This result shows that the AEADS features are appreciated in terms of usefulness by the users in my test sample, and that the positive difference, when compared to a neutral response of 3, is statistically significant.

The usability of the distinct features was separately evaluated through questionnaire questions. As indicated below, in Table 9.5, the majority of users found the AEADS system easy or very easy to use. This indicates that the system in general has a high degree of usability, as all features and functions can be utilised without any requirement for specialised training or advanced knowledge. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.8.

Table 9.5 Usability of the AEADS System

No.	Features and Functions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	Registration is easy process	4.17	4	.50	34.42	.0001	16.61	800	.0001	H0b
2	Logging in using Facebook account is easy to use	4.74	5	.45	57.15	.0001	17.21	100	.0001	H0b
3	I can manage my profile easily	4.18	4	.50	35.68	.0001	16.69	700	.0001	H0b
4	Automatic extraction of device information (location, device type, device software, bandwidth) is useable	4.45	4	.50	41.32	.0001	17.30	0	.0001	H0b
5	I see the advertisements that are appropriate for me	4.53	5	.50	43.24	.0001	17.30	0	.0001	H0b
6	The personalised advertisements is acceptable for me	4.54	5	.50	44.74	.0001	17.30	0	.0001	H0b
7	I notice that the advertisements were personalised	4.46	4	.51	40.63	.0001	17.21	100	.0001	H0b
8	The system collects enough information from you easily	4.43	4	.45	41.02	.0001	17.30	0	.0001	H0b
9	Your behaviour on the website is tracked to give you suitable advertisements	4.70	5	.45	55.46	.0001	17.30	0	.0001	H0b

In terms of usability and ease of use, the mean values fell between 4.17-4.74. In addition, the standard deviation values for usability fell between .45-.51. These results indicate that the AEADS system can be considered usable, as it can be easily operated by any user, without the requirement for formal training, or an existing knowledge of online platforms. In addition, the Cronbach's Alpha score is $0.91 \in [\geq 0.9]$, meaning that the reliability of the questionnaire is excellent [51]. These findings were then subject to analysis and it was discovered that the most popular elements in terms of usability were 'Your behaviour on the website is tracked to give you suitable advertisements' and 'login via Facebook is easy to use'.

Conversely, the least popular features were ‘Registration is easy process’ and ‘I can manage my profile easily’. However, although these features received the lowest scores, they still obtained a minimum rate of 4, which means that they can still be considered usable; however, they simply may not be as easy to use in comparison to the other more highly-rated features. Broadly speaking, these findings imply that the system as a whole is easy to use. Thus, the participants preferred to login into the system using their Facebook account, as discussed in section 9.4.4. These findings also substantiate hypothesis H0b, which posits that the AEADS system and its functions is easy to use for adaptive advertising.

The average for all the AEADS features in term of ease of use is of 4.47. When compared with the neutral response (3), this shows a difference of 1.47.

Performing a parametric paired T-test for all users, comparing their average score for ease of use of all AEADS features, with the neutral response, the T-value is 118.80, and the probability is 0.0001 < 0.05 (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all users, the Z-Score is 16.61. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 800. The distribution is approximately normal because of the U-value.

This result indicates that, in terms of ease of use, the AEADS features are appreciated by the users in the test sample, and that the positive difference, when compared to a neutral response of 3, is statistically significant.

Additionally, as presented in Table 9.6, the respondents were asked to measure their level of satisfaction with the system’s numerous features and functions. The results were once again quite positive in relation to each element of the AEADS system, as indicated below. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.8.

Table 9.6 Satisfaction of the AEADS System

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	Registration process is sufficient	4.33	4	.47	39.97	.0001	17.30	0	.0001	H0c
2	Logging in using Facebook account is sufficient	4.44	4	.51	42.76	.0001	17.30	0	.0001	H0c
3	Managing the profile is pleased	4.44	4	.51	40.86	.0001	17.13	200	.0001	H0c
4	Automatic extraction of device information (location, device type, device software, bandwidth) is sufficient	4.43	4	.50	40.52	.0001	17.21	100	.0001	H0c
5	I see the advertisements that are appropriate for me	4.73	5	.45	54.97	.0001	17.30	0	.0001	H0c
6	The personalised advertisements is acceptable for me	4.71	5	.46	61.99	.0001	17.30	0	.0001	H0c
7	I notice that the advertisements were personalised	4.46	4	.50	42.18	.0001	17.30	0	.0001	H0c
8	The system collects enough information from you	4.12	4	.46	33.86	.0001	16.52	900	.0001	H0c
9	Your behaviour on the website is tracked to give you suitable advertisements	4.67	5	.47	52.74	.0001	17.30	0	.0001	H0c

With mean values of between 4.12-4.73 and standard deviation values of between .45-.50, the various functions and featured provided by the AEADS system can be regarded as satisfactory. In addition, the Cronbach's Alpha score is $0.91 \in [\geq 0.9]$, meaning that the reliability of the questionnaire is excellent [51]. More specifically, the analysis demonstrates that the majority of users were pleased with the feature, which showed them only advertisements relevant to their needs and preferences. Most users were satisfied with the feature, which monitored online behaviour, in order to personalise advertisements more effectively, and were extremely satisfied with how the system customised advertisements based on each user's unique profile and interests. In comparison, only 82.3% were satisfied with the fact that the system required personal information, in order to function effectively. Nonetheless, such a high percentage indicates that the majority found this feature both reasonable and acceptable. Broadly speaking, these findings suggest that Internet users are very satisfied with the AEADS system and its various functions and features, which support hypothesis H0c.

The average for all AEADS features in terms of satisfaction is of 4.48. When compared with the neutral response (3), this shows a difference of 1.48.

Performing a parametric paired T-test for all users, comparing their average score for satisfaction of all AEADS features with the neutral response, the T-value is 131.70, and the probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all users, the Z-Score is 17.30. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 0. The distribution is approximately normal because of the U-value.

This result shows that the AEADS features are appreciated in terms of satisfaction by the users in the test sample, and that the positive difference, when compared to a neutral response of 3 is statistically significant.

Next, questions about the desirability were considered. The majority of responses to the desirable attributes question were favourable, as delineated in Table 9.7 below. As with each previous question, each user was asked to evaluate each feature, using the Likert scale provided. Once more, the majority of responses were extremely positive, as a minimum score of 4 was obtained. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.8.

Table 9.7 Desirability of the AEADS System

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	Registration process is desirable	4.25	4	.51	34.03	.0001	16.61	800	.0001	H0d
2	Logging in using Facebook account is desirable	4.35	4	.49	40	.0001	17.30	0	.0001	H0d
3	Managing the profile is desirable	4.24	4	.53	32.38	.0001	16.35	1100	.0001	H0d
4	Automatic extraction of device information (location, device type, device software, bandwidth) is desirable	4.34	4	.49	39.16	.0001	17.21	100	.0001	H0d
5	I see the advertisements that are appropriate for me	4.65	5	.48	50.49	.0001	17.30	0	.0001	H0d
6	The personalised advertisements is acceptable for me	4.38	4	.49	39.93	.0001	17.30	0	.0001	H0d
7	I notice that the advertisements were personalised	4.68	5	.47	47.91	.0001	17.30	0	.0001	H0d
8	The system collects enough information from you	4.38	4	.50	39.28	.0001	17.21	100	.0001	H0d
9	Your behaviour on the website is tracked to give you suitable advertisements	4.31	4	.47	40.35	.0001	17.30	0	.0001	H0d

Based on the analysis of the questionnaire results, the most popular system features, in terms of desirability, according to participants included ‘I see advertisements that are appropriate for me’ and ‘I notice that advertisements are personalised’. The least popular features, relatively speaking, were those of ‘Registration process is desirable’ and ‘managing the profile is desirable’. However, as these features still achieved a minimum score of 4, they can nonetheless be deemed desirable as the majority of users believed them to be both reasonable and acceptable. Thus, based on the survey responses provided in this section, all AEADS system features are desirable to Internet users. These findings are quite promising in terms of system functionality and system features, which support hypothesis H0d, as mean values of between 4.24 and 4.68 were obtained, along with standard deviation values of .47-.53. As a result, it is possible to regard the overall system as desirable, as all average values are higher than 3. In addition, the Cronbach's Alpha score is $0.86 \in [\geq 0.8]$, meaning that the reliability of the questionnaire is good [51].

The average for all the AEADS features in term of desirability is of 4.40. When compared with the neutral response (3), this shows a difference of 1.40.

Performing a parametric paired T-test for all users, comparing their average score for desirability of all AEADS features, with the neutral response, the T-value is 117.91, and the probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all users, the Z-Score is 16.61. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 800. The distribution is approximately normal because of the U-value.

This result shows that, in terms of desirability, the features of the AEADS system are appreciated by the users in the test sample, and that the positive difference, when compared to the neutral response of 3, is statistically significant.

Table 9.8, below, shows the aggregated hypotheses for all questions, in order to better illustrate how the features explored directly support the hypotheses. The scores are constructed by averaging all answers regarding the features which correspond to a particular hypothesis, from a functionality, usability, satisfaction and desirability perspective. In this manner, the support of all hypotheses by Internet user respondents are clearly illustrated.

Table 9.8 Aggregated Hypotheses of the AEADS System

No.	Hypothesis	Average for all questions							
		Mean	Median	SD	T-test		Mann-Whitney		
					T-value	P-value	Z-score	U-value	P-value
1	H0a	4.48	4.40	.50	41.15	.0001	17.11	220	.0001
2	H0b	3.73	3.80	.50	42.59	.0001	16.97	385	.0001
3	H0c	4.47	4.30	.48	44.83	.0001	17.18	140	.0001
4	H0d	4.40	4.22	.49	40.39	.0001	17.10	233	.0001
5	H1	4.45	4	.50	40.83	.0001	17.30	0	.0001
6	H2	3.35	3	.51	36.02	.0001	16.72	666	.0001
7	H3	4.76	5	.43	61.99	.0001	17.30	0	.0001
8	H4	4.33	4	.51	35.45	.0001	16.78	600	.0001
9	H5	4.66	5	.48	53.55	.0001	17.07	266	.0001
10	H6	4.29	4	.49	39.31	.0001	17.21	100	.0001
11	H7	4.46	4.5	.50	41.36	.0001	17.30	0	.0001
12	H8	3.98	4	.42	38.08	.0001	15.91	1600	.0001
13	H9	4.40	4	.51	39.63	.0001	17.21	100	.0001
14	H10	4.36	4	.51	38.46	.0001	17.13	200	.0001
15	H11	4.67	5	.48	47.67	.0001	17.13	200	.0001

9.4.4. Internet Users Qualitative Answers and Discussion

The final section of the user questionnaire asked participants to offer qualitative feedback regarding their experiences with the AEADS system in terms of its features, functions and usability. Participants were encouraged to express their views of the system freely in this section and were asked to share any information or thoughts they might have had with regards to the system as a whole. The users' responses that were given are discussed in this section, as well as the implications for this feedback on the effectiveness of the system in its current format. These insights will additionally be analysed in terms of improvements that could be made to the future versions of the system.

One user made the comment that it was clear how each of the displayed advertisements were linked. In other words, they understood how each advertisement related to one another as well as related to the interests or preferences of the users. Basically, the users acknowledged the effectiveness of the system in customising the selection of advertisements based on the unique details of each user. Another user also highlighted how the advertisements that were displayed reflected aspects of the user's profile, which again indicates that the system worked effectively for the majority of participants. In fact, many of those questioned expressed their appreciation of personalised advertisements and were impressed with how the system tailored the advertisements displayed, based on their profile, user preferences and online behaviour. The system also allows the user to accept or reject the use of cookies, which was highlighted by one user as a useful feature. However, another user stated that the system did not include their personal hobbies in their list of common interests. This fell in line with the quantitative data, as they considered the registration and managing of their profiles as their least popular features. It should be noted that the attributes are a changeable list that can be modified, based on the business owner's view. More details about attributes are discussed in Chapter 8, section 8.2.

One user asserted that they did not have a Facebook account, a comment most likely made in reference to the Facebook login feature offered by the system. It is therefore important to make users aware that the Facebook login feature is only one of the possible login options. In other words, a user does not have to have a Facebook account in order to use the AEADS system. However, one user expressed their appreciation for the Facebook login feature, stating that it made it much more convenient to log into the system. Moreover, within the quantitative data analysis, participants stated that they would login via Facebook, if they were to use this system regularly. Furthermore, most of the users logged into the system using their Facebook accounts.

Another issue highlighted by the users within the qualitative section of the questionnaire concerns the security of private data and the system's monitoring of online activity. For instance, one user wondered whether the system would continue to track their online activities once they had closed the webpage. This implies that some users might be concerned about the possibility of the system monitoring all of their online behaviour. Thus, measures should be taken to ensure that the system's users are fully aware of how the system operates and when the system is tracking activity, in order to deliver the most relevant and user-specific advertisements. This is perhaps one of the most important considerations, given the increasing concern for online security and the protection of confidential data. In other words, it is imperative that users are confident in the system and its ability to prevent the unauthorised use of their confidential data. In a similar vein, another user expressed concern about the need to submit personal information in order for the system to function effectively and the user wondered whether or not their personal data would be used for other purposes. In effect, while the user was willing to provide certain personal details in order to receive a more effective adaptive advertising service, they were concerned that this data might be used by a third party, without their explicit permission. Thus, the users require a guarantee that their data will not be shared with a third party or utilised for alternative purposes at this point in the proceedings. However, one user who completed this questionnaire stated that the information requested by the AEADS system was more than sufficient, as the system performed effectively using this data in conjunction with the online behaviour of system users. In addition, in the quantitative data analysis, most of the users stated that they would be willing to disclose some of their personal data, in order to gain the benefit of personalised content.

Another user commented that the user interface of the website needs to be more attractive. Again, this relatively low level of satisfaction could be attributed to the interface inherited from the website, upon which the assessment was performed. Though the original design of the website was beyond the control of the researcher and the AEADS extensions were applied in a manner that was true to the principles of the research, in a lightweight manner, without changing the look&feel of the original website, the system nonetheless scored highly overall in terms of usability and efficiency.

Within the analysis of the quantitative data process, users revealed the belief that AEADS had aided them in receiving personalised advertisements much more than any normal e-business system would have. The users stated that they had been confused by Google advertisements when attempting to find certain content and most especially when trying to download specific software. Another user also commented that the AEADS system is 'not noisy like Google advertisements', as these advertisements are hiding the contents – especially the download buttons in software and movies websites – which confuse some users. This implied that they found the noise levels of Google alerts quite irritating and prefer the less distracting AEADS system. This is an important consideration, as advertisements should be attention grabbing, but not necessarily intrusive on the user's online activity. Furthermore, the vast majority of users had no issues in utilising the system, so it is unlikely that many people would encounter issues in terms of usability. Within the quantitative data analysis process, they strongly agreed that the AEADS system is easy to use and they felt very confident using the system. One user also stated that they liked the location of the advertisements, which indicates that the AEADS system displays advertisements in an eye-catching, yet unobtrusive manner. Another user claimed that the frequent display of different advertisements was both convenient and effective. In addition, another user stated that the system pushed them to think about developing their own online business, as the features and functions of the system facilitated the marketing and advertising required for their company.

These insights into the system reflect the effectiveness and functionality of the current system from the perspective of Internet users, while highlighting possible areas in which future versions of the system could be modified. Overall, the feedback on the AEADS system has been predominantly positive, though there are some minor improvements that could be made, in order to increase the overall levels of user satisfaction with the system's features and functionality.

9.4.5. Analysing User Tracking Data

As stated above, the profile attributes of a classic user model within the AEADS system had been integrated into the user profiles found in the online bookstore.

During the process of evaluation, in which the users' actions were tracked, most users were found to be using their Facebook accounts to log in to the AEADS system, as Figure 9.21 denotes. This mirrors the results from the questionnaires, where most users agreed that logging in using their Facebook accounts was useful and a system that was easy to use, overall. Within the process of quantitative data analysis, participants stated that they would login via Facebook, if they were to use this system regularly. Moreover, users expressed their appreciation for the Facebook login feature within the qualitative data analysis process, stating that it made it much more convenient to log in to the system. This supports hypothesis H6 in that users prefer to login via their Facebook accounts rather than register.

Figure 9.21 Users Login to the AEADS System

As denoted by Figure 9.22, each webpage displays a certain number of advertisements, which are personalised in line with the specifics of users' individual profiles. Furthermore, as discussed in section 9.2.3, the social data are overlaid [29, 36] over the advertisements, in order to allow the user to 'like' or 'stop' actions (among others) on any advertisements. This social data provide the delivery aspect with the ability to apply some action based on this data, according to those rules, as chosen by the business owner, or else set as a default action by the AEADS system. For instance, selecting 'stop' for an advertisement will block any advertisements from within that specific advertisement's subcategory. This social data are stored in a new component, called *social data*, within the user model, to support social interactions. This data are acquired from the user, through the adding of linked buttons under each advertisement, after which the user can click on those links to choose the data that is appropriate for them. Figure 9.22 shows two button-like links, 'like' and 'stop', under each advertisement, which increase the opportunities for users to be involved in the adaptation process.

Figure 9.22 Book Store Webpage

The longer that the system is used, the more the number of clicks increases. This result can thus reflect the predilections of the system's use, as time progresses. An assumption can therefore be made that advertisements can be matched better to users after a long term tracking of the users' action is applied, as illustrated in Figure 9.23. This is related to the well-known *cold-start* problem [121] within any system that relies on user data. Overall, the data collected from the users' tracking within the AEADS system supports the possibility that such a system attracts users to view advertisements, as the advertisements are personalised based on their characteristics and preferences. In the quantitative data analysis process, the majority of those questioned agreed that the advertisements shown were suitable, given their interests and preferences. In addition, the majority found the advertisements shown to be acceptable and they were satisfied that their behaviour on the website was monitored, in order to generate the most relevant advertisements. They strongly agreed that the system would encourage them to click on more links and make more purchases. Clearly, users liked the advertisements that were presented to them during the evaluation processes, as these advertisements were personalised based on their data within the user profiles and their behaviour, which was monitored by the system.

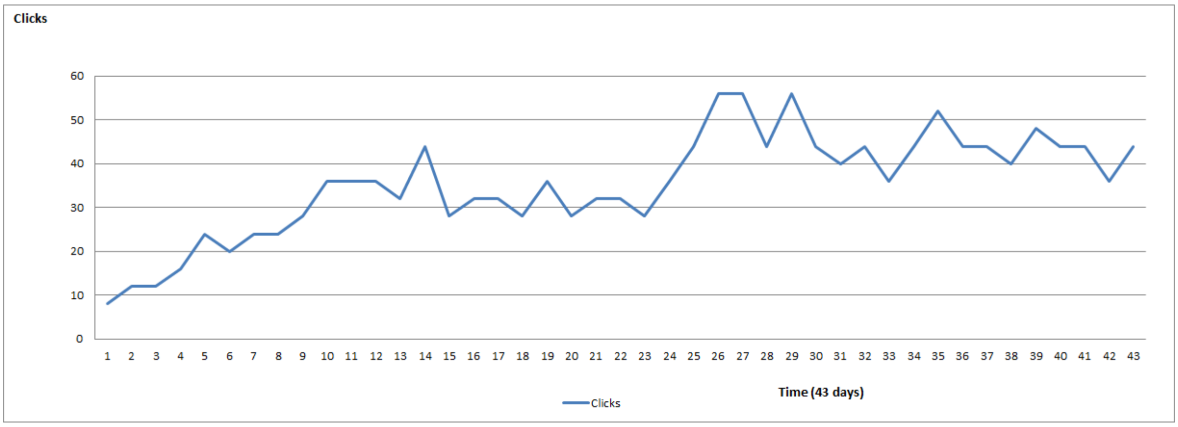

Figure 9.23 Clicks progress against time

From the monitoring of the data analysis, which was obtained when users entered social data, it became evident that the majority appreciated the advertisements they were exposed to. Some users also used the ‘stop’ button to stop the advertisements that were presented to them. Figure 9.24 below shows the analysis of the social data process, which took place during the evaluation with the Internet users.

As discussed above, the data collected from the users’ tracking within the AEADS system attracted users towards viewing advertisements, as the advertisements were personalised, based on their characteristics and preferences. In the quantitative data analysis, most of the users agreed that the advertisements shown were suitable, given their interests and preferences, because the ‘stop’ button was pressed much less than the ‘like’ button. This is because the majority of users found the advertisements that were shown to them to be acceptable, as they stated within the quantitative questions process. Overall, users liked the advertisements that were presented to them during the evaluation processes, as these advertisements were personalised based on their data given within the user profiles and their behaviour, which was monitored by the system.

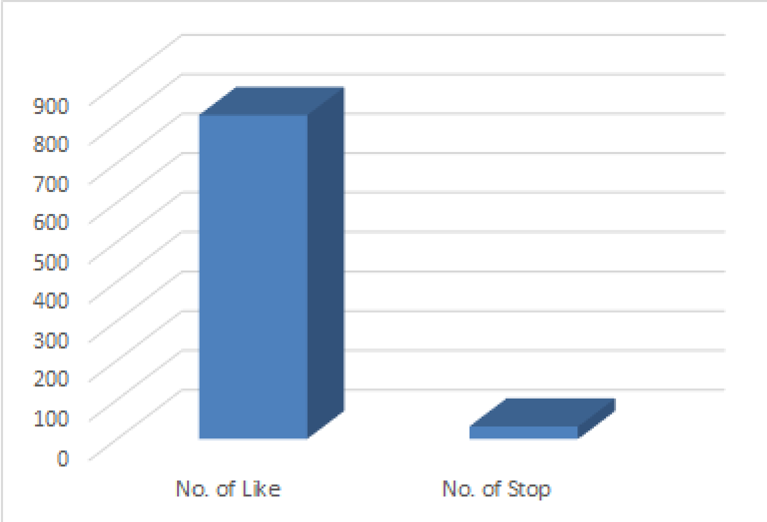

Figure 9.24 Number of clicks for Social Data Component

In the next section, the data that were obtained from Internet users' use of the AEADS system is analysed. The users' tracking data show that the advertisements in the category books have a higher rate of clicks, as shown in Figure 9.25. Businesses categorise advertisements within the first level of adaptation within the processing sequence of the AEADS system, based on the users' characteristics. According to the dominant characteristics of most participants, namely the 18-24 year-old age group, along with a bachelor's degree level of education, the book group became the most highly clicked on, by participants. In other words, as the participants were students and their ages were between 18-24 years old, they clicked most often on the books category. Moreover, the advertisements that were presented to them were based on their characteristics.

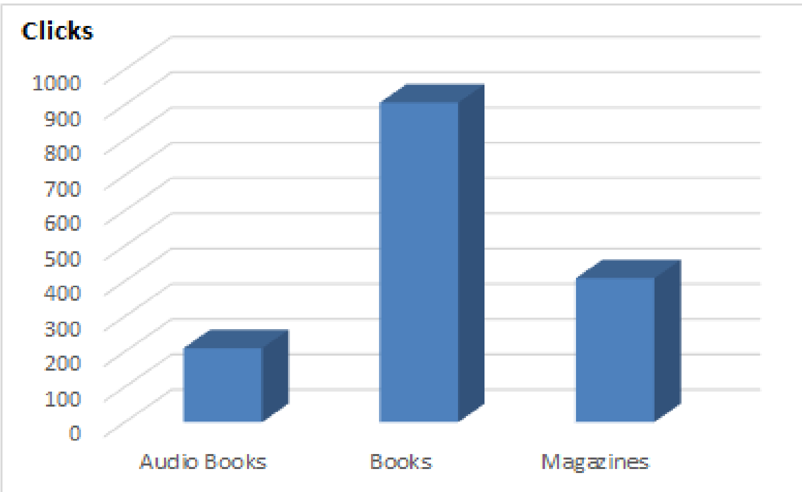

Figure 9.25 Number of clicks for different groups

Sub-categories were also tracked, such as sub-groups for the books category, the most popular of which are computer science books, as shown in Figure 9.26. Most of the participants were studying some courses of computer science, therefore most of their clicks were on the computer science books subcategory. Furthermore, as said, the advertisements that were presented to them were based on their characteristics.

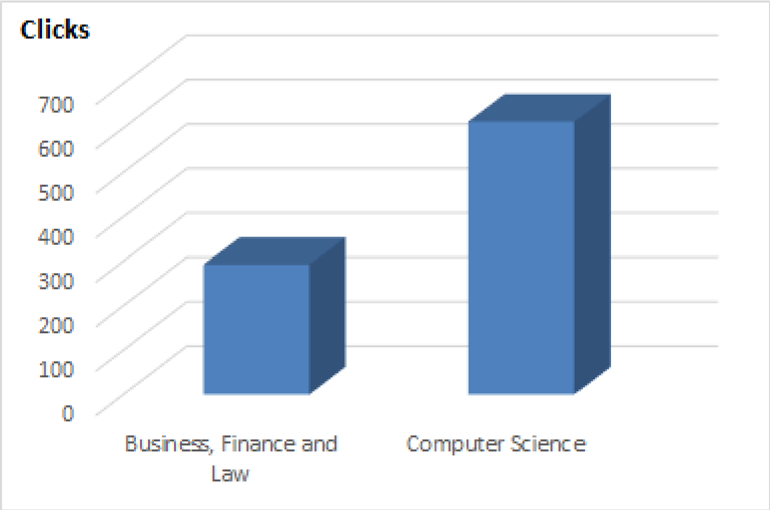

Figure 9.26 Number of clicks for books sub-groups

Thus, in the data analysed above, computer science books will be mostly recommended to the users, by showing them advertisements about these topics. Additionally, less frequently, advertisements about business-related books, most especially finance and law books, will be shown to the users. Other, generic advertisements covering popular books, will also be shown, with a lesser frequency, to the users. Finally, some advertisements for magazines and a few for audio books will appear from time to time.

Furthermore, the searches conducted by users were monitored and recorded, so that the system could display advertisements that were relevant to the users' actions. However, a few users had used the search feature to find suitable books for themselves.

9.4.6.Hypotheses for Business Owners

The following hypotheses have been defined to evaluate the AEADS system, from a business owner perspective.

H0a: *The AEADS system is <u>useful</u> for adaptive advertising.*

H0b: *The AEADS system is <u>easy to use</u> for adaptive advertising.*

H0c: *The AEADS system is <u>sufficient</u> for adaptive advertising.*

H0d: *The AEADS system is <u>desirable</u> for adaptive advertising.*

H0x are the basic hypotheses, which were tested directly via the questionnaire and interview methods. More specific hypotheses, as defined below, were also tested via the questionnaire and interview methods:

H1: *The various functions in the AEADS system are well integrated.*

H2: *The AEADS system has a shallow learning curve.*

H3: *The AEADS system adapts advertisements better than regular e-business systems.*

H4: *The AEADS system is very easy to remember how to use, in comparison to other e-business systems.*

H5: *The AEADS system is important for businesses.*

H6: *The AEADS system was integrated in the website easily.*

H7: *The AEADS system interface is user-friendly.*

H8: *The AEADS system performance is adequate.*

H9: *The AEADS system reliability is achieved.*

H10: *Storing all data in a lightweight fashion (XML) facilitates the integration on commercial webpages.*

H11: *Creating the advertisements domain is an easy process.*

H12: *Creating the adaptation rules (general and behaviour) is an easy process.*

H13: *Advertisers prefer to send the appropriate advertisement to the respective users.*

H14: *Building tools, representing the domain model, adaptation model, and user model can support website owners to personalise their advertisements delivery.*

These hypotheses were evaluated by surveying a sample group of business owners and analysing their answers, as further described below.

9.4.7. Evaluation Setup for Business Owners

A number of entrepreneurs were chosen to participate in the next data collection phase, which involved the administration of a second evaluation, the structured interview used, composed of six parts. It was believed that the questionnaire results would provide valuable information and understanding regarding companies' opinions of the implemented model and system. It was also believed that the questionnaire results would enable discovering clients' perspectives, raise issues and generate tips related to the implementation of the model and offer information about the system's appropriateness.

Participants were selected from various industries, in order to obtain results that could be representative of broader populations. A total of seventeen respondents were selected for participation in this stage of the research, all of whom were requested to test the authoring of the AEADS system from various aspects. Firstly, the idea of adaptive advertising was presented and explained to all of the participants. At this stage, participants were provided with a basic understanding of the system and how to use it. Once participants sufficiently understood the information provided during this initial stage, they were required to test the AEADS system in practice. All of the respondents then assessed the system, in order to offer feedback enabling the researcher to gain the required information to improve the system.

The questionnaire itself consisted of six subsections (the entire system questionnaire can be found in Appendix G). The first section asked participants to provide generic information, such as the type of business, size of business, etc. The second part requested that respondents offer their own personal feedback on the overall function of the AEADS system. The third section of the questionnaire required participants to evaluate the strengths and weaknesses of the AEADS system, compared to alternative systems utilised for online business. The fourth section of the questionnaire asked participants to share information regarding the entire system. Additionally, the fifth part of the questionnaire requested further feedback on the AEADS system's practical implementation. This section included a Likert scale for respondents' answers. Here, numerical data is used to represent a certain feeling or opinion: for instance, 1 = 'not at all useful' / 'very difficult' / 'not at all sufficient' / 'not at all desirable'; whereas 5 = 'very useful' / 'very easy to use' / 'very sufficient' / 'very desirable'.

A number of open questions were asked in the final section of the questionnaire. These questions were created and included, in order to obtain evaluative information from the entrepreneurs, regarding the implementation of the AEADS system.

9.4.8. Business Owners Evaluation Results

A different experiment was run with business owners, to gather their perspective on the AEADS system. Here, the sheer numbers were less important, than the spread of business types (on the Internet), as well as the qualitative feedback. As illustrated in Table 9.9, the respondents selected for participation in this study were representative of a number of sectors. Specifically, the respondents represented the construction industry, online education industry, telecommunications industry, retail industry, consultation industry, transportation sector and the media industry. Figure 9.27 depicts the mix of companies by size, with most (41%) companies being small and medium-sized enterprises (SMEs), around one third (35%) being medium-sized enterprises and around one quarter (24%) being large-sized enterprises. Thus, a good representation in terms of business size is also achieved. As shown in Figure 9.28, the company participants involved in this study were also representative of two different countries, with 29% being located in the UK and the remaining 71% in Saudi Arabia, as these were the two countries the researcher had access to. By selecting such a mix of participants, with as varied characteristics as possible, the aim is that the findings of this study can allow improved insight into the perspectives of individuals from a variety of sectors, company sizes and countries, making the findings more applicable to a wider range of businesses.

Table 9.9 Type of businesses

	Type	Frequency
Type of Business	Communication	5
	Constructing	2
	Consulting	2
	Education	1
	Media	2
	Online Education	1
	Trading	2
	Training	1
	Transportation	1
	Total	17

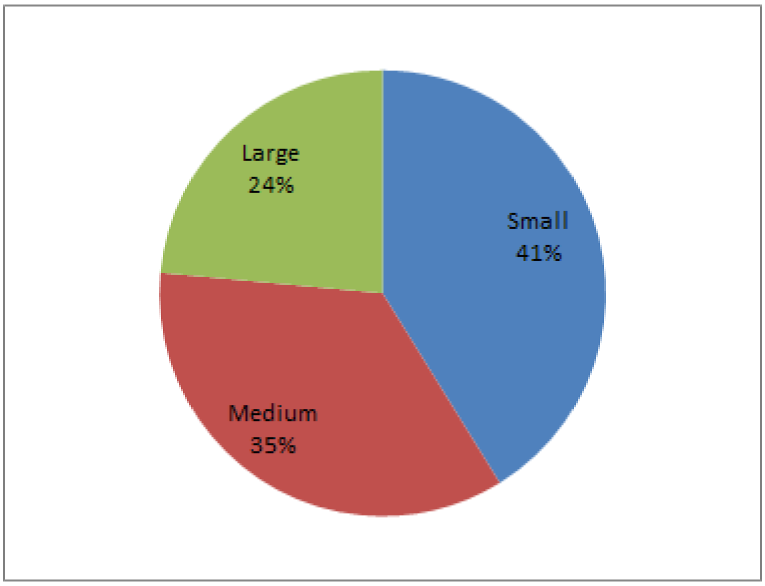

Figure 9.27 Size of Businesses

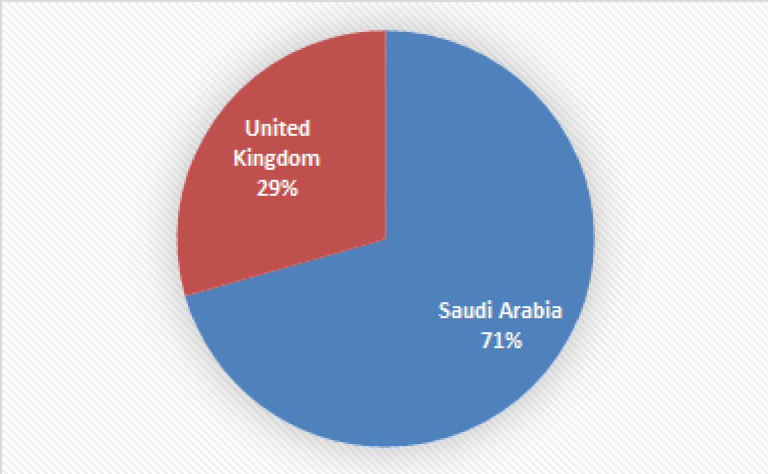

Figure 9.28 Country

In order to avoid the presence of researcher bias and endeavour to enable respondents to answer questions in the most authentic way possible, the questionnaire included the ten system usability scale (SUS) standard questions [10], which alternated between negative and positive wordings when asking respondents for their views on the proposed system (Table 9.10). The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.17.

Table 9.10 System Usability Scale (SUS) of the AEADS System

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	I think that I would like to use this system frequently	4.35	4	.48	11.32	.0001	4.96	0	.0001	H0a
2	I found the system unnecessarily complex	1.47	1	.50	12.26	.0001	4.96	0	.0001	H0b
3	I thought the system was easy to use	4.59	5	.49	12.91	.0001	4.96	0	.0001	H0b
4	I think that I would need the support of a technical person to be able to use this system	1.53	2	.50	11.79	.0001	4.96	0	.0001	H0b
5	I found the various functions in this system were well integrated	4.76	5	.42	16.64	.0001	4.96	0	.0001	H0b, H1
6	I thought there was too much inconsistency in this system	1.59	2	.49	11.47	.0001	4.96	0	.0001	H0b
7	I would imagine that most people would learn to use this system very quickly	4.82	5	.38	19.13	.0001	4.96	0	.0001	H0b, H2
8	I found the system very cumbersome to use	1.65	2	.59	9.20	.0001	4.67	8.5	.0001	H0b
9	I felt very confident using the system	4.41	4	.49	11.47	.0001	4.96	0	.0001	H0b
10	I needed to learn a lot of things before I could get going with this system	1.53	1	.61	9.71	.0001	4.67	8.5	.0001	H0b, H2

The analysis of the participants' questionnaire responses offers various insights into businesses' opinions of the AEADS system. These findings will now be outlined. Firstly, most respondents stated that they would have a preference for utilising the AEADS system on a regular basis. Furthermore, many respondents thought that every element of the AEADS system was effectively integrated, making it streamlined and well-functioning. Every company representative felt that the usability of the system was good, because the AEADS system was uncomplicated. They stated these views in the section including open-ended question, as is discussed below, in section 9.4.9. It can thus be stated that the respondents felt very confident when using the AEADS system. The score, according to the participants' responses, was great. It was clear, during the evaluation processes, that the short presentation offered enough training for them to be able to use the system, organise advertisements and apply the adaptation rules. Thus, the result was that they felt confident when using the system.

Furthermore, in accordance with hypothesis H0b, the majority of participants felt satisfied (91.8%) with the usability of the system. Additionally, nearly all participants found the integration of multiple AEADS system elements to be effective. With regards to this factor, the score was a highly promising. Thus, the findings of this section, as previously stated, support H0b and H1.

The questionnaire results also indicate that the majority (96.5%) of businesses believed that the AEADS system could be implemented effectively within actual companies, without the need for extensive system training, as they further comment on that in the open-ended questions that are discussed in section 9.4.9 below. This means that employees should find the system relatively easy to install and use without many complications, which supports hypotheses H0b and H2. Furthermore, the SUS score for AEADS is 87.90 out of 100, This finding suggests that the validity and reliability of the findings are positive. These findings support hypothesis H0b, which posit that the AEADS system is easy to use. The answers of business owners with the negative questions mapped onto the positive domain, via the following formula (eq. (1)).

$$new\_question\_value = 6 - old\_question\_value \qquad (1)$$

This mapping allows the direct comparison of all the question results, regardless if they were initially posed in a positive or negative manner.

A score of at least 4 was achieved for every item in the system evaluation questionnaire. All company representatives involved in the study reported high levels of satisfaction with the AEADS system.

Performing a parametric paired T-test for all businesses, comparing their average score for all AEADS, with the neutral response, the T-value is 37.75, and the probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all businesses, the Z-Score is 15.67, while the p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 170. The distribution is approximately normal because of the U-value.

In the next part of the questionnaire, respondents were asked to compare the AEADS system to other systems used for online business. A total of seven questions were included in this section, as illustrated below in Table 9.11. The purpose of this part of the questionnaire was to shed light on companies' perspectives and opinions. This allows to effectively improve the system in a way that is meaningful to real companies and that offers value, in comparison to other systems which already exist on the market. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.17.

Table 9.11 Comparison of the AEADS with other e-business systems

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	I believe AEADS helps me adapt my advertisements more than a regular e-business system	4.47	4	.50	11.79	.0001	4.96	0	.0001	H3
2	I believe that, compared to another e-business system, AEADS is: - Much more difficult to use - More difficult to use - Neither easier nor more difficult to use - Easier to use - Much easier to use	4.35	4	.48	11.32	.0001	4.96	0	.0001	H0b
3	I believe that, compared to another e-business system, AEADS is: - Very Useless - Useless - Neither useful nor useless - Useful - Very useful	4.71	5	.46	14.98	.0001	4.96	0	.0001	H0a
4	I believe that, compared to another e-business system, the interaction with AEADS is: - Very hard to learn - Hard to learn - Neither easy nor hard to learn - Easy to learn - Very easy to learn	4.59	5	.49	12.91	.0001	4.96	0	.0001	H2
5	I believe that, compared to another e-business system, the interaction with AEADS is: - Very hard to remember how to use - Hard to remember how to use - Neither easy nor hard to remember how to use - Easy to remember how to use - Very easy to remember how to use	4.29	4	.46	11.36	.0001	4.96	0	.0001	H4

6	**For a business like ours, this AEAD would be** **- Not at all important** **- Not really important** **- No difference** **- Important** **- Very important**	**4.76**	**5**	**.42**	**16.64**	**.0001**	**4.96**	**0**	**.0001**	**H5**
7	**The various parts/ functions of the system are:** **- Not well integrated at all** **- Not really well integrated** **- Somewhat integrated** **- Well integrated** **- Very well integrated**	**4.88**	**5**	**.32**	**23.37**	**.0001**	**4.96**	**0**	**.0001**	**H1**

The majority (94.1%) of participants felt that AEADS could be used more effectively than other systems currently available for e-business use. This finding supports hypothesis H0a. Furthermore, the majority (95.3%) of participants felt that the AEADS system could become a significant part of their specific business types and operational processes. The concept that AEADS would play a significant role in companies was predicted in hypothesis H5; the findings are in support of this hypothesis.

The integration of the AEADS system's numerous components and operations was assessed as being highly effective by the vast majority (97.6%) of participants. During the discussion with the participants, it became clear that they had good opinions of commercial systems (both adaptive and non-adaptive), while agreeing that the various companies' websites definitely required integrated systems, as users otherwise ignored these advertisements. For example, one participant stated that Google advertisements are an inconvenience for users, as they hide the webpages' content. Therefore, the findings of the questionnaire are in support of hypothesis H1. Additionally, most (91.8%) of the questionnaire respondents reported that it would be relatively easy for new users to learn how to use the AEADS system and that it could be used without too much difficulty or without the need for extensive training, as it was clear during the evaluation processes that the short presentation was enough for them to be able to independently use the system, organise advertisements and apply adaptation rules. This finding is in support of hypothesis H2. In terms of the AEADS system's ability to deliver advertisements, the findings revealed that every participant considered the AEADS system to be more effective than other currently-available e-business systems. The participants' satisfaction levels were all strong with regards to the AEADS system. This is indicated through the mean values of 4.29-4.88 and standard deviation of .32-.50.

The average for all the AEADS comparing with other e-business systems is of 4.58. When compared with the neutral response (3), this shows a difference of 1.58.

Performing a parametric paired T-test for all businesses, comparing their average score for all the AEADS comparing with other e-business systems, with the neutral response, the T-value is 34.77, and the probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all businesses, the Z-Score is 13.33. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 0. The distribution is approximately normal because of the U-value.

The next section of the questionnaire was designed to uncover participants' thoughts and perspectives regarding the AEADS system in general. As shown below in Table 9.12, this section of the questionnaire included ten questions and the topics covered included issues such as website integration, system performance, integration problems, user-friendliness, reliability, etc. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.17.

Table 9.12 General Questions about the AEADS System

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	The system was integrated in the website easily	4.53	5	.50	12.26	.0001	4.96	0	.0001	H6
2	The system interface (author part) is user-friendly	4.29	4	.46	11.36	.0001	4.96	0	.0001	H7
3	The system performance is adequate	4.41	4	.49	11.47	.0001	4.96	0	.0001	H8
4	The system reliability is achieved	4.53	5	.50	12.26	.0001	4.96	0	.0001	H9
5	Overall, are you satisfied with our service	4.41	4	.49	11.47	.0001	4.96	0	.0001	H0c
6	XML Data store enhance the integration process	4.53	5	.50	12.26	.0001	4.96	0	.0001	H10
7	Creating advertisements domain is easy process	4.76	5	.42	16.64	.0001	4.96	0	.0001	H11
8	Creating adaptation rules (general and behaviour) is easy process	4.65	5	.48	13.79	.0001	4.96	0	.0001	H12
9	Advertisers prefer to send the appropriate advertisement to appropriate users	4.82	5	.38	19.13	.0001	4.96	0	.0001	H13
10	AEADS supports me, as business owner, to appropriately represent, for personalised advertisements delivery : domain model, adaptation model, user model, all of them	4.71	5	.46	17.98	.0001	4.96	0	.0001	H14

As indicated in Table 9.12, the level of difficulty involved in the process of generating general and behavioural adaptation rules and building the advertising domain are shown to be the two key questions within this section. This helps to determine whether or not the AEADS system can easily create adaptation rules and advertising domains, which are both important considerations for businesses. According to the findings of the questionnaire, the majority of respondents (95.3%) stated that they found that the AEADS system made it extremely easy to build advertising domains. Furthermore, 92.9% of participants found generating general and behavioural adaptation rules in AEADS to be extremely simple. Therefore, hypotheses H11 (Creating advertising domains is a simple process) and H12 (Creating adaptation rules (general and behavioural) is a simple process) are supported by the results of this section of the questionnaire.

The questionnaire results also support hypothesis H6, with the vast majority (90.6%) of participants stating that the AEADS system achieves excellent website integration and they felt that the system is easily integrated into websites. The results of the questionnaire also show that the majority of respondents (90.6%) felt that the AEADS integration process was improved through the XML data store. This finding offers support to hypothesis H10 of this study. Additionally, the majority of the respondents involved in this study believed that they were better able to suitably reflect user model, adaptation model and domain model for the tailored delivery of advertisements through the use of AEADS. This finding represents the strongest of all participant opinions regarding the AEADS system. This belief was stated by 94.1% of participants and supports hypothesis H14.

Other findings obtained from this section of the questionnaire support hypothesis H13. Almost all of the respondents involved in this questionnaire (96.5%) believed that it is better for advertisers to broadcast advertisements to audiences in a way that is relevant and suitable for the specific target audience. This finding represents the strongest of all participant opinions regarding the AEADS system, as it was clear from the beginning of this research that all the business owners who participated in the evaluations preferred to send the appropriate advertisement to appropriate users.

This section of the questionnaire revealed that the company representatives involved in this study were extremely satisfied with the effectiveness of the AEADS system. Furthermore, all of the participants felt that the system had good performance and that it was reliable. These findings support both hypotheses H8 and H9.

Whilst businesses' satisfaction level can still be considered high for the authoring element of the system interface, it should be noted that this factor received the lowest level of businesses satisfaction, with a rating of more than 4. Specifically, respondents were asked to rate whether or not they felt that the authoring element of the AEADS system was user-friendly. Though the result does appear to support hypothesis H7 (i.e. there is strong user-friendliness within the AEADS system interface), some participants felt that the interface was less user-friendly than it could be, therefore, these participants were not fully satisfied with this element of the system. This is a relatively minor issue and, due to the time limitations, the authoring toolset will not be improved within this version of the AEADS system. However, the user-interface received a score of more than 4, which supports hypothesis H7.

The mean values of 4.29-4.82 and standard deviation of .38-.50. The average score for all of the AEADS elements is 4.54. When compared with the neutral response (3), this shows a difference of 1.54.

Performing a parametric paired T-test for all businesses, comparing their average score for all of AEADS with the neutral response, the T-value is 43.41, and the probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all businesses, the Z-Score is 17.30. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 0. The distribution is approximately normal because of the U-value.

As previously mentioned in this Chapter, the next section of the questionnaire utilised a Likert scale to assist respondents in expressing their opinions and feedback about the AEADS system. Table 9.13, below, outlines the participants' responses to the questions contained in this section. This section of the questionnaire requested that respondents provide an overall evaluation of the AEADS system's operations and elements. Participants were asked to rate features such as advertisement location control, clicking and purchasing opportunities, advertisement quantity control, application of behaviour rules, etc. The findings from this section of the questionnaire reveal that users were very pleased with the system's operations and components. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.17.

Table 9.13 Usefulness of the AEADS System

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	The system increases the clicking opportunity on advertisements effectively	4.71	5	.46	14.98	.0001	4.96	0	.0001	H0a
2	The system increases the buying opportunity for advertisements effectively	4.35	4	.48	11.32	.0001	4.96	0	.0001	H0a
3	The system controls the location of advertisements effectively	4.82	5	.38	19.13	.0001	4.96	0	.0001	H0a
4	It controls the number of advertisements in each webpage effectively	4.76	5	.42	16.64	.0001	4.96	0	.0001	H0a
5	The system applies the general rules effectively	4.41	4	.49	11.47	.0001	4.96	0	.0001	H0a
6	The system applies behaviour rules effectively	4.47	4	.50	11.79	.0001	4.96	0	.0001	H0a
7	The system applies the plan recognition process effectively	4.24	4	.42	11.65	.0001	4.96	0	.0001	H0a
8	The overall authoring part is useful	4.41	4	.49	11.47	.0001	4.96	0	.0001	H0a
9	The overall delivery part is useful	4.53	5	.50	12.26	.0001	4.96	0	.0001	H0a
10	The Facebook login (against the fill in data process) is more useful	4.53	5	.50	12.26	.0001	4.96	0	.0001	H0a
11	The user information acquisition via system registration is useful	4.24	4	.55	9.06	.0001	4.67	8.5	.0001	H0a

Overall, the rating of the AEADS system was positive, with every system component receiving a rating of 4 or more. These figures suggest that the participants involved in testing the system for the purposes of this study considered it to be highly useful. This argument is further supported by the standard deviation values of 0.38 - 0.55 and mean value of 4.24 - 4.82. Because of this, it can be concluded that the AEADS system is 'useful', based on the responses of the participants involved in this study. This is also highlighted through the minimum score of '4' for each item.

Although the requirement for systems to ensure sufficient registration in order to obtain information about users received a rating of 4 or more, this nonetheless appears to be considered the least important element of the AEADS system among participants. It is suggested that the reason behind the lack of emphasis on this particular element is that the amount of user information offered may have been too low. This may consequently have led a number of business owners to feel that other system components were more important than this particular feature. This reasoning is supported by an individual participant who commented that the system should be able to provide further information about users to the business owner, to be more effective and beneficial for businesses. This idea is further discussed in section 9.4.9 below. Despite this viewpoint, this feature still rated highly, thus indicating its usefulness for many businesses. This indicates that the participants involved in this study believe that the adaptive advertising process can be effectively assisted by the AEADS system. These findings support hypothesis H0a.

The average for all the features of AEADS in terms of usefulness is 4.50. This shows a difference of 1.50 when compared with the neutral response (3).

Performing a parametric paired T-test for all businesses, comparing their average score for usefulness of all AEADS features, with the neutral response, the T-value is of 39.99, and the probability is of $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all businesses, the Z-Score is 16.64. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 93.50. The distribution is approximately normal because of the U-value.

The usability of the distinct features was separately evaluated through questionnaire questions. Table 9.14, below, outlines the participants' perspectives of AEADS with regards to its usability. According to the data analysis, the findings of this section reveal that the usability of the AEADS system is very good, with participants stating that they found using the system to be 'easy' to 'very easy'. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.17.

Table 9.14 Usability of the AEADS System

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	The system increases the clicking opportunity on advertisements easily	4.53	5	.50	12.26	.0001	4.96	0	.0001	H0b
2	The system increases the buying opportunity for advertisements easily	4.41	4	.49	11.47	.0001	4.96	0	.0001	H0b
3	The system controls the location of advertisement easily	4.35	4	.48	11.32	.0001	4.96	0	.0001	H0b
4	Control number of advertisements in each webpage is easy	4.53	5	.50	12.26	.0001	4.96	0	.0001	H0b
5	The system applies the general rules easily	4.82	5	.38	19.13	.0001	4.96	0	.0001	H0b
6	The system applies behaviour rules easily	4.47	4	.50	11.79	.0001	4.96	0	.0001	H0b
7	The system applies the plan recognition process easily	4.88	5	.33	23.37	.0001	4.96	0	.0001	H0b
8	The overall authoring part is useable	4.47	4	.50	11.79	.0001	4.96	0	.0001	H0b
9	The overall delivery part is useable	4.29	4	.46	11.36	.0001	4.96	0	.0001	H0b
10	The Facebook login (against the fill in data process) is more useable	4.53	5	.50	12.26	.0001	4.96	0	.0001	H0b
11	The User information acquisition via system registration is useable	4.35	4	.48	11.32	.0001	4.96	0	.0001	H0b

According to the data analysis, the participants involved in testing the AEADS system felt that the system was satisfactory in terms of usability and accessibility. This suggestion is supported by the mean values of 4.29-4.88 and the standard deviation of .33-.50. In addition, subsequent data analysis showed that the elements ‘The system applies the general rules easily’ and ‘The system applies plan recognition process easily' were highly rated by participants, which supports hypothesis H0b. Thus, they clearly liked the fact that rules can be applied to individual advertisements and that multiple rules can be applied at the same time. Furthermore, they clearly like the general rules that have been improved in the second version of the adaptation model, as they can manage the rules using the help tool (a help tool is to support the tool that provides the main functionality) that has been implemented in the second version of the adaptation model. The second feature, the one applying the plan recognition process, was considered to be one of the best, as they could link the relevant advertisements together easily.

While some features received a slightly lower rating, the overall level of usability remained high. For instance, a score of more than 4 was achieved with regards to the usability of the system's delivery process. This might have been because there is nothing to be used in practice in the delivery process, as the delivery process only interprets the authoring process. Nevertheless, this was the lowest-rated system element with a score of more than 4, which is just high enough to indicate good system usability.

The suggestion that the AEADS system and its functions would be useable in adaptive advertising was proposed in hypothesis H0b, which is supported by the results of this questionnaire section.

The average for all the AEADS features in term of ease of use is of 4.51. When compared with the neutral response (3), this shows a difference of 1.51.

Performing a parametric paired T-test for all businesses, comparing their average score for ease of use of all AEADS features, with the neutral response, the T-value is 41.29, and the probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all businesses, the Z-Score is 16.73. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 0. The distribution is approximately normal because of the U-value.

Additionally, the businesses satisfaction ratings for a number of system features are outlined in the following table (Table 9.15), which illustrates the results of the data analysis. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.17.

Table 9.15 Satisfaction of the AEADS System

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	The system increases the clicking opportunity on advertisements sufficiently	4.41	4	.49	11.47	.0001	4.96	0	.0001	H0c
2	The system increases the buying opportunity for advertisements sufficiently	4.35	4	.48	11.32	.0001	4.96	0	.0001	H0c
3	The system controls the location of advertisements sufficiently	4.88	5	.32	23.37	.0001	4.96	0	.0001	H0c
4	It controls number of advertisements in each webpage sufficiently	4.47	4	.50	11.79	.0001	4.96	0	.0001	H0c
5	The system applies the general rules sufficiently	4.29	4	.46	11.36	.0001	4.96	0	.0001	H0c
6	The system Applies behaviour rules sufficiently	4.24	4	.42	11.65	.0001	4.96	0	.0001	H0c
7	The system Applies the plan recognition process is sufficient	4.18	4	.51	9.18	.0001	4.67	8.5	.0001	H0c
8	The overall authoring part is sufficient	4.71	5	.46	9.18	.0001	4.67	8.5	.0001	H0c
9	The overall delivery part is sufficient	4.47	4	.50	11.79	.0001	4.96	0	.0001	H0c
10	The Facebook login (against the fill in data process) is sufficient	4.35	4	.48	11.32	.0001	4.96	0	.0001	H0c
11	The user information acquisition via system registration is sufficient	4.53	5	.50	12.26	.0001	4.96	0	.0001	H0c

The findings show that participants' ratings of all system components had mean values of 4.18 - 4.88, with standard deviations of .32 - .51. Consequently, it can be said that the respondents felt the system operations and attributes to be sufficient.

The findings reveal that respondents gave the highest ratings to two of the system's features in particular: firstly, the system's ability to manage the location of advertisements sufficiently; and, secondly, the system's authoring component is sufficient. Thus, they were clearly satisfied with the overall authoring process, including the managing of the advertisements' locations, which gives them the ability to create and organise their advertisements on their websites. The authoring process also helped them apply adaptation rules to their advertisements easily. This was especially relevant to the second version of the authoring tool set, as they were improved and additional help tools were added (a help tool functions as a support for the tool that provides the main functionality).

The system was deemed adequate in its ability to apply plan recognition processes. This feature received a satisfaction score of more than 4, which is the lowest of all the system components. However, this feature received a high usability score, as discussed above. It is possible that the reason behind this satisfaction level was that business owners might have required a certain degree of further assistance when applying advertisement plan recognition processes, as they should link the advertisements together manually. In light of this finding, the system was updated and in the process, this issue was addressed.

The findings obtained from the participants' responses in this section of the questionnaire suggest high overall user satisfaction with the AEADS system, which support hypothesis H0c.

The average for all of the AEADS features in term of satisfaction is of 4.44. When compared with the neutral response (3), this shows a difference of 1.44.

Performing a parametric paired T-test for all businesses, comparing their average score for satisfaction of all AEADS features, with the neutral response, the T-value is 38.80, and the probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all businesses, the Z-Score is 16.64. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 93.50. The distribution is approximately normal because of the U-value.

Next, questions about the desirability were considered. As illustrated below in Table 9.16, the analysis of the Likert scale responses regarding the desirability of the system's features and functions primarily reflect promising feedback. In this section of the questionnaire, respondents were asked to rate the desirability of each system component. The findings show that each component achieved a score of 4 or higher among respondents. The questions are also mapped to the hypotheses above, for easier referencing. The overall answers for all hypotheses are later grouped in Table 9.17.

Table 9.16 Desirability of the AEADS System

No.	Questions	Mean	Median	SD	T-test		Mann-Whitney			Hypothesis
					T-value	P-value	Z-score	U-value	P-value	
1	The system increases the clicking opportunity on advertisements desirably	4.59	5	.49	12.91	.0001	4.96	0	.0001	H0d
2	The system increases the buying opportunity for advertisements desirably	4.41	4	.49	11.47	.0001	4.96	0	.0001	H0d
3	The system controls the location of advertisement desirably	4.82	5	.38	19.13	.0001	4.96	0	.0001	H0d
4	It controls the number of advertisements in each webpage desirably	4.76	5	.42	16.64	.0001	4.96	0	.0001	H0d
5	The system applies the general rules	4.47	4	.50	11.79	.0001	4.96	0	.0001	H0d
6	The system Applies behaviour rules desirably	4.24	4	.42	11.65	.0001	4.96	0	.0001	H0d
7	The system Applies the plan recognition process desirably	4.53	5	.50	12.26	.0001	4.96	0	.0001	H0d
8	The overall authoring part is desirable	4.47	4	.50	11.79	.0001	4.96	0	.0001	H0d
9	The overall delivery part is desirable	4.41	4	.49	11.47	.0001	4.96	0	.0001	H0d
10	The Facebook login (against the fill in data process) is desirable	4.35	4	.48	11.32	.0001	4.96	0	.0001	H0d
11	The user information acquisition via system registration is desirable	4.35	4	.48	11.32	.0001	4.96	0	.0001	H0d

According to the findings, the two most desirable features among participants were the system's ability to manage the quantity of advertisements per page and the ability to manage their location.

Whilst the system's application of behaviour rules scored 4 or higher, this was the least positive system feature. A possible reason for this result could be that businesses require additional behaviour rules within the system. During the qualitative data-gathering phase, it was suggested that the system could be better if further adaptation behaviour rules were to be added, as some participants demonstrated a lack of satisfaction with the current quantity of adaptation behaviour rules. Therefore, the general adaptation rules have been modified, allowing them to be flexible, based on the customers' needs and the company's views. However, the behaviour adaptation rules have not changed within this version of AEADS, due to time limitations. In spite of this, the findings indicate high levels of desirability across all system components, which support hypothesis H0d, with mean values of 4.24 - 4.82 and standard deviations of .38-.50. Due to mean scores above 3, it is possible to say that businesses found the AEADS system to be desirable overall.

The average for all the AEADS features in term of desirability is 4.49. When compared with the neutral response (3), this shows a difference of 1.49.

Performing a parametric paired T-test for all businesses, comparing their average score for desirability of all AEADS features with the neutral response, the T-value is 40.70, and the probability is $0.0001 < 0.05$ (the significance threshold most commonly used in significance research).

As the above test makes the assumption of normally distributed data, a non-parametric test was also used, to back up the results of the previous test. When performing a Mann-Whitney test for all businesses, the Z-Score is 16.73. The p-value is 0.0001. The result is clearly significant at $p \leq 0.05$. Additionally, the U-value is 0. The distribution is approximately normal because of the U-value.

Table 9.17, below, shows the aggregated hypotheses for all questions, in order to better illustrate how the features explored directly support the hypotheses. The scores are constructed by averaging all answers regarding the features which correspond to a particular hypothesis, from a functionality, usability, satisfaction and desirability perspective. In this manner, the support of all hypotheses by business owner respondents are clearly illustrated.

Table 9.17 Aggregated Hypotheses of the AEADS System

No.	Hypothesis	Average for all questions							
		Mean	Median	SD	T-test		Mann-Whitney		
					T-value	P-value	Z-score	U-value	P-value
1	H0a	4.51	4.50	.47	13.08	.0001	4.94	.71	.0001
2	H0b	3.85	3.82	.48	12.98	.0001	4.93	.77	.0001
3	H0c	4.44	4.25	.47	12.18	.0001	4.91	1.42	.0001
4	H0d	4.49	4.36	.47	12.89	.0001	4.96	0	.0001
5	H1	4.82	5	.37	20	.0001	4.96	0	.0001
6	H2	3.65	3.67	.49	13.92	.0001	4.86	2.83	.0001
7	H3	4.47	4	.50	11.79	.0001	4.96	0	.0001
8	H4	4.29	4	.46	11.36	.0001	4.96	0	.0001
9	H5	4.76	5	.42	16.64	.0001	4.96	0	.0001
10	H6	4.53	5	.50	12.26	.0001	4.96	0	.0001
11	H7	4.29	4	.46	11.36	.0001	4.96	0	.0001
12	H8	4.41	4	.49	11.47	.0001	4.96	0	.0001
13	H9	4.53	5	.50	12.26	.0001	4.96	0	.0001
14	H10	4.53	5	.50	12.26	.0001	4.96	0	.0001
15	H11	4.76	5	.42	16.64	.0001	4.96	0	.0001
16	H12	4.65	5	.48	13.79	.0001	4.96	0	.0001
17	H13	4.82	5	.38	19.13	.0001	4.96	0	.0001
18	H14	4.71	5	.46	17.98	.0001	4.96	0	.0001

9.4.9. Business Owners Qualitative Answers and Discussion

As part of the businesses evaluation of the AEADS system within this study, the qualitative data collection was conducted with the same seventeen participants, in order to gain a fuller understanding of the participants' thoughts regarding the system. This section provides the answers and suggestions given by participants during this stage of the data collection process.

Business owners believed that the AEADS system could be implemented effectively within actual companies, without the need for extensive system training, as they commented that the various functions of the system were easy to use and their staff does not need extensive training to use the system. These findings reflected the quantitative data analysis process, as in this process the AEADS system had achieved a high score regarding usability from most businesses that were participants.

According to the qualitative data analysis, one of the major benefits of the system is its ease-of-use. One participant offered positive feedback, stating that when they previously attempted to gain an understanding of Amazon, they were unable to do so; however, they were able to fully grasp and understand the workings of the AEADS system with much greater ease. Consequently, this participant's satisfaction levels were high.

It was also highlighted that the system should be able to provide further information if it is to be useful and beneficial for businesses. For instance, one participant stated that it would be useful if they could obtain reports offering insight into factors such as non-clicked advertisements, clicked advertisements and system users. The report can be generated from XML files.

On the other hand, one participant offered negative feedback and said that the system currently contains an excessive number of XML files. However, in the quantitative data analysis, the majority of respondents felt that the AEADS integration process was improved through the XML data store. It should be noted that the XML representation is there to allow the system to be easily integrated into any website, with only minor changes needing to be made to the database. This has been done with the AEADS system that was integrated with an online bookstore for evaluation purposes, as can be seen in section 9.4. Moreover, these files can be used to generate reports, as requested by the other business owners.

Another participant noted that the system's ability to provide user information to the business owner needs further adjustment, as he asked "Can we get more information about users?". This finding reflects the analysis of the quantitative data, in which the user information acquisition by the system registration received an unfavourable score from the participants. However, the system implemented is intended to be a lightweight adaptive advertising system, which includes simple tools for businesses and Internet users. In addition, users' privacy was respected and the test results showed that users would be unwilling to disclose any more information at this stage. Thus, the data required for customising advertisements for individual users' are obtained and must only be used for this purpose.

During the qualitative data-gathering phase, it was suggested that the system could be better if further adaptation behaviour rules were to be added, as some participants demonstrated a lack of satisfaction with the current quantity of adaptation behaviour rules. As a result, the general adaptation rules have been modified, allowing them to be more flexible, based on the customers' needs and the company views. Additionally, most business owners agreed that the system applies the general rules easily. Nevertheless, improving the behaviour adaptation rules lies beyond the boundaries of this study, because of time and literature limitations.

Additionally, the process of manually linking one advertisement to another within the plan library was reported by business owners to be a time-consuming task. One participant stated that "It is a long process to link advertisements together in the plan library and a time consuming task". This feature received a satisfaction score of more than 4, which is the lowest score amongst all the system's components. However, the plan library feature was considered one of the best in terms of usability levels within the quantitative data analysis, as they could link the relevant advertisements together easily. Therefore, this was further improved within the second version of the delivery model, as explained in section 9.6, below.

Aside from the recommendations given by some participants as to how to improve the AEADS system, as well as the shortcomings that they highlighted, the general consensus during this stage of data collection was that the system was well-received and considered to be highly useful. One participant stated that "the concept of the system was interesting and that it had the potential to be beneficial". Another participant pointed out that "managing the adverts' numbers and location on the webpage is one of the most important feature in this system". An individual owner of a business was struggling to add advertisements, including some generic advertisements, to his site, and he stated that every page of a commercial website should contain a significant amount of advertisements, which are coordinated solely by business owners or an assigned staff member. This reflected the analysis of the quantitative data, in which it was revealed that the ability to set the location of advertisements was considered to be an important system feature by the businesses. This feature should be viewed as vastly important within this research study, as it is hugely valued by business owners.

Another benefit of the system, as emphasised by one participant during this stage of the data collection, relates to system integration. Specifically, one participant reported that the system's ability to integrate the website's user profiles and the system's user profiles was desirable and useful, presenting a key strength of the AEADS system. This feature should be viewed as vastly important within this research study, as it is hugely valued by business owners. During the discussion with participants, it was clear that they had a good impression of the adaptive and non-adaptive commercial systems and that they agreed that an integrated system for companies' websites has recently become essential, as their advertisements are ignored by users. For example, one participant stated that Google advertisements are an inconvenience for users, as they hide the webpage's content. This is in line with the quantitative data analysis, in which participants considered the AEADS system to be more effective than other currently available e-business systems.

The participants involved in the qualitative data collection phase conveyed the same opinions as they did during the quantitative data collection phase, in that they considered the system's interface to be effective in many ways, but that it could be improved. This was a minor issue and due to the time limitations, the authoring toolset was not further improved in this version of the AEADS system. However, the user-interface received a satisfaction score of more than 4 within the quantitative data analysis.

9.5. Comparison with other Delivery Models and Discussion

Many methods of modelling delivery specification have been proposed. In this section, three popular delivery models will be compared with the AEADS delivery model tool, as introduced in the previous section. These tools are delivery models in the ADE [127], AdRosa [88], and MyAds [4] systems. The selection of these tools is based on the similarity of the approach between AEADS and these systems, as there are a great number of adaptive systems proposing a variety of delivery models to choose from. In the first part, a summary of each tool is provided, and then a comparison is made, and explained, between these tools and the newly introduced tool.

ADE [127] was written in Java using Servlets and JSP technology, and can be run on a standard Tomcat server and displays any content which can be described using standard web mark-up languages (i.e., HTML5, (X)HTML, and XML). Delivery processes in ADE are located in the adaptation and presentation layers; thus, based on the user model, domain model, and adaptation strategies, this system delivers appropriate course contents to users. Indeed, this system is even able to adapt a page, or its content presentation, based on the type of device being used via a modular tool with different presentation-specific handles that adapt to the needs of the user request. The ADE system also uses AJAX to actively track the network status of a current user's connection and to update the bandwidth variable in their profile. These network connection parameters can be used to tailor adaptive strategies according to users' network connection speeds.

The AdRosa [88] system, on the other hand, extracts knowledge via data-mining that is embedded in the web content page, historical user sessions, and the recent behaviour of the online user. However, web usage and content-mining take differing approaches to integration, as banners visited by users are stored in the form of vectors to represent user behaviour. The delivery section of the AdRosa system applies policies and priority features to advertisements in addition to monitoring user behaviour, in order to display the most appropriate advertisements to each user. Limitations to certain web browsers, and time of day, are used as additional filters to personalise advertisements.

Based on the LAOS framework [50], the MyAds system [4] encapsulates a delivery part in its adaptation model, as a connection between the user model and the appropriate advertisement is established before a presentation model, where the personalised advertisement is displayed to the user. These personalisation and decision making engine is responsible for delivering adaptive advertisements: it matches the user model to appropriate product, to show adaptive advertisements and application interface to appropriate users.

Although the ADE system delivers adaptive content efficiently, because it is mainly concerned with course adaptation, there are certain limitations to its use in the delivery of advertisements. This is because the parameters applied to introduce adaptive advertisements and adaptive courses are different. The former, for example, depends mainly on experience. Moreover, because the MyAds system is standalone, it cannot easily be incorporated into websites. Indeed, both the AdRosa and MyAds systems are designed to be used as part of an advertising portal model, as they match both publishers' and many advertisers' interests. The delivery tools in the AEADS system thus attempts to control and adapt advertisements that are located and owned by businesses, directly on their own websites. Indeed, the AEADS delivery engine is superior to both AdRosa and MyAds, in that it allows businesses to control the number and location of advertisements on a given webpage automatically. An author can set any number of advertisements at a given location on each page far from the adaptation system, and the HTML code with a specified identification is inserted at any location in the webpage. The system discovers this code and arranges it in an array each time the page is visited. This allows the author to update the number and location of advertisements in a simple manner. Additionally, as said, this system can be integrated easily into a wide range of websites.

9.6. Second Iteration of the Delivery Model (DM)

The second version of the delivery model includes some improvements, based on the evaluations of the AEADS system. This has not been additionally evaluated with businesses or Internet users, as all improvements were internal. Therefore, instead, the appropriate tests have been performed to establish that the system was working well. Below, the improvements and their connection to the previous evaluations is explained.

During the evaluation process with business owners, the process of manually linking one advertisement to another within the plan library was reported as a time consuming task, as one participant stated that "It is a long process to link advertisements together in the plan library and a time-consuming task". In this second version, an *assistive tool* (a help tool that supports the tool that provides the main functionality) has been created for authors to build plan libraries. This tool is there to remove the burden from the author, to write the plan libraries in XML files and to maximise the integration process of the system. It graphically links groups of advertisements based on the author's decisions. This tool should overcome an invalid advertisement's name when displayed by the decision engine, as shown in Figure 9.29. The author selects 'add plan' and chooses the advertisements which they wish to link to. These linked advertisements will be saved in the aforementioned plan library XML file. In addition, the author has a degree of control over this library (linking, modifying and deleting).

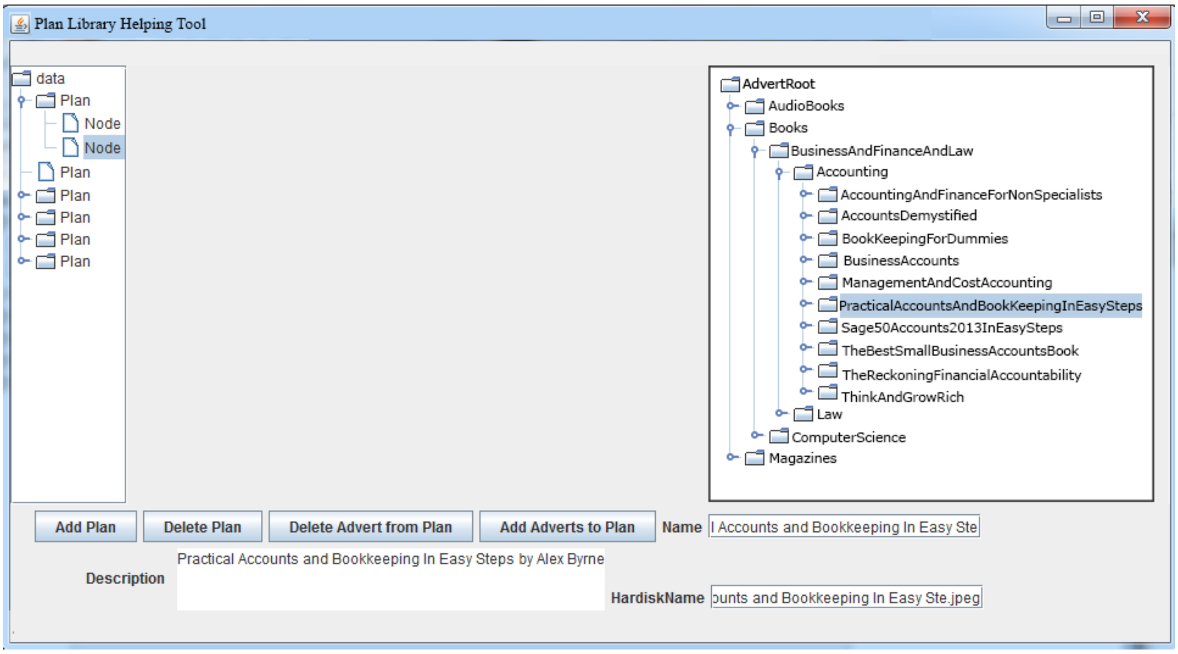

Figure 9.29 Plan Library Creation Tool

As part of the testing phase of the AEADS system, a series of duplicate advertisements were shown on the same webpage. This process could ultimately decrease the efficiency of the delivery engine, but in the second version, *duplication was avoided*. Advertisements were collected based on a series of rules, arranged in storage according to priorities specified by the system and author (discussed in Chapter 5, section 5.6 and in section 9.3), then checked by the delivery engine to avoid duplication. Furthermore, the AEADS system stored data on the server, potentially decreasing the speed of retrieval and the time taken to load data onto each webpage. Thus, in the second version of the decision engine, *speed to retrieve and load data onto each webpage was improved*, by reducing the overall reliance on the server, using sessions for storing arrays of data, and enhancing some algorithms within the decision process.

9.7. Conclusion

The implementation of the second iteration of the AEADS authoring toolset (domain model (DM), adaptation model (AM), User model (UM)), which have been introduced, in their first version, in Chapters 6, 7, and 8, respectively, is presented in this Chapter. In addition, the first version of the delivery model is introduced in this Chapter, and its design and internal processes are described in detail. It consists of three engines: *inference*, *decision*, and *modifier* engines. The division of the delivery process between these three engines should enhance the adaptation process, as well as allowing the possibility for future expansion. A comparison is conducted between the delivery model of the AEADS system with other delivery models from the ADE, AdRosa, and MyAds systems. Based on this comparison, it can be seen that the delivery model in the AEADS system is necessary and introduces flexible adaptation, by involving businesses in the adaptation process, starting from system design to implementation.

As discussed, the system, its features and usability have been evaluated, both theoretically and by established businesses, as well as by real users, and the overall outcome has been positive. Moreover, a further improvement of the delivery model has been done, based on previous evaluations, by enhancing the overall functionality and usefulness of the model and adding a help tool, supporting authors in building plan libraries.

Finally, this research is based on the belief that an adaptive strategy creation system would allow businesses to increase their sales potential, by facilitating the accurate targeting of advertisements, based on a series of predefined demographic attributes and rules. The delivery model has been tested by companies who wish to direct their advertising campaigns at specific consumer groups, as it enables them to quickly and effectively assign a series of rules based on their target market.

In summary, the research discussed in this Chapter has implemented various objectives and research questions, as follows (the implemented parts are underlined): the research objective **O5:** "*Implement* *a delivery engine that resides on the businesses' own websites, to support delivering personalised advertisements to the users*". In addition, for the evaluation part, this Chapter has implemented the research objective **O6:** "*Evaluate each design and implementation step, both technically and, where appropriate, with real businesses and internet users*". The procedure of analysing these objectives are outlined and the outcomes have helped to answer the research question **R2:** "*How can we create a model for lightweight adaptive advertising and design the corresponding system that can be integrated with most websites?*". This research question has been partly answered previously in Chapter 5, by proposing a new model for adaptive advertising, and in Chapters 6, 7, and 8, by implementing and evaluating the domain model (DM), adaptation model (AM), and user model (UM). It is also answered in this Chapter, through the implementation of the delivery model tool of the overall AEADS system. Furthermore, the process of investigating the objectives above are outlined and the outcomes support answering the research question **R3:** "*How can we support website owners in the creation of adaptive advertising, in order to be able to efficiently add adaptive advertising in a lightweight manner to their website?*". The answer of this research question is finalised in this Chapter, through the implementation and evaluation of the delivery model (DM). The final research questions will be presented and fully answered in the following Chapter, based on the outcomes of this Chapter, as well as the rest of the thesis.

Chapter 10

Conclusions and Recommendations for Future Work

As presented earlier, the main focus of the research presented in this thesis is aimed at *lightweight adaptive e-advertising*. The main result is the use of a relatively novel technical methodology to investigate and develop an innovative process for delivering e-advertisements. This has involved research into previous models and frameworks of adaptation, with elements incorporated from different fields. Some modifications have been implemented to existing models, in addition to a number of new features that are based on the needs of business owners and Internet users. The purpose of this is to *facilitate the process of achieving a higher level of generalisation, portability*, and *efficiency*.

It is important that the theoretical model is given full consideration, as earlier research in the area of e-advertising has not considered adaptation theories. Thus, there is an opportunity to develop an appropriately configured and definitive theoretical model that can be applied to the topic of e-advertising. In this thesis, such a model has been proposed, named *LAAI*.

In the final phase, investigations into the impact that the use of a range of data sources has on user experiences have also been conducted.

It was important that the business owners and Internet users were involved in all aspects of the research process. This has not always been the case in e-business and e-advertising studies – due to the fact that research was often proprietary, belonging to one business only, and thus not easily generalisable to others. Moreover, data were often not available. An additional factor was also possibly the added difficulty in involving different business owners in academic research. In addition to this, a user-centred design methodology has been employed, in order to involve end-users in the process; they were able to contribute to the conception, implementation, and validation of the research to be carried out.

As an element of the process, the theoretical model developed (LAAI) was used to design and produce a new e-advertisement delivery system, and this has been called *AEADS*.

The development process for this new system, AEADS, has involved two iterations, with the second one having a more progressive and comprehensive set of features, to facilitate the development of on-line adaptive e-advertisements on most commercial websites.

The final conclusions of the whole research process, showing the total research contribution, are presented in this Chapter. They also highlight the fact that, as the work in this thesis is research-based, there will always be room for further enhancements of the outcomes. At the end of the Chapter, these suggestions for further research will be discussed.

The present Chapter is structured in the following way: the next section summarises the research approach and outlines the research questions, in addition to presenting a summary of the responses; section 10.2 addresses the crucial question of whether and how the research objectives were achieved; section 10.3 examines the extent to which the employed approach was original; section 10.4 explains the challenges and constraints that were encountered over the course of the research process; and, finally, conclusions and recommendations for future work are provided in section 10.5.

10.1. Answering the Research Questions

One of the most difficult issues in relation to e-advertisements is authoring and delivering adaptive e-advertising – these are tricky jobs for business owners, and can have undesirable effects on Internet users. The research presented in this thesis considered these problems and then aimed at *improving the authoring and delivery of e-advertisements*, through the use of more personalised and reactive examples. In addition to this, the proposition that an innovative *lightweight model and system* be built was considered, in order to facilitate the more straightforward authoring and delivery of adaptive advertising.

In the following, the research questions that were formulated in Chapter 1 are critically reviewed, and the corresponding responses given within this thesis are summarised below.

10.1.1. Main Research Question

R0: Does adaptation/ personalisation of advertising make sense?

This research question lays the basis of the research topic and defines the main focus of this thesis. It also allows questioning if introducing personalisation would be useful at a general level, before embarking on the opportunity to analyse the effect of personalisation on the advertising process, in a progressive and a methodical way. Logically following from the methodical analysis, this question then enables one to examine the extent to which adaptation *enhances*, *generalises*, and *facilitates* e-*advertising*. Included as an *integral part* of the process are the principal stakeholders, the data inputs, the technological approach, and the unique features. To address the issue, further research questions were developed, to be more precise and comprehensive, as follows in the next section. The response to the overall question is summarised below.

Answer: In considering the responses to the questions and the additional research, it can be inferred that the adaptation and personalisation of e-advertising makes sense, when compared to non-personalised advertisements. This response can be viewed as an amalgamation of the answers to the more precise questions, as below.

10.1.2. Detailed Research Questions

R1. Is adaptive advertising useful for businesses and users?

Answer: The overall answer is yes. Although they may be seen as having conflicting goals, both business owners, as well as their clients (users) have confirmed that they consider adaptive advertising as *acceptable* and *useful*, when compared with non-adaptive advertising. Businesses will like to see their clients pay attention to advertisements, click on them and ultimately buy the products they advertise. Clients would like to not receive irrelevant ads, but are eager, nevertheless, to receive ads that are mindful to their needs. Thus, for both, adaptive advertising seems to be the answer. Additionally, adaptive hypermedia (AH) provides the theoretical underpinning for the personalisation process. The work contained in the present thesis demonstrates that AH is not only theoretically sound, but also it provides a number of models/frameworks and systems that have proved to be extremely helpful in praxis, and which were able to be extended for the current research. This response can be viewed as an amalgamation of the answers to the more precise questions, as below.

R1.1. Is it more acceptable for users to have adverts personalised to them and their environment? (i.e., do users find personalised adverts more acceptable than non-personalised)

Answer: From the responses provided in the user questionnaire, which was conducted in the initial stages of the present study, it was clear that users are more likely to accept adaptive advertising. They find it acceptable to have advertisements that are adapted based on their characteristics and environment, as explained in Chapter 4, section 4.3. In addition, in the evaluation of the AEADS system with Internet users in Chapter 9, section 9.4.3, the participants strongly agreed, in a statistically significant way, that personalised advertisements are acceptable to them, when compared to non-adaptive advertisements.

R1.2 Is it more acceptable for businesses to deliver adaptive advertising? (e.g., do business users find adaptive advertising more acceptable when compared to non-adaptive advertising, and do they expect the former to provide a better income)

Answer: From the responses provided by the businesses interviews, which were conducted at the beginning of this research, it was noted that all businesses interviewed would prefer to send the appropriate advertisement to appropriate users. Importantly, it was noted that this necessitates the personalisation of advertising. Additionally, all of the participants agreed that adaptive advertising would provide an enhanced income, compared to the one that non-adaptive advertising would provide. This research question is addressed in Chapter 4, section 4.3. In addition, the question has been revisited in the evaluation of the AEADS system with business owners in Chapter 9, section 9.4.8, where they strongly agreed again, in a statistically significant way, that advertisers prefer to send the appropriate advertisement to appropriate users. The latter showed that the tool itself delivered according to the initial expectations of the businesses, and thus was fit for purpose – and that the instantiation of the theoretical model confirmed the initial findings.

R1.3. What is a good source of information for adaptive advertising?

Answer: The data about users can be retrieved both through *implicit* and *explicit* means. Users can login into the system via two methods: *registration* (explicit data retrieval) and *social network login*. By logging in via the latter, the user model can be automatically populated (*implicitly*) with the necessary information for the adaptation of advertisements. Social data collated with the use of the social login permit the retrieval of sufficient user information and inference from specific to general cases. This can be retrieved with the use of social network authorisation and authentication APIs. Portions of the data may be obtained automatically, so that part of the burden can be removed from the system component, thereby enhancing generalisation and making the integration process easier. Similarly, the specific device being used, for instance, can be also automatically determined at user login. This research question is addressed in Chapter 8, section 8.2. Notably, based on the responses provided in the user questionnaire, which was conducted in the initial stages of the present study, it was possible to see clearly that social networks are extremely effective for user behaviour extraction. This is discussed in greater depth in Chapter 4, section 4.3. In addition, the question has been revisited in the evaluation of the AEADS system with Internet users in Chapter 9, section 9.4.3, where they strongly agreed, in a statistically significant way, that logging-in using the Facebook account is useful. Furthermore, this question has been addressed in the evaluation of the AEADS system with business owners in Chapter 9, section 9.4.8, where they strongly agreed, in a statistically significant way, that the Facebook login is more useful than the process of filling-in data manually.

R2. How can we create a model for lightweight adaptive advertising and design the corresponding system that can be integrated with most websites?

Answer: Based on the analysis of existing models and frameworks, and the fact that they cannot be directly applied to the current work, this thesis proposed a new lightweight adaptation model, named the *Layered Adaptive Advertising Integration (LAAI)*. The purpose of the formulation of the new model was to specifically target advertising. Whilst LAAI was based on previous hypermedia adaptation models, it was found that they were not directly applicable to the advertising area, hence the need for a new model emerged. LAAI seeks to introduce common abstractions, in order to provide a basis for the development of advertising adaptation applications. Furthermore, it aims to support the extent to which these applications are portable. LAAI ensures the *separation of content*, adaptation requirements, and delivery within an adaptive advertising application [50, 53]. This is important for higher-level strategies, as it enables content (here, advertisements) to be reused. The structure of the LAAI model is constituted of four lightweight layers: *domain model (DM)*, *adaptation model (AM)*, *user model (UM)*, and *delivery model (DM)*.

The *LAAI* model aimed to reuse certain features from previous models, such as AHAM [53] and LAOS [50], while simultaneously increasing *portability*. Some elements of previous models, such as LAOS's goal model, have been discarded. This is primarily owing to the fact that the goal model was formulated in accordance with a pedagogical narrative, meaning that it was not useful in the context of adapting advertising content. Despite this, a number of features from the LAOS presentation model have been integrated as a sub-model in the user model. These are known as '*Future Advertisements*'.

The first three layers of the LAAI model comprise the storage area. The first layer, the *domain model (DM)*, describes entities in an application that represent advertisements and, in addition, the relationships between them. These are represented by grouping the advertisements into levels in lightweight manner. The next layer, the lightweight *adaptation model (AM)*, includes simple adaptation rules that personalise advertisements in relation to each user. The lightweight *user model (UM)* layers, which includes small amount of attributes, store four different types of data: social data, basic data, behaviour data, and future advertisements data. The final layer, the *delivery model (DM)*, uses the data stored in other layers, to generate adapted advertisements. This layer also monitors user behaviour and updates the other layers with the current user status. The business rules that are stored within the delivery model layer are a new concept in adaptation frameworks, and they will enable businesses to modify the priorities and actions of inference and decision engines. The full discussion of the LAAI model is presented in Chapter 5.

The second part of the research question above was answered together with the research question immediately following.

R3. How can we support website owners in the creation of adaptive advertising, in order to be able to efficiently add adaptive advertising in a lightweight manner to their website?

Answer: In order to incorporate the main features extracted in the data gathering stage, a suitable system for advertisement adaptation has been built. The system was formulated in accordance with the underlying theories associated with the *LAAI* model, and the result was a system for any independent business website, called the *AEADS* system. This system allows the website owners to categorise their advertisements and adapt them to their website users, the decisions are based on various adaptation strategies. The system has four lightweight layers: *domain model (DM)*, *adaptation model (AM)*, *user model (UM)*, and *delivery model (DM)*. All these layers have been implemented and evaluated with Internet users and business owners. The results show that AEADS was appreciated by business owners and Internet users, and that the positive difference is statistically significant, when compared to the neutral response of 3. Moreover, based on the responses provided by both Internet users and business owners, a second iteration of the AEADS system has been implemented. Furthermore, the AEADS system has a simple structure, usable and flexible functions, and several help tools, in order to make it easy and simple for business owners and Internet users to use. To this end, this research question has been addressed, and it is fully discussed in Chapters 6, 7, 8, and 9.

10.2. Research Objectives

Six different objectives have been developed, and these can be directly related to the research questions and the methodology for answering these questions in the thesis. They are described as follows:

Objective O1. *Review the state of art in the area of adaptive advertising, as well as related areas, such as web personalisation and e-advertising, in order to find information for creating a model of adaptive e-advertising.*

The work concerned with this objective has been ongoing throughout the research process of this thesis, since new ideas and information were required when each new situation within the research became evident. The information relating to the theoretical basis for this work, as well as the related research, are detailed in Chapter 3. The area of e-advertisement personalisation is extremely challenging, as it is not purely a research area. From a business perspective, commercially aggressive businesses strive to gain competitive advantages through commercial growth, increased sales, more customers, whilst retaining current ones, the reduction of the frequency of e-advertisement rejection, and the enhancement of the click-through rate for customers. This is hardly surprising and indeed, in research terms, the area has also been continually evolving. As a result of this, it has been referred to as a "hot area" [88]. *Generalisation*, *integration*, and *simplicity* are key factors in developing an adaptive e-advertising system and the present research has concentrated on these aspects. Currently, there are only a few e-advertising models based on adaptation and personalisation. This can be attributed to the fact that this area has not been extensively investigated in terms of a systematic view on introducing adaptation to e-advertisements. In other areas, models and frameworks for adaptation and personalisation exist, for example, e-learning platforms such as LAOS [50] and AHAM [53, 144].

The basis of the research investigation was derived from identifying the constraints and omissions found from the theoretical background and associated research. A number of areas, which were initially missing, were identified. As highlighted previously, for example, adaptive content has not been used for personalised e-advertisements. In more general terms, adaptive hypermedia methodologies, such as adaptive e-advertising authoring or delivery, have not been fully utilised either. Traditional approaches, such as banner advertisements, as opposed to other types of e-advertisements, such as classified ads, seem to have been the main focus in the past, for implementation, as well as research. The *LAAI* model presented within this thesis is drawn from a variety of approaches for the design, realisation, and evaluation of the Information Retrieval process. Finally, it is important to note that the literature cited provides a sound theoretical and technical basis for this research.

Conducting and achieving research objective O1 provided background knowledge for answering the research questions R1, R1.1, R1.2, R1.3.

Objective O2: *Design a set of preliminary studies with businesses and users, to establish the current state of art in the area of adaptive advertising and to gather the requirements for the design and implementation of an appropriate theoretical model and system.*

This research objective has been realised through the use of two main experiments with Internet users and business owners. It was presented as the start of the design phase, in Chapter 4. The exploratory study was initiated in relation to the challenges and primary elements of the overall research in this thesis. Moreover, the user-centred design method has been utilised in this study, according to ISO-standard 13407. This is due to the fact that it facilitated the examination of the preferences of both Internet users and business owners. Overall, the primary result of this objective, along with the outcome of the research, has indicated that businesses prefer to send out personalised or segmented advertising messages. Additionally, it was shown that personalisation issues are a key feature of advertisements that will either attract or repel users. Based on research results, a new theoretical model and system have been proposed, to enhance the organisation and adaptation of advertisements on a wide range of websites. In other words, this methodology creates a generalised system that can integrate and work with a wide range of websites. Moreover, the importance of social networks, as the primary sites for extracting users' characteristics, came to the fore and was discussed in Chapter 4. The outcomes of the exploratory study are published [118].

In this study, the researcher worked according to the ISO-standard 13407 human-centred design processes for interactive systems [139]. The purpose of this standard is to provide instructions that enable one to achieve high quality conclusions, by employing user-centred design processes over the course of the life cycle of computer systems. The collection of information relating to user requirements is a method that was conducted from the initial stages of the present research; this is outlined in Chapter 4. The central aim is to clarify the correct definition and to readdress the developmental phase. It describes why the research is useful and it shows how the outcome can be comprehended. A number of the foremost empirical methods have been employed in experiments, with the aim of identifying the user and organisational needs. Questionnaires and interviews were used, as these methods are the most relevant for the type of data that was collected; in this context, the data was related to the preferences and demands associated with adaptive advertising. Despite this, the study also provides an indication of end users' perceptions relating to the elements that the system should incorporate. In doing so, the study provides insight into what should and should not be incorporated into the system.

A unique theoretical model and system have been proposed, in this stage, to enhance the organisation and adaptation of advertisements on a wide range of websites. This model has produced a generalised system that can work with a wide range of websites. In addition, social networks now have an important part to play in identifying user attributes and preferences.

Conducting and achieving research objective O2 provides real-life input towards answering the research questions R1, R1.1, R1.2, R1.3.

Objective O3: *Based on the outcomes from O1and O2, propose an appropriate theoretical model (new or extended) for lightweight adaptive advertising.*

Based on the outcomes from O1, which is the analysis of existing models and frameworks, and the fact that they cannot be directly applied to the current work, combined with the outcome from O2, which details the requirements that have been gathered from Internet users and business owners during the exploratory study, this thesis proposed a new adaptation model. The model was called the *Layered Adaptive Advertising Integration (LAAI)*, and it can be used to disseminate advertising. It is based on previous hypermedia adaptation models. This model seeks to introduce common abstractions, in order to provide a basis for the development of advertising adaptation applications and to support the portability of these applications. *LAAI* ensures the *separation of content*, *adaptation requirements*, and *delivery*, within an adaptive advertising application [50, 53]. This is important for higher-level strategies, as it enables content to be reused. The LAAI model is constituted of four lightweight layers: *domain model (DM)*, *adaptation model (AM)*, *user model (UM)*, and *delivery model (DM)*. The full investigation of this objective is presented in Chapter 5. A brief summary of LAAI can be found as an answer to research question R2.

Conducting and achieving research objective O3 provides the means for answering the research question 2.

Objective O4: *Based on the outcome from O3, implement tools for the theoretical model, to support the creation of adaptive advertising by website owners.*

AEADS is a unique adaptive e-advertising delivery system that has been implemented based on the LAAI model. The overall authoring model of Adaptive E-Advertising, as informed by prior research and implementations, especially in the area of personalised e-learning, includes the following.

The lightweight *domain model (DM)* tool, which is the first tool of the AEADS system. This was introduced in Chapter 6. This first tool of AEADS has been implemented in order to allow businesses to organise their advertisements in groups and subgroups. It also enabled these organisations to attach any necessary information (meta-data) to these advertisements. In this way, it made their work easier and saved time. The information attached to each advertisement refers to the name, location on the storage media, and a description about the advertisement, to be used later, in the delivery part of the AEADS system. Furthermore, the tool has been evaluated by a number of business owners, who were positive towards all of the features and functions of the domain model tool. Notably, business owners, who are considered to have extensive knowledge of this field, found that it had a promising degree of utility and functionality. Moreover, they strongly agreed that the domain model tool could be employed, in order to save time and to train new staff in efficient ways. The domain model (DM) implementation and evaluation is discussed in Chapter 6 and it has been published [115].

The lightweight *adaptation model (AM)* tool allows businesses to increase their sales potential, by facilitating the accurate targeting of advertisements. The targeting is based on a series of predefined demographic attributes and rules. This tool of the AEADS system has been implemented, in order to allow businesses to control the adaptation process, by creating, adding, and removing rules for advertisements in the domain model. The adaptation model tool divides the rules for the author into general, which relate to user characteristics, and behaviour rules, which relate to user behaviour. This division allows the AEADS system to enhance the process of adaptation of the delivery component. Additionally, an extension of these rules can be developed easily.

It is often the case that business owners would like to direct their advertising campaigns towards specific consumer groups. Thus, the value of the present model is insofar as it can enable them to assign a series of rules based on their target market in a quick and effective manner. As aforementioned, the initial version of the system and its features and usability have been evaluated, in both theoretical and practical business settings, and the overall outcome has been significantly positive. The *adaptation model (AM)* implementation and evaluation is discussed in Chapter 7 and it has been published [114].

A lightweight *user modelling* approach was implemented over the course of the present research. This approach could have a certain degree of utility in relation to the way it could assist Internet users in accessing e-commerce systems. In this way, it helps companies to target their audience in a more direct fashion, by tailoring their marketing campaigns towards specific consumer demographics. Furthermore, they can focus their advertisements on those users who satisfy predetermined criteria. Based on theoretical considerations and practical testing outcomes, a minimum set of user model dimensions have been validated (correspondent to the lightweight approach followed throughout). The evaluation results indicate that the initial functionality and usability of the tool is promising. The *user model (UM)* implementation and evaluation is discussed in Chapter 8 and it has been published in two papers [116, 117].

Finally, the evaluation of the authoring toolset of the AEADS system with Internet users and business owners resulted in some additional suggestions for improvement. These have been addressed in the second version, which is discussed in Chapter 9.

Conducting and achieving research objective O4 provides the means for answering the research question R3.

Objective O5: *Implement a delivery engine that resides on the businesses' own websites, to support delivering personalised advertisements to the users.*

The *delivery model (DM)* is introduced in Chapter 9, and its design and internal processes are described in detail. It should be noted that the delivery model is constituted of three engines: *inference*, *decision*, and *modifier* engines. The division of the delivery process between these three engines enhances the adaptation process, by allowing the possibility of simple, straightforward future modular expansion. A comparison is conducted between the *delivery model (DM)* of the *AEADS* system and other similar delivery models from different systems. Based on this comparison, it can be seen that the *delivery model (DM)* in the *AEADS* system is necessary. Furthermore, it can be observed that it has introduced flexible adaptation, by involving businesses in the adaptation process, ranging from authoring to decision-making.

As discussed in Chapter 9, the system, its features, and usability have been evaluated. The evaluation was carried out with both Internet users and business owners, and the overall outcome has been significantly positive.

Finally, the evaluation of the delivery model of the AEADS system with Internet users and business owners resulted in some suggestions for improving the delivery model. These have been addressed in the second version, which is discussed in Chapter 9.

Conducting and achieving research objective O5 provides the means for answering the research question R3.

Objective O6: *Evaluate each design and implementation step, both technically and, where appropriate, with real businesses and internet users.*

The *AEADS* system has been evaluated primarily in order to investigate how useful it is, how easy it is to use, in addition to the extent to which is was effective in acquiring user data and, following this, making inferences based upon it. Furthermore, the delivery mechanism was evaluated by monitoring the data usage and, having done this, collecting quantitative and qualitative data relating to user satisfaction and the usability criteria. This process is explained in more detail in Chapter 2. Notably, four evaluations were carried out with business owners and Internet users, as discussed below.

As the *domain model (DM)* and its implementation is aimed at adaptive advertising for businesses, it was crucial to evaluate it initially with business owners, and this is described in greater depth in Chapter 6. The *domain model (DM)* has been tested and evaluated with business owners in relation to its *effectiveness* (usefulness) and *efficiency* (ease of use), as described in Chapter 2. This was based on the implementation (see Chapter 6, section 6.2) and the hypotheses. The full results and discussion are presented in Chapter 6.

As the *adaptation model (AM)* and its implementation is also aimed at adaptive advertising for businesses, it was crucial to evaluate it firstly with business owners, as described in Chapter 7. The *adaptation model (AM)* has been tested and evaluated with business owners in relation to its *effectiveness* (usefulness) and *efficiency* (ease of use), as described in Chapter 2. This was based on the implementation (see Chapter 7, section 7.2) and the hypotheses. The full results and discussion are included in Chapter 7.

The *user model (UM)* was also evaluated from *effectiveness* (usefulness) and *efficiency* (ease of use) perspectives, as described in Chapter 2. The user model describes the clients. Thus, the evaluations were performed with clients – here, students, as they are eager Internet clients, as well as they are more accessible in academic research. Questionnaires were used to collect user opinions and, in combination with this, data usage was tracked. The full results and discussion are presented in Chapter 8.

For the *delivery part (DM)* and the whole system (*AEADS*), the system was evaluated by employing a questionnaire and interviews; these are useful, as they provide both qualitative and quantitative data. Furthermore, these methods can gather suitable amounts of information in a structured manner, and they also provide a good overview of the participants' beliefs, opinions, and perceptions [129]. Moreover, the data usage (number of clicks, searches, 'like's' and 'stop's') of Internet users has been tracked. In order to test the *AEADS* system and obtain valuable feedback in terms of its *effectiveness* (usefulness), *efficiency* (ease of use), and *satisfaction*, as discussed in Chapter 2, the *AEADS* system was integrated with an online bookstore. Following this, samples of businesses and Internet users were asked to use the system and evaluate it. The full results and discussion are presented in Chapter 9.

Conducting and achieving research objective O6 provides the knowledge for answering the research question R3.

10.3. Original Contributions

The main research question to be reviewed here was "**R0:** *Does adaptation/ personalisation of advertising make sense?*". It should also be noted that the research that has been carried out has reviewed frameworks, theories, and various methodologies and technologies in an attempt to generate both a theoretical and technical solution to the present issue.

- The *theoretical model* for lightweight adaptive e-advertisements was derived from the critical review of a range of previous studies carried out in the fields of e-learning and e-advertising model/frameworks. The developed model is flexible, it enhances the organisation and adaptation of advertisements on websites, and it can be extended, according to the requirements of the businesses and the customers. In this way, it creates an architecture that is powerful in its nature.
- From a technological viewpoint, the research involved investigates new and innovative ways in which a *unique system* could be created in such a way so as to function as a system for lightweight personalisation specifications. Through these innovations, lightweight adaptive advertising tools are offered for the creation and

authoring of adaptive advertising; in turn, this supports the delivery of personalised advertisements to each user. Moreover, the *generalisation*, *portability*, and *efficiency* of the user model and delivery model have been enhanced and improved, which means that a wide range of businesses are able to adapt their advertisements, based on user profiles and behaviour. Notably, this has been met by extensive user satisfaction. The tools are designed and implemented to support and facilitate a certain degree of integration among adaptive systems and a wide range of websites.

- The present research implemented a number of innovative functions and features in an attempt to facilitate the authoring of adaptive advertisements; these include a simple (lightweight) domain model tool that allows easy creation and organisation of adaptive advertisements, and a simple (lightweight) adaptation model tool that enables easy application of adaptation rules.
- The *adaptation rules* in the *adaptation model* are separated into two groups – *general* and *behaviour* – in order to facilitate authoring and to ensure that advertisement adaptation is simple, yet relatively comprehensive – giving thus clear hints to businesses of the type of adaptation rules expected from them. This grouping of adaptation rules is also intended to facilitate any future extensions of the rules, by mapping the relationships between adaptation rules, user model and decision engine. Furthermore, applying template adaptation rules within these categories precludes the need to write complex adaptation rules by hand.
- Additionally, the research includes a *lightweight user model*, which includes several features, such as *simple user profiles*, *social media layer*, *automatic data retrieval*, *handling negative responses to advertisements displayed to end users*, and *future advertisements*.
- The *future advertisements* component in the user model includes advertisements that will be shown to each user in the future, based on the previous components in the user model and delivery model. Based on the delivery model, this component stores advertisements that will be shown to users on their next log-in. The delivery model

stores the remaining advertisements that will be shown to the user based on the decision engine, which is a component of the delivery model. These future advertisements will be stored and shown at a future login.

- Furthermore, the methodology includes a *lightweight and integrated delivery model*, which incorporates three engines (*inference*, *decision* and *modifier*) to facilitate adaptation and personalisation. The advertisement's location on the webpages can be easily chosen by business owners – for their own convenience, or for the convenience of Internet users.
- The methodology has been evaluated and investigated by business owners, who found it satisfactory – which is especially promising, as these individuals are considered to be experts in this field. Thus the work in the thesis has a good chance to make a real-life impact.
- In addition, it has been evaluated by a large number of Internet users whose data usage has been tracked.

10.4. Challenges and Limitations

From the outset of this research, it has been obvious that there exists a relatively high competitive factor in the area of e-commerce. It should be noted that this is both in terms of the academic/research approach and the commercial/industry approach. The amount of money and resources, which are available to contribute to this competition in combination with commercial platforms, is being maintained in commercially sensitive environments with no access to the outside world, unless companies permit it. As a result, there are only a few informed research publications available. This means that there has to be a certain level of guesswork and reverse engineering taking place as to what is really going on within these commercial platforms, which is a drawback for the current research. To alleviate this, comparisons were made with existing systems with features that could be documented, to some extent.

The fact that this research utilises two areas in this sector, namely e-commerce and adaptive hypermedia, has meant that a considerable amount of work was needed, in order to compile a comprehensive data log that could be used as the basis for the present thesis. Indeed, the fact that there is a paucity of literature providing any structured theoretical models and approaches between the two domains means that this thesis is likely to be the first to make these connections.

In addition, the theoretical model and the implemented system are heavily based on e-learning adaptive models. Importantly, however, similar models were not implemented in the area of adaptive e-advertising. Thus, it is worth recognising that this is novel for the area of advertising.

Receiving responses from businesses was more difficult, but it did lead to some interesting conversations at each evaluation with business owners; this is discussed in Chapter 2, section 2.5. Although the sample of businesses considered was not extensive, the present analysis aims at specialist knowledge and not general knowledge. In addition, the business owners come from a wide range company types, therefore, their response can be considered important, as discussed in Chapter 2, section 2.5.

Furthermore, as the study required a large sample population of users, students were deemed suitable participants, as this decision simplified access. It must be noted that, although all students within the sample population were familiar with the Internet and Internet use, they were not all Computer Science specialists; the sample incorporated students studying a wide range of subjects, from different backgrounds, with a wide range of knowledge specialisations and interests. However, using a sample of students also presents a number drawbacks to the approach. Notably, while they represent the fact that the young population is knowledgeable about the Internet and its tools, especially e-business tools, they do not represent the population as a whole. This is discussed in Chapter 2, section 2.5.

Moreover, AEADS was integrated with only one website, as discussed in Chapter 9. However, it has not been integrated to another website, due to time limitations.

10.5. Recommendations for Future Work

From the detailed discussions above, it can be concluded that the approach presented is innovative and well researched. However, it has been shown that, in this particular area, there are always additional improvements that can be made. These are listed below.

- The theoretical model that has been implemented in this research is simple, reusable, and extendable. It would be useful to implement more adaptive systems based on this model.
- The implemented system has been integrated with one website. However, it would be useful to integrate the implemented system with other websites.
- Social networks are good sources of user information, from which user behaviour and characteristics to personalise advertising can be extracted. These social networks reflect and record the social practices, behaviour, preferences, and concerns of their users. The forms of social networks vary, from those where users take an active part in content creation and production, to those where content is shared. In this research, Facebook has been one of the central sources of user information. It would be useful to embed other social network platforms within the implemented system.
- The adaptation model in the implemented system includes two types of simple adaptation rules: *general* rules and *behaviour* rules. The general rules are flexible, and in this way, business owners can manage them by adding and removing rules based on their needs. However, behaviour rules are fixed in the implemented system. Therefore, it would be useful to improve these rules to be flexible, based on varying company needs.

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Appendix A

Internet User Questionnaire for Data Gathering

1. Age...........
2. Gender...............
3. Nationality.........................
4. How often do you visit the Internet?
   a) Several hours a day
   b) More than once a day
   c) Daily
   d) Weekly
   e) Monthly
   f) Yearly
   g) A few times
   h) Never
5. If you visit the Internet, what is your purpose:
   a) Work (mostly, sometimes)
   b) Study (mostly, sometimes)
   c) Shopping (mostly, sometimes)
   d) Social (mostly, sometimes)
   e) Play (mostly, sometimes)
   f) Other: (mostly, sometimes)

6. When I shop:

   a) I normally shop online

   b) I sometimes shop online

   c) I normally shop in shops (offline)

   d) I sometimes shop in shops (offline)

   e) I shop in shops (offline), but I look up the products first online

7. Did you find the advertising you were exposed to useful?

   a) Always

   b) Often

   c) Sometimes

   d) Never

   Please explain..

8. Did any of the advertising adapt to your preferences?

   a) Mostly Yes

   b) Sometimes

   c) Mostly No

   Explain...

9. Did any of the advertising adapt to any other of your characteristics?

   a) Mostly Yes

   If yes, mention which...

   b) Sometimes

c) Mostly No

10. Did any of the advertising use reasonable media according to your bandwidth?

    a) Mostly Yes

    b) Sometimes

    c) Mostly No

    Explain..

11. Did any of the advertising use reasonable screen outline for your Device?

    a) Mostly Yes

    b) Sometimes

    c) Mostly No

    Explain..

12. Did any of the social networks you are using provide you with useful advertising?

    a) Mostly Yes

    b) Sometimes

    c) Mostly No

13. Please write which social networks, and what kind of advertising.

14. Did any of the social networks that provided you with advertising adapt to your user characteristics?

    a) Yes, If yes, write which networks and to what characteristics.

    b) No

15. How did the advertising attract you?

Appendix B

Business Owner Questionnaire for Data Gathering

1. What type of business are you:

    a) Financial

    b) Manufacturers

    c) Real estate

    d) Transportation

    e) Agriculture

2. What size of business are you:

    a) Small

    b) SME

    c) Medium

    d) Large

3. Country / Countries..............................

4. Any other info on the company (name, etc.)

5. What type of advertising do you use:

    a) Online advertising

    b) email advertising

    c) Newspaper advertising

    d) brochure advertising

6. For your online adverts, what channels do you use for advertising? Add also the percentage of goods that are advertised this way:
   a) Own website
   b) Social networks (name which)...................
   c) Online newspapers
   d) Online journals
   e) email
   f) Others...
7. Out of your online adverts, what is the percentage of access versus display for your adverts?
8. For your accessed online adverts, what percentages of products are sold with respect to the number of accesses for its advertising?
9. What is the percentage of income from online advertising compared to the overall income?
10. Are you using any type of personalisation or adaptation in your online advertising, and if yes, mention what type?
11. If you are using any type of adaptive advertising for your online advertising, then what percentage does this represent out of your online advertising?
12. Does adaptive advertising provide better income? (compared to non-adaptive advertising) Give examples, and if possible, compare the two in terms of percentage of income.
13. Do you prefer that your advertising is categorized on hosting websites and directed to specific groups of people?

Appendix C

Survey for the First Tool (Create Domain Model)

This survey will help us with the research and design of the next generation of e-advertisement systems. The data collected is going to be further anonymised.

Type of Business: _____________ *Size of Business:* _____________ *Country:* _____________ *Company Name:* _____________

1. General Questions

	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
The tool is important for my business					
The GUI of the tool is NOT attractive					
This tool makes our work easier					
This tool is NOT enough to create and organize all of your advertisements					
This tool must be used by any websites to create and arrange any advertisements domains					
This tool is NOT saving time					
A new member of staff can understand and use this tool with minimal training					

2. Likert Scale Usefulness

Usefulness: 1: Very useless; 2: Useless; 3: Neither useless nor useful; 4: Useful; 5: Very Useful

Ease of Use: 1: Very hard to use; 2: Hard to use; 3: Neither hard nor easy to use; 4: Easy to use; 5: Very easy to use

A. Overall

Sub-system	Usefulness					Ease of Use				
Domain Model - Home	1	2	3	4	5	1	2	3	4	5
Registration	1	2	3	4	5	1	2	3	4	5
Login	1	2	3	4	5	1	2	3	4	5
Creation Functions	1	2	3	4	5	1	2	3	4	5
Logout	1	2	3	4	5	1	2	3	4	5

B. Registration

Functionality	Usefulness					Ease of Use				
Registration Process	1	2	3	4	5	1	2	3	4	5
Sufficient Data	1	2	3	4	5	1	2	3	4	5
Reset Information	1	2	3	4	5	1	2	3	4	5
Submit Information	1	2	3	4	5	1	2	3	4	5
Creating Account	1	2	3	4	5	1	2	3	4	5

C. Login

Functionality	Usefulness					Ease of Use				
Login Process	1	2	3	4	5	1	2	3	4	5
Reset Password	1	2	3	4	5	1	2	3	4	5

D. Domain Model Creation Functionality

Functionality	Usefulness					Ease of Use				
Adding Category - Subcategory	1	2	3	4	5	1	2	3	4	5
Removing Category - Subcategory	1	2	3	4	5	1	2	3	4	5
Adding Advertisement inside subcategory	1	2	3	4	5	1	2	3	4	5
Adding Advertisements Name	1	2	3	4	5	1	2	3	4	5
Adding Advertisements Description	1	2	3	4	5	1	2	3	4	5
Adding Advertisements file name	1	2	3	4	5	1	2	3	4	5
Saving the Tree into XML	1	2	3	4	5	1	2	3	4	5
Load the XML file(Domain Model) as tree	1	2	3	4	5	1	2	3	4	5

3. Open questions

A. What are your suggestions for improving the Domain Model? What other features would you like to see? Please list below

Appendix D

Survey for the Second Tool (Adaptation Strategy Model)

This survey will help us with the research and design of the next generation of e-advertisement systems. The data collected is going to be further anonymised.

Type of Business: _____________ *Size of Business:* _____________ *Country:* _____________ *Company Name:* _____________

Scale: **Usefulness:** 1: Very useless; 2: Useless; 3: Neither useless nor useful; 4: Useful; 5: Very Useful

Ease of Use: 1: Very hard to use; 2: Hard to use; 3: Neither hard nor easy to use; 4: Easy to use; 5: Very easy to use

Please evaluate each of the items below, from the point of view of Usefulness and Ease of Use, on the Scale as defined above:

A. Overall

System	Usefulness					Ease of Use				
Whole Tool	1	2	3	4	5	1	2	3	4	5

B. General Rules

Functionality	Usefulness					Ease of Use				
Having a rule on age	1	2	3	4	5	1	2	3	4	5
Having a rule on gender	1	2	3	4	5	1	2	3	4	5
Having a rule on device type	1	2	3	4	5	1	2	3	4	5
Having a rule on bandwidth	1	2	3	4	5	1	2	3	4	5

C. Behaviour Rules

Functionality	Usefulness					Ease of Use				
After (1,2,3,4) clicks then (1,2,3,4) items from its subgroups displayed	1	2	3	4	5	1	2	3	4	5
After (1,2,3,4) clicks on this advertisement then (1,2,3,4) items in groups are displayed	1	2	3	4	5	1	2	3	4	5
If this advertisement appear to the current user (1,2,3,4) and not clicked then disappear it for (1,2,3,4) visits	1	2	3	4	5	1	2	3	4	5
Show this advertisement after advertisement (1,2,3,4) is clicked	1	2	3	4	5	1	2	3	4	5

D. Rules Usage

Functionality	Usefulness	Ease of Use

Applying rule on item	1	2	3	4	5	1	2	3	4	5
Combining multiple rules on Item	1	2	3	4	5	1	2	3	4	5
Changing rules for item	1	2	3	4	5	1	2	3	4	5
Deletion rules for item	1	2	3	4	5	1	2	3	4	5

E. What other features would you like to see? Please list/comment below.

H. What other rules would you like to see? (general/behavioural/others). Please list/comment below.

I. What other type of Rules Usage would you like to see? Please list/comment below.

Appendix E

Survey for the User Profile Tool

This survey will help us with the research and design of the next generation of e-advertisement systems. The data collected is going to be further anonymised.

Age: _____________ *Gender:* _____________ *Country:* _____________ *Education Level:* _____________

Scale: **Usefulness:** 1: Very useless; 2: Useless; 3: Neither useless nor useful; 4: Useful; 5: Very Useful

Ease of Use: 1: Very hard to use; 2: Hard to use; 3: Neither hard nor easy to use; 4: Easy to use; 5: Very easy to use

Please evaluate each of the items below, from the point of view of Usefulness and Ease of Use, on the Scale as defined above:

A. Overall

System	**Usefulness** for User Profile Creation and Maintenance					**Ease of Use**				
Whole User Profile Tool	1	2	3	4	5	1	2	3	4	5

B. Registration and Export

Functionality	**Usefulness** for User					**Ease of Use**				
User Registration Process	1	2	3	4	5	1	2	3	4	5
Login Process	1	2	3	4	5	1	2	3	4	5
Facebook Login Process	1	2	3	4	5	1	2	3	4	5
Submitting Information	1	2	3	4	5	1	2	3	4	5
Updating User Profile	1	2	3	4	5	1	2	3	4	5
Saving Information in XML as Export Format	1	2	3	4	5	1	2	3	4	5

C. User Profile Attributes for Recommendation of Adverts

Functionality	**Usefulness** for Adverts Recommendation					**Ease of Use**				
Location	1	2	3	4	5	1	2	3	4	5
Device Type	1	2	3	4	5	1	2	3	4	5
Software Used on Device	1	2	3	4	5	1	2	3	4	5
Username	1	2	3	4	5	1	2	3	4	5

Passwords	1	2	3	4	5	1	2	3	4	5
Email	1	2	3	4	5	1	2	3	4	5
Age	1	2	3	4	5	1	2	3	4	5
Gender	1	2	3	4	5	1	2	3	4	5
Education Level	1	2	3	4	5	1	2	3	4	5
Education Type	1	2	3	4	5	1	2	3	4	5
Hobbies	1	2	3	4	5	1	2	3	4	5
Bandwidth	1	2	3	4	5	1	2	3	4	5

D. Automatic User Profile Attributes Generation

Functionality	**Usefulness** for User					**Ease of Use**				
Get Location Automatically	1	2	3	4	5	1	2	3	4	5
Get Device Type Automatically	1	2	3	4	5	1	2	3	4	5
Get Software Used Automatically	1	2	3	4	5	1	2	3	4	5

E. Importing User Profiles

Functionality	**Usefulness for Adverts Recommendation**					**Ease of Use**				
Facebook User Profile Import	1	2	3	4	5	1	2	3	4	5

F. Stereotype

Functionality	**Usefulness**					**Ease of Use**				
Match User Characteristic with Stereotype	1	2	3	4	5	1	2	3	4	5
Adding your own Stereotype	1	2	3	4	5	1	2	3	4	5
Modifying existing Stereotype	1	2	3	4	5	1	2	3	4	5
Deleting Stereotype	1	2	3	4	5	1	2	3	4	5

G. Gathering Additional User Information: Tracking User Behaviour

Functionality	**Usefulness**					**Ease of Use**				
Number of Show for Each User	1	2	3	4	5	1	2	3	4	5
Number of Click for Each User	1	2	3	4	5	1	2	3	4	5
Last 10 Sequence of Click for Each User	1	2	3	4	5	1	2	3	4	5

H. What other features/ functions would you like to see in the User Profile Tool? Please list/comment below.

I. What other features would you think appropriate to collect (automatically or manually) about the User, for Adverts Recommendation? Please list/comment below.

Appendix F

Survey for AEADS (Internet Users)

This survey will help us with the research and design of the next generation of e-business systems. The data collected is going to be further anonymised.

Age: _____________ *Gender:* _____________ *Country:* _____________ *Education Level:* _____________

A. General Usability for the Adaptive Advertisement added to the Company Website (add an X for each line)

	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
I think that I would like to use this system frequently					
I found the system unnecessarily complex					
I thought the system was easy to use					
I think that I would need the support of a technical person to be able to use this system					
I found the various functions in this system were well integrated					
I thought there was too much inconsistency in this system					
I would imagine that most people would learn to use this system very quickly					

I found the system very cumbersome to use					
I felt very confident using the system					
I needed to learn a lot of things before I could get going with this system					

B. Comparison of AEADS with other e-business Systems (circle one answer for each line)

I believe AEADS helps me to receive personlised advertisements more than a regular e-business system	Definitely false	Somewhat false	Neither true nor false	Very true	Definitely true
I believe that, compared to another e-business system, AEADS is:	Much more difficult to use	More difficult to use	Neither easier nor more difficult to use	Easier to use	Much easier to use
I believe that, compared to another e-business system, AEADS is:	Very Useless	Useless	Neither useful nor useless	Useful	Very useful
I believe that, compared to another e-business system, the interaction with AEADS is:	Very hard to learn	Hard to learn	Neither easy nor hard to learn	Easy to learn	Very easy to learn

I believe that, compared to another e-business system, the interaction with AEADS is:	Very hard to remember how to use	Hard to remember how to use	Neither easy nor hard to remember how to use	Easy to remember how to use	Very easy to remember how to use
I am willing to disclose some of my personal data to gain personalisation benefits	Not at all	Very little	No difference	Some information	Any information needed

C. Overall System (add an X for each line)

	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
I prefer to login via Facebook account rather than register					
The collected data are enough and acceptable					
The system interface is user-friendly					
The system performance is adequate					
The system reliability is achieved					
Overall, are you satisfied with our service					
I would buy/ click more					

I am NOT worry about my privacy					
The information requested by the system is sufficient for the personalisation I need					
The information requested by the system overcomes privacy concerns with me:					

D. Advertisements

For the following please state all the usefulness, ease of use, accurate, satisfaction and desire for the following functionalities, where 1 is the lowest value and 5 is the highest:

Functionality	Useful					Usable					Satisfactory					Desirable				
Registration process is:	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Logging in using Facebook account is	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
I can manage my profile	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Automatic extraction of device information (location, device type, device software, bandwidth) is:	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
I see the advertisements that are appropriate for me	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
The personalised advertisements is acceptable for me	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
I notice that the adverts were personalised	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
The system collects enough information from you	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Your behaviour on the website is tracked to give you suitable adverts	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5

E. Generic open questions

1. What are your suggestions for improving AEADS? Please list below.

2. What other features/ functions would you like to see in AEADS? Please list/comment below.

3. What else you want to tell us? (Anything please).

Appendix G

Survey for AEADS (Business Owners)

This survey will help us with the research and design of the next generation of e-business systems. The data collected is going to be further anonymised.

Type of Business: _____________ *Size of Business:* _____________ *Country:* _____________ *Company Name:* _____________

A. General Usability of Whole System (authoring and delivery) (add an X for each line)

	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
I think that I would like to use this system frequently					
I found the system unnecessarily complex					
I thought the system was easy to use					
I think that I would need the support of a technical person to be able to use this system					
I found the various functions in this system were well integrated					
I thought there was too much inconsistency in this system					
I would imagine that most people would learn to use this system very quickly					

I found the system very cumbersome to use					
I felt very confident using the system					
I needed to learn a lot of things before I could get going with this system					

B. Comparison of AEADS with other e-business Systems (circle one answer for each line)

I believe AEADS helps me adapt my advertisements more than a regular e-business system	Definitely false	Somewhat false	Neither true nor false	Very true	Definitely true
I believe that, compared to another e-business system, AEADS is:	Much more difficult to use	More difficult to use	Neither easier nor more difficult to use	Easier to use	Much easier to use
I believe that, compared to another e-business system, AEADS is:	Very Useless	Useless	Neither useful nor useless	Useful	Very useful
I believe that, compared to another e-business system, the interaction with AEADS is:	Very hard to learn	Hard to learn	Neither easy nor hard to learn	Easy to learn	Very easy to learn

I believe that, compared to another e-business system, the interaction with AEADS is:	Very hard to remember how to use	Hard to remember how to use	Neither easy nor hard to remember how to use	Easy to remember how to use	Very easy to remember how to use
For a business like ours, this AEAD would be	Not at all important	Not really important	No difference	Important	Very important
The various parts/ functions of the system are:	Not well integrated at all	Not really well integrated	Somewhat integrated	Well integrated	Very well integrated

C. Overall System (add an X for each line)

	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
The system was integrated in the website easily					
The system interface (author part) is user-friendly					
The system performance is adequate					
The system reliability is achieved					
Overall, are you satisfied with our service					

XML Data store enhance the integration process					
Creating adverts domain is easy process					
Creating adaptation rules (general and behaviour) is easy process					
Advertisers prefer to send the appropriate advertisement to appropriate users					
AEADS supports me, as business owner, to appropriately represent, for personalised adverts delivery : domain model, adaptation model, user model, all of them					

D. Advertisements

For the following please state all the usefulness, ease of use, accurate, satisfaction and desire for the following functionalities, where 1 is the lowest value and 5 is the highest:

Functionality	**Useful**					**Usable**					**Satisfactory**					**Desirable**				
The system increases the clicking opportunity on adverts	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
The system increases the buying opportunity for adverts	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
The system controls the location of advertisement	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
It Controls the number of advertisements in each webpage	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
The system applies the general rules	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
The system Applies behaviour rules	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5

The system Applies the plan recognition process	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
The overall authoring part is	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
The overall delivery part is	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
The Facebook login (against the fill in data process) is	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
The user information acquisition via system registration is	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5

E. Generic open questions

1. What are your suggestions for improving AEADS? Please list below.

2. What other features/ functions would you like to see in AEADS? Please list/comment below.

3. What else you want to tell us? (Anything please).