A Framework for Adaptive Personalised e-Advertisements

By

Dana A. Al Qudah

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Supervisor: Dr A. I. Cristea

University of Warwick, Department of Computer Science

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To where the heart belongs;

Dad and Mum,

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To the dear people I lost through this PhD; my grandmother, uncle and aunt

May your souls rest in peace

Finally to the place I call home; Jordan

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.

Dana A. Al Qudah

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. **Al Qudah, D. A.**, A. I. Cristea, S. Hadzidedic, Al-Sayyad, R.M.H, S. AL-Saqqa (2015). A Taxonomy-based Evaluation of Personalized E-advertisement. 15th IEEE International Conference on Computer and Information Technology. Liverpool, UK**:** To appear
2. **Al Qudah, D. A.**, A. I. Cristea, S. Hadzidedic, S. AL-Saqqa, A. Rodan and W. Yang (2015). Personalized E-advertisement Experience: Recommending User Targeted Ads. 12th International Conference on e-Business Engineering. Bejin, China**:** To appear.
3. **Al Qudah, D. A.**, I. A. Cristea, L. Shi and J. f. Alqatawna (2015). Designing an Adaptive Online Advertisement System: A Focus Group Methodology. 10th International Conference on Computer Science & Education, Cambridge, UK.
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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., Gkotsis, G., Stepanyan, K., **Al Qudah, D**., & Cristea, A. I. (2013, January). Social personalized adaptive e-learning environment: Topolor-implementation and evaluation. In *Artificial Intelligence in Education* (pp. 708-711). Springer Berlin Heidelberg.
3. Shi, L., **Al Qudah, D**., & Cristea, A. I. (2013). Social e-learning in topolor: a case study. *The 7th IADIS Conference e-Learning 2013 (IADIS-EL). Prague*, Czech Republic, 23-26 Jul 2013. IADIS Press.
4. Shi, L., **Al Qudah, D**., & Cristea, A. I. (2013, July). Designing social personalized adaptive e-learning. In *Proceedings of the 18th ACM conference on Innovation and technology in computer science education* (pp. 341-341). ACM.
5. Shi, L., Stepanyan, K., **Al Qudah, D.**, & Cristea, A. I. (2013). Evaluation of social interaction features in topolor-a social personalized adaptive e-learning system. In *Proceedings of 13th IEEE International Conference on Advanced Learning Technologies (ICALT 2013)* (pp. 294-295). IEEE Computer Society.
6. 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.
7. 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.
8. L. Shi, **D.A. Al-Qudah**, A.I. Cristea, (2012) "Exploring Participatory Design for SNS-based AEH Systems". The 11th IADIS International Conference WWW/INTERNET (ICWI). Madrid, Spain, 18-21 Oct 2012. IADIS Press.

9. Shi, L., **Al Qudah, D**., & Cristea, A. I. (2012, November). Apply the We! Design methodology in E-learning 2.0 system design: a pilot study. In *2012 Imperial College Computing Student Workshop* (Vol. 28, pp. 123-128). Department of Computing, Imperial College London.

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Abstract

The art of personalised e-advertising relies on attracting the user's attention to the recommended product, as it relates to their taste, interest and data. Whilst in practice, companies attempt various forms of personalisation; research of personalised e-advertising is rare, and seldom routed on solid theory. Adaptive hypermedia (AH) techniques have contributed to the development of personalised tools for adaptive content delivery, mostly in the educational domain. This study explores the use of these theories and techniques in a specific field – adaptive e-advertisements. This is accomplished firstly by structuring a theoretical framework that roots adaptive hypermedia into the domain of e-advertising and then uses this theoretical framework as the base for implementing and evaluating an adaptive e-advertisement system called "MyAds". The novelty of this approach relies on a systematic design and evaluation based on adaptive hypermedia taxonomy. In particular, this thesis uses a user centric methodology to design and evaluate the proposed approach. It also reports on evaluations that investigated users' opinions on the appropriate design of MyAds. Another set of evaluations reported on users' perceptions of the implemented system, allowing for a reflection on the users' acceptance level of e-advertising. The results from both implicit and explicit feedback indicated that users found the MyAds system acceptable and agreed that the implemented user modelling and AH features within the system contributed to achieving acceptance, within their e-advertisement experience due to the different personalisation methods.

Keywords: adaptive e-advertising, personalisation, user modelling, user centric methodology, adaptive navigation support, adaptive presentation.

Abbreviations and Acronyms

AEH	Adaptive Educational Hypermedia
AH	Adaptive Hypermedia
AHAM	Adaptive Hypermedia Application Model
CSCL	Computer Supported Collaborative Learning
CSS3	Cascading Style Sheets Version 3
DM	Domain Model
GM	Goal Model
GUI	Graphical User Interface
HCI	Human Computer Interaction
HTML 5	Hypertext Mark-up Language Version 5
***k*NN**	*k*- Nearest Neighbour
ITS	Intelligent Tutoring Systems
IR	Information Retrieval
LAOS	Layered WWW AH Authoring Model and their Corresponding Algebraic Operators
PHP	Hypertext Preprocessor, an open source general-purpose scripting language
PIR	Personalised Information Retrieval
SLAOS	Social Layered WWW AH Authoring Model and their Corresponding Algebraic Operators
SN	Social Networks
UM	User Model

Chapter 1

1. Introduction

1.1. Background and Motivation

Interdisciplinary research is considered challenging, as it needs to deal with two or more intersecting fields of work. *Online advertising* (or e-advertising) is one area of such interdisciplinary research that relies on two important areas, computer science and business and commerce, with the combination raising new important challenges. E- Advertisement falls under the umbrella of e-commerce. It includes several popular models for ad-focused sites, such as portals, search engines, sites supporting classifieds and information exchange [1]. E- advertisement aims at delivering a marketing message using the World Wide Web [2]. Recent numbers have shown that there are more than 2.9 billion internet users exploring various facilities and applications provided on the web [3].

Although companies focus on online advertisements and are expanding the available virtual space for this form of technology, *current attempts have not increased the click-through rate* [4]. From a business perspective, in the United States alone, $23.1 billion have been generated as profit from e-advertisements, over the span of only six months - from January 2014 until June 2014, with an increment percentage of 15.1% since December 2013 [5]. Companies are practising different strategies to generate revenues via online advertising [6]. Nevertheless, currently, online advertisements are still considered *more inconvenient than enticing* with their forms of pop-ups, musical advertisements and floating advertisements forcing the users to see them, even if the user does not want to [7]. As a result, users have become more efficient at blocking the advertisements rather than clicking on them, illustrating so called “acute editing skills”, choosing what to see and what to block [8]. In 2010 , the statistics show that the click-through rate of banner online advertisement has decreased from 3% to 1%, leaving online advertisement in need of further exploring [4]. Similarly, other researchers suggest that users give little attention to advertisements, as they use minimum cognitive capabilities to process online advertisements [9-11].

Psychological theories suggest that customers usually tend to go through three different stages from the time they are exposed to advertisements, until the time they actually consider buying the suggested product or service.

The first stage is the *exposure* to the advertisement, followed by the cognition or *judgment* over what they have been exposed to, then the final *decision* of whether to buy or not, based on the previously formed opinion [12]. Thus, in order to influence the last stage, advertising systems have to intervene efficiently in the first stage. One of the famous advertising-related psychological models is “The Perceptual Fluency/Misattribution Model (PF/M)” that uses a metacognition-based mechanism. This mechanism suggests that human minds deal better with already familiar approaches, rather than new ones [13]. Most advertising systems use an approach influenced by this model, and attempt, in the first stage, to just repetitively present the same adverts. As discussed above, this brute-force approach leads to undesired results. Another related model [14] was found to solve the issues related to the (PF/M) model, by additionally focusing on cognitive abilities, including effective ones. The implications are that, modelling some user traits is a far better approach than pure repetitious exposure. Further on, other researchers noticed that even 'simple' personalised advertising is more successful in generating a higher click-through rate, in comparison to non-personalised advertisements [15]. While personalised advertisements aim at tailoring the presented advertisements based on the users’ preferences, interests, backgrounds and demographics, etc. [16], *personalised advertisement is not a straightforward task and it can be rather complex* [17]. Clearly, additional research is needed, to understand how personalisation can be applied to e-advertising.

1.2. Problem Statement and Challenges

Summarising, this research addresses the following problems in relation to e-advertisements:

- The current technological form of the delivery of e-advertisements is not accepted by users, as demonstrated in the previous literature [4], [1]. [7] and [8], where researchers indicated a lack of acceptance via a *low click through-rate*.
- There is a clear *demand for personalised advertisement*. However:
  - There is no research based on a *conclusive, structured study, rooted in the adaptation theory* for e-advertisements.
  - The *data sources* that are used to initiate user profiles and recommend e-advertisements are *limited and not adequate* [18].

This research addresses the problem of rejected e-advertisements and aims to achieve users' acceptance of these advertisements, by providing the users with more personalised and adaptive ones. It also establishes a research–based study to link adaptation to e-advertisements. The acceptance of users is measured based on perceived usefulness, usability and, in specific cases, their needs and desires. This problem was addressed through establishing a theoretical framework that is based on previous extensive research of the literature. The theoretical framework found by the author of this thesis has then, instantiated the theoretical framework via an implemented system, called MyAds, which was built, based on user modelling and adaptation techniques, as well as machine learning and data mining algorithms.

1.3. Research Questions

In order to address the problems above, the following research questions were formulated, to address each aspect of the problem and provide a better understanding of the contribution.

Q1: Can adaptive e-advertising lead to users' acceptance in terms of being usable and useful from a user perspective?

In this context, *adaptive* means automatic, system-driven changes to the output shown to a user, as is understood in the area of adaptive hypermedia [19]. Changes in the output considered in this thesis are changes in content or formatting.

By *users' acceptance*, “demonstrable willingness within a user group to employ information technology for the tasks it is designed to support” [20] is used. Acceptance is used in this thesis based on usefulness and usability from a user perspective, and is further detailed in Chapter 3.

The expectation was that users' acceptance of adaptive e-advertising, which caters to their needs, would be higher than the middle of the scale (representing indifference). Where possible, the users were asked to compare their acceptance between adaptive and non-adaptive e-advertising, with the expectation that the former would rank higher.

This question is posed, in order to gradually and systematically understand how the various aspects of personalisation affect the advertising process, and its main stakeholder, the user.

This research question addresses the two aspects of personalisation: the user and the adaptation performed for the user. As 'adaptation' is rather a broad term, this question needs to further divided, but prior to the sub-questions, the following terms are defined;

- Usable: Usability is defined as “the extent to which a product can be used by specified users to achieve specified goals within a specified context of use” [21].
- Useful: “the degree to which a user believes that using the system will enhance his or her performance” [20].

This work measures the perceived usability and usefulness, from a user perspective, as is stated above and is further detailed in Chapters 4, 5, 6 and 7.

Q1.1. What features from adaptive hypermedia users would want to have in adaptive advertising and how are they related to user acceptance?

Whilst, in general, the research aims to identify whether adaptive hypermedia techniques are going to lead to users’ acceptance for adaptive advertising, it is possible that not all features in adaptive hypermedia are adequate for the application purpose. For this reason, it is essential to separately test a variety of features from a user perspective, to find out if individual features are accepted (higher than the middle of the scale) or not. The terms in this question are the same as those used in Q1.

Question Q1.1 is addressed in Chapter 2, theoretically by exploring the current state-of-the-art. In Chapter 4, an exploratory design experiment is further conducted to explore these features. In Chapter 5, practical developments of the features explored earlier are then evaluated. In Chapter 6, a revisited design experiment is conducted to generate an extended set of features, based on the results of the previous experiment. In Chapter 7, a large scale evaluation is conducted to assess the final set of adaptive features.

Q1.2. How can user modelling contribute to users' acceptance of the e-advertising experience?

As users are the central focus of this research, user profiling and modelling are paramount factors in assessing the user e-advertisement experience; this is further explored in Chapter 2 Section 2.3.2 from a theoretical angle. This question aims to identify the user modelling techniques that are used to construct user profiles.

Question Q1.2 is addressed in parallel to Question 1.1, as follows. From a design perceptive, it is targeted in Chapters 4 and 6 as an exploratory design experiment and a revisited design experiment, respectively. It is addressed from an implementation perspective, in Chapters 5 and 7, where user modelling and adaptive features were implemented and then evaluated.

Q1.3. What are the main sources of user information would users want to have for adaptive advertising?

As it is important to build proper user profiles and models, in order for appropriate adaptation to be performed, the different data sources to initialise these user profiles play a decisive role in constructing distinctive models for each user. Throughout the research, two sources of data have been analysed: data from direct input from the users, through a registration form, and data fetched from Facebook. The uses of these two approaches for implicit and explicit data harvesting has been investigated in the current state-of-the-art as described in Chapter 2.

Question Q1.3 is addressed in parallel to Questions 1.1 and 1.2. From a user's perspective, it is addressed in Chapters 4 and 6, as an exploratory design experiment, and a revisited design experiment, respectively. From an implementation viewpoint, it is further explored in Chapters 5 and 7, where user modelling and adaptive features were implemented and then evaluated, respectively.

Q2: How can adaptive e-advertising be generated theoretically?

The field of personalised e-advertising has not been widely exploited theoretically, as there are different advertising models and different personalisation models, but not an intersecting interdisciplinary model to combine the two. It is important to establish if existing theories can be directly applied to online adaptive advertising, or if a new theory needs to be developed.

This research question is addressed in Chapter 2, by pointing out gaps in related work. Additionally, Chapter 4 introduces the theoretical framework, by exploring both the gaps in the literature and the outcomes from the exploratory study. In Chapter 5, the theoretical framework is then revisited to address the practicalities of design and system development. Chapter 6 finalises the framework, based on additional theoretical and practical work.

Q3: What technology is acceptable for e-advertising?

This question investigates the acceptable technological approach, as well as helps to generate the technological model for e-advertising. It also aims at testing the current, state-of-the-art e-advertising platforms and the proposed adaptive e-advertising platform.

The question is addressed, from a design perspective, in Chapters 4 and 6, as an exploratory design experiment, and a revisited design experiment, respectively. From an implementation perspective, it is explored in Chapters 5 and 7, where user modelling and adaptive features were implemented and then evaluated, respectively.

1.4. Objectives

Based on the above research questions, the following research objectives have been formed:

Objective 1: *Conduct an extensive theoretical background study, to investigate the area of research that needs further exploring, by extracting the main gaps found in the literature and focusing on the contribution on this area.*

This is achieved through studying the previous literature on personalised e-advertisements, adaptive hypermedia and information retrieval. This objective works as an umbrella for all the research questions, as it generates the theoretical basis that the research is based upon. The outcomes of this objective is summarised in Chapter 2.

Objective 2: *Conduct a series of experiments that investigate the appropriate approach and features to design adaptive e-advertisements, and then test the practical development of these features in an adaptive e-advertising system, addressing the acceptance of this form of ads in the targeted evaluations.*

Here, a systematic, research-oriented approach to introducing adaptation in e-commerce has been deployed. Based on the popular existent taxonomies, such as Brusilovsky's and Knutov's taxonomies [22, 23], this research explored which adaptive hypermedia features contribute to user acceptance. This objective addresses research question Q1, Q1.1, Q1.2 and Q1.3. The objective is covered in Chapters 4, 5, 6 and 7.

Objective 3: *Propose a suitable (new or extended) theoretical framework/model for the adaptive features necessary in advertising, such as a layered model.*

The aim of this objective is to create the means by which to test theoretically the extent to which this new framework addresses the features necessary for adaptive e-advertising (as defined by research Question 2). This objective is necessary for answering research question Q2. This objective is covered in Chapters 4, 5, 6.

Objective 4: *Design, implement and update a dedicated system for testing the adaptive advertisements and measure the level of acceptance from the end users through the evaluation of their subjective and objective feedback.*

This objective answers research question Q3. The chapters that describe the implementation of this objective are 5 and 7.

Objective 5: *Ensure that each research question is represented in the framework and in the delivery system.*

In other words, use the framework to evaluate the system features acceptance, in terms of usability, usefulness, as well as, in the final large scale evaluation, users' satisfaction and desires, by analysing the social interaction conducted in the system, log files stored, and questionnaires answered by the users.

This objective is formed to address to all the research questions. The evaluations and the application of the objective can be found in Chapters 4, 5, 6 and 7.

Objective 6: *Ensure that each step of the research is conducted based on established research methodology.*

This objective influences all other objectives, and helps to address, in a methodologically consistent way, all research questions. The methodological choices in this work are further described in more details in Chapter 3.

The table below summarises the mapping of the research problems with the research questions and research objectives.

Table 1.1: Mapping research problems to research questions and objectives

Research Problem	Research Question	Research Objective
The current technological form of the delivery of e-advertisements is not accepted by users due to low click through rate.	Q1 Q 1.1 Q 1.2 Q3	O2 O4 O5 O6
The data sources that are used to initiate user profiles and recommend e-advertisements are limited and not adequate.	Q1 Q 1.3	O1 O2
There is no research-based conclusive, structured study, rooted in adaptation theory of e-advertisements.	Q2	O1 O2

1.5. Thesis Outline

The thesis is constructed of eight chapters in total that are organised as follows:

Chapter 1 is the introduction chapter, which is the current chapter that has introduced the problem statement and motivation; research questions and objectives and finally the thesis outline.

Chapter 2 is the literature review chapter. This chapter elaborates on the state-of-the-art in each different discipline of the research. The first section of the background study includes e-commerce and e-advertising theoretical and conceptual frameworks, as well as related e-advertising models, followed by research on adaptation, including user modelling techniques, models, approaches and adaptive hypermedia techniques. Chapter 2 also discusses the adaptive recommendation systems specification of information retrieval systems and their related techniques. The final section addresses the gaps found in the previous sections and summarises the chapter.

Chapter 3 is the methodology chapter. In this chapter, the user-centric methodology is explained in details. Moreover, a comparison between this approach and other approaches is conducted. The methodology of all research aspects is touched upon. In particular, the application of the methodology throughout all the experiments, and their logical progression, is discussed.

Chapter 4 establishes the concept of adaptive e-advertising used in this thesis, and the initial setting of the theoretical framework. The chapter starts with the description of an exploratory study that was conducted to extract an initial understanding on how an adaptive e-advertising system can be. The experiment was focused on the design process of the system. Then, by using the gaps in the related work and results from the exploratory study, the initial theoretical framework and system architecture are defined.

Chapter 5 describes the research that aimed to test and evaluate the initial reflection of the suggested framework, architecture and design, generated in Chapter 4. The first system iteration implementation is discussed, as well as an experiment to evaluate the theoretical framework, architecture and implemented features that are derived from the research objectives. Chapter 5 presents an expanded and more flexible version of the theoretical framework, which additionally encompasses functionality that was not originally addressed by the first implementation of MyAds. Moreover, the system architecture and its updated versions are also discussed, based on an improved architecture representation. Discussions for the enhanced version are discussed, by highlighting the features that were missing from the first version.

Chapter 6 discusses the final and foremost refined design of MyAds. It combines the set of user modelling and adaptation features that have been explored in the previous chapters with the new updated and modified features. It also presents the final update of the theoretical framework and architecture, which are necessary to emulate the extended set of adaptation features. It also present the focus group experiment conducted to finalise the design phase and generate a detailed requirements list. The chapter also describes the adaptation features that exist within MyAds and the user interfaces of MyAds, in a process breakdown approach.

Chapter 7 is the last chapter in the cycle of evaluations to address the research questions. An experiment is conducted based on a set of hypotheses that address to the research questions, in a more detailed context. A large-scale evaluation has been conducted, to emphasise the results concluded from earlier chapters. It elaborates about the results of two practical evaluations and discusses the results of these experiments.

Chapter 8 is the final chapter; it presents the conclusions and recommendations for future work. In this chapter, the research questions are answered and the implementation of the objectives is clarified. It also contains a theoretical system comparison between MyAds and related theoretical frameworks, architectures and commercial platforms, to address the actual research contribution in terms of features, mathematical models and interfaces. Finally, it describes the challenges and limitations of the research presented in this thesis, as well as the recommendations for future work.

Chapter 2

2. Background and Related Literature

"Advertising maybe described as the science of arresting the human intelligence long enough to get money from it" said Stephen Bulter Leacock, as per the Crown's Book of Political Quotations (1982) as referenced in (Heath, 2012).

2.1. Introduction

This Chapter aims at exploring the background literature through researching the theory that has inspired the production of this work and research. Also, the related work in the area of adaptive e-advertisements is explored to identify the gaps in the existing work. The state-of-the-art described in the literature is also identified. This is conducted so that areas of research that have not been well explored can be further investigated. This will eventually demonstrate how this research has contributed specifically to the field of adaptive advertisements.

As this work represents interdisciplinary research, this chapter covers the state-of-the-art for both areas; e-commerce and e-advertisement on the one hand, and adaptive hypermedia and personalisation on the other.

In relation to this research, this chapter aims at addressing research Objective 1 as follows;

Objective 1: *Conduct an extensive theoretical background study, to investigate the area of research that needs further exploring, by extracting the main gaps found in the literature and focusing on the contribution on this area.*

Outcomes of this Chapter: This chapter works at the theoretical background for all the work proposed in this thesis. It explores theoretical ideas, techniques, methods and solutions for the research problems discussed in Chapter 1 (Section 1.2).

The chapter is divided into six sections. The first section is the introduction that outlines the chapter. The second section is concerned with personalisation in e-commerce and e-advertisements – in terms of ideas, functionalities, frameworks and examples. The third section is the adaptive hypermedia section. This section addresses the user modelling techniques, models, approaches and data mining aspects related to constructing user models. It also discusses the techniques, functionalities, models, architecture and theoretical frameworks of adaptive hypermedia. It furthermore reviews different models and applications in adaptive hypermedia – mainly in the well explored research area of e-learning. The fourth section describes information retrieval systems and the personalised ones, their respective techniques and models. The final section is the summary, which highlights the gaps found in the literature and the areas that need further exploring so the contributions in relation to the literature can be explained.

2.2. Personalisation and Adaptation in E-commerce and E-advertisements

Personalisation is considered one of the critical elements on the modern approaches of e-commerce. This concept, however, remains vague due to the fact that the measures of design, delivery and evaluation of e-commerce applications are not well explored and structured [24]. In order to help contribute to the current state-of-the-art, this research proposes a personalised adaptive e-advertisement delivery system that works with well-defined measures for design and evaluation. To emphasise the importance of personalisation in different domains, and more particularly in e-commerce, the Personalisation Consortium summarises the aims of personalisation as an approach to enhance the service to the users by; anticipating their needs, interacting with them in an efficient and satisfactory way, and building a sustainable relationship between the different business model stakeholders [25]. The aim of personalisation is based on the main functionality of e-commerce applications that is defined as the process of selling and buying online [2]. However, this very broad definition does not actually address one of the common e-commerce activities conducted in the virtual world of the Internet such as advertising, so scholars still try to explore more detailed and well-structured frameworks for e-advertising. E-commerce framework consists of five main support areas; people, public policy, marketing and advertising, support services and business partnerships [26].

Online products serve as advertisements for themselves, because users can actually view them, look up pictures, and check specifications without the need for the physical presence in the store. This makes an e-commerce website also an "*effective advertising tool*" [27]. This leads to a combination of two different business models. One is in the form of a warehouse system that can lead simultaneously to another model that serves as an advertisement platform. This research uses this approach to design and develop the adaptive delivery system for e-advertisements.

Whilst e-commerce is one of the most common activities online, the absence of human interaction often leads to a "*one size fits all*" approach, meaning that all customers will be served by the same means [27]. As a reflection of minimum personalisation users tend to be reluctant to actually buy the products online [24]. Thus, with e-commerce evolving dramatically over the past years, users are now demanding more sophisticated and personalised advertisements [28]. In the domain of e-commerce, the emerging requisite for companies to provide personalisation was derived from their strategy to keep existing customers and win new ones via using personalisation as a tool for business loyalty strategies [29].

Turban, King *et al.* (2015) define personalisation in e-advertisement as the process of matching the advertising content, service or product with the interests, preferences and needs of the user. Usually, each user will have a distinct user profile that has all the related information. Data and information collection methods can vary based on the technique to be used for harvesting this information. This approach is the blueprint for personalising e-commerce platforms that has been adopted throughout the thesis. One of the common approaches is to use cookies; these cookies are data files that contain the user's activities online and are placed on the user's hard drive [30]. A relatively recent study in 2012 [31] has shown that customers exposed to more personalised content have ended up as the largest spenders and preferred personalised advertisements. While 20% of these users actually conducted a purchasing transaction after viewing "recommended for you" in an advertisement, numbers show that 48% of the customers found the advertisements shown to them rather annoying, because the personalised content delivered to the users did not actually address their needs, so the actual personalisation was weak and not well constructed. However, 36% of the customers took more time to actually explore and search the suggested advertisements so they can look further into the recommended advertisement and investigate if it matches their interests or not. [31].

As users using the web tend to be anonymous, personalised advertising can be a difficult task to achieve. In order to overcome such a problem, websites now tackle different approaches to harvest as much available information as possible about the users [32]. In this context, it has been found that profile-driven personalisation based on demographics, interests and social data seems to be an appropriate and fruitful type of personalised advertising [33]. This approach was used within the research by harvesting as much as possible data about the user so maximum personalisation can be achieved.

The main players in the advertising process as defined by Kazienko, are the *publisher*, *advertiser*, and in some case the *advertising intermediate* that links the publisher and the advertiser. These intermediates work as a connecting tool to certify that users get the appropriate advertisements – such as DoubleClick and Google AdSense – and deliver banners related to the publisher website [32]. The main factors that contribute to personalised web advertisements are described in Figure 2.1 below.

In this research these factors are taken into consideration, in the process of design, implementation and evaluation of the proposed personalised adaptive e-advertisement system. The research provided by Kazienko was an inspiration for the research presented in this thesis.

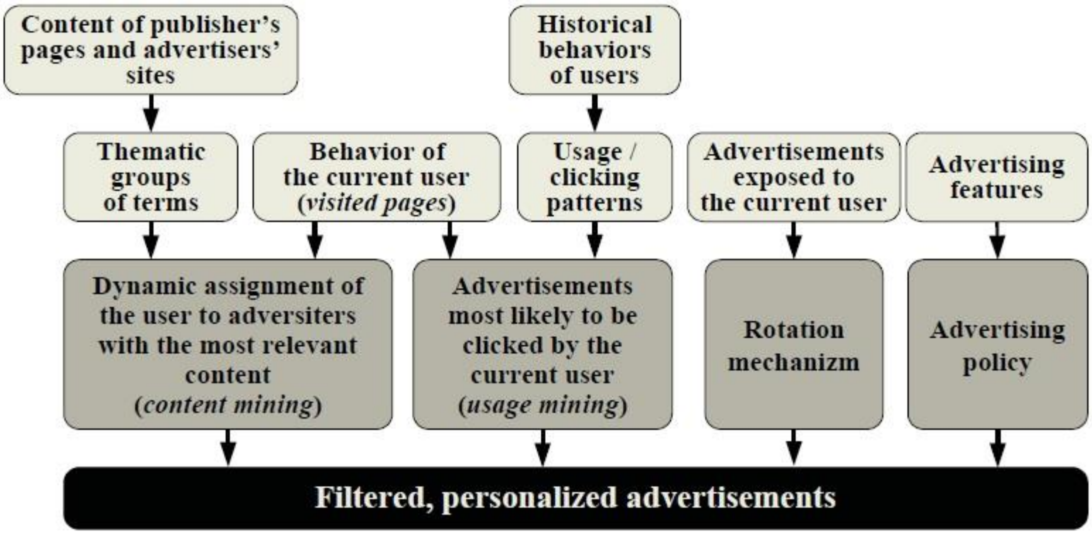

Figure 2.1: Factors effecting personalised ads [32]

As the Figure above illustrates, the main factors are; the content for both the publisher and the advertiser, historical and current behaviour of the users, features of the advertisements and, finally, the recently clicked-through advertisements [32].

The main technique used in personalisation in the domain of e-advertising is "*customer profiling"*, to provide the *"one-to-one"* marketing and advertising. These user profiles are categorised as *basic*-, *preferences*- and *rule profiles* through the processes of modelling, data input, data processing and information output [29]. The previously mentioned approach is a general one that has also influenced the research in this thesis. Many approaches provided the ability to recommend appropriate products via filtering techniques, such as *collaborative filtering*, *content-based filtering* and *hybrid filtering* which are all extensively investigated and used in different e-commerce applications. Well-known platforms, such as Amazon, are based on *item-based collaborative filtering*, which is a technique of suggesting similar items for the user [34, 35]. The most common information types collected about the users are the previous purchasing and navigation history, the content of both the publishers' and the advertisers' websites, current users' behaviours and the clicks on banner advertisements [32]. Scholars emphasise that in e-commerce and e-advertisements behavioural targeting and user personalisation rely heavily on filtering techniques as the common approach adopted by numerous platforms. As mentioned above, these techniques consist of collaborative filtering that is based on a mathematical formula, which calculates the similarity between the preferences of users and activities performed by different users, and therefore recommending products that are based on the matches between these users. Another filtering method is the rule-based filtering; it bases its recommendations on the user's direct input of information via system queries. Content based filtering takes place when companies suggest products that the user may show interest in, through examining the user's profile. Finally, the activity-based filtering is a filtering technique that focuses on understanding the users' patterns through the analysis of their online activity and then providing the recommendations based on these activities [30].

This lengthy introduction aimed at clarifying the research direction as well as giving a summarised idea about what is going to be discussed in the more detailed sub-sections. The highlight of the work is the focus on the importance of personalisation; particularly in the domain of e-commerce and e-advertisements. This is an important research contribution, as the current state-of-the-art lacks the structured frameworks and models.

2.2.1. Conceptual Frameworks of Personalised e-Advertisements and e-Commerce

The current state of the art has provided some conceptual frameworks that have been proposed to address the personalisation within e-commerce applications. These frameworks have introduced a cluster of features to offer the user a personalised experience. The reviewed frameworks are Schubert and Leimstoll [36], Sicilia [37] and Murthi and Sarkar [38].The frameworks discussed below also inspired the work presented in the thesis. Koutsabasis [24] has highlighted the importance of these frameworks due to the following:

- The frameworks rely on practical work on personalisation and collect different observations and practices in e-commerce.
- They focus on the business model that is the Business to Customer (B2C) which is a key type of application in personalisation in e-commerce.

- The frameworks have been evaluated through use cases that utilise the features presented by these frameworks.

The first framework to be discussed is the Schubert and Leimstoll. The framework is pretty simple as it summarises the main steps in a personalised e-commerce application. It also visualises the various functionalities of the cycle of the personalised features taking into consideration both explicit and implicit user profiles. It's particularly important that it can be used as a guideline for the design and implementation of a personalised e-commerce application. Figure 2.2 summaries the process of personalised e-commerce applications as described by [36]. The process is divided into four main steps. The first step includes the modelling of the user profile through deciding on the structure of the profile, source of data and metadata collected, and the storage type. Then the model starts inputting the data into the "data input controller". This controller divides the profiles into explicit or implicit profiles. In the explicit profiles, parameters are collected through direct user input into variables. Here the framework provides identification, preference of the user and rating. The implicit profiles study the interaction of the user over the system and build both a transaction and an interaction profile to keep track of the user's behaviour. This approach is similar to the one used in MyAds (as described in Chapter 6). However, in the model, the data processing is then conducted, by mining the data and then carrying out content based filtering over the metadata tags of the products, before using this information to actually recommend products to the users.

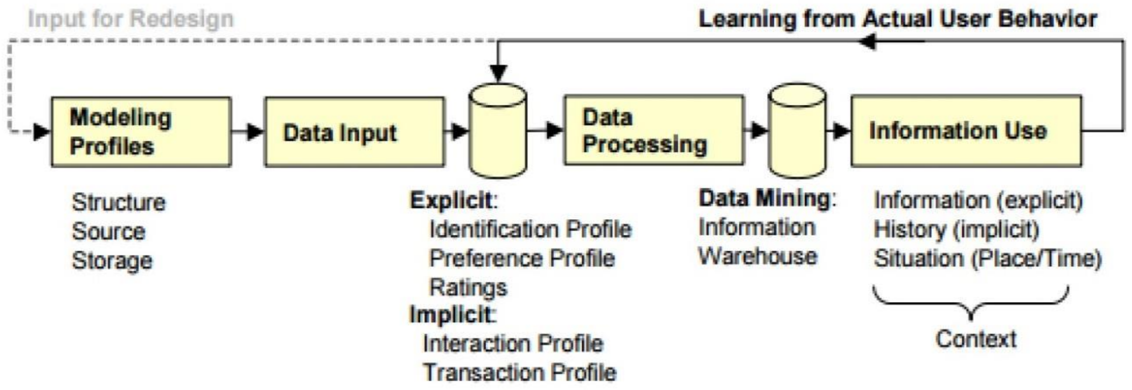

Figure 2.2: Schubert and Leimstoll summery for personalised e-commerce applications [36]

The second framework is the Sicilia framework. This framework focuses on the goal of the e-commerce application. Some applications are marketing and advertising oriented and some are technical and functioning platforms. An important part of this framework is to distinguish which features to use base of the different purpose of the applications. This important for designers and, more precisely, students trying to understand the different stakeholders and business models around [37]. In Figure 2.3 the distinction is clear on what is used when marketing and advertising within e-commerce applications. The well advocated approaches include adaptive hypermedia, information and collaborative filtering, etc. All of these are important for the work presented in this thesis as it emphasises the importance of the approaches used.

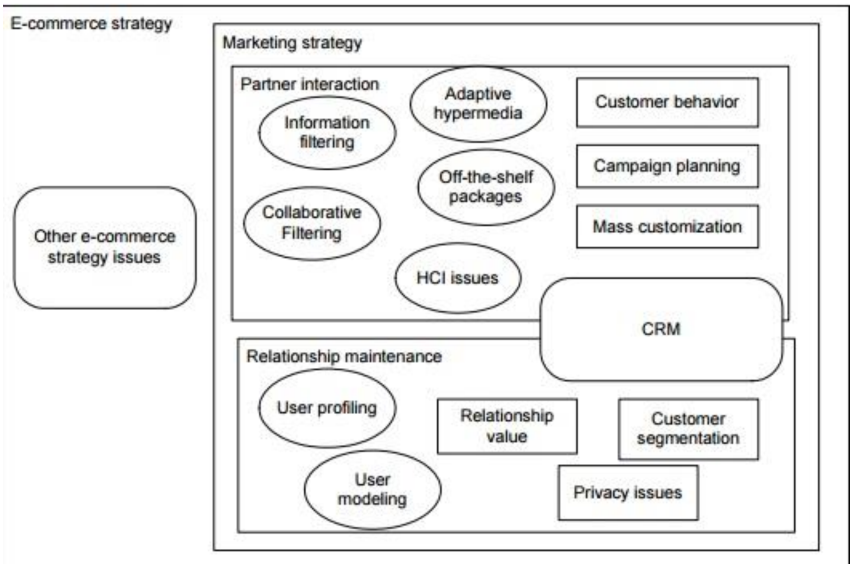

Figure 2.3: Sicilia framework for personalisation of e-commerce [37]

The final framework is by Murthi and Sarkar. This framework focuses on both the stakeholders in the e-commerce application, as well as the main stages to be taken into consideration. This is all done from the perspective of the user. The approach is established in three main steps. The first step is learning the users' preferences, then matching the products with these preferences as well as matching people with the same preferences together and finally evaluating the matching process [37].

All the previously mentioned frameworks provided an understanding of personalised e-commerce applications and made it clear that using a dedicated system for marketing and advertising is well acknowledged in the field of e-commerce.

2.2.2. E-advertisement and E-commerce models

As the previous Section focused on the theoretical and conceptual frameworks available, this Section addresses the actual "competitors" – or applications – that are working in the domain of personalised e-commerce and e-advertising. The models discussed in this Section are the ones that are mostly relevant to the approach used in the thesis. However, as the Section will explain in more detail there are not many models to actually discuss, since most of the models focus on the traditional approach of e-advertisement; banner advertisements. In this section, both research based and commercial based models and systems are discussed.

A variety of e-commerce models are implemented by various players, including the major ones, such as Amazon, eBay and Google. However, even amongst these, Google is the most successful in providing targeted advertisements, working not only as a search engine, but combining various e-commerce models [26].

In e-advertising, the models are constructed based on which party leads the advertisement management process. Thus, there are three main models: the *broker-model*, the *portal model*, and the *advertiser model*, each functioning differently.

The *broker model* facilitates the communication between the advertiser and the publisher. It works as the host and manager of the advertisements and displays them directly to the end-user. One problem with this type of model is that the personalisation is not as powerful as in other models, because the user's information is not adequate enough for targeting and personalisation [39].

In the *portal* (or the *publisher model*), the portal works as the host of the advertisements, and manages the advertisement process. It is stable and large enough to offer advertising services. This model is known for providing personalised content, as it can use different adaptation and personalisation techniques, due to the fact that it collects information about the users that can be used in the personalisation process [15]. A discussion of Google as a well-known example will follow later on in detail.

The *advertiser model* is another advertising model, where the publisher is large and famous enough to work as the publisher of its own advertisements and other companies' advertisements. A famous example is Amazon, which both publishes its own advertisements, as well as provides other businesses with advertisement space on its own platform [27, 40].

One of the successful e-commerce systems that provide personalisation for its customers is BroadVision. It adapts two personalisation strategies: the *pull* and *push*. The system leads the push strategy, by providing the recommendations and suggesting related applications and features for the customers. The pull strategy works the other way round, as it allows the customer to ask for information and then provides it in a personalised approach. Moreover, BroadVision provides a qualifier-matching filtering strategy that focuses on other stakeholders, i.e., the companies. This strategy allows the companies to target the delivered content to the users [27]. In MyAds, the adaptive delivery system explored through this thesis, there is a personalisation and adaptation process the user goes through. Adaptation starts from the moment users' login to the system till the moment they logout. It depends on multiple adaptation techniques rather than only on one filtering approach. Details of the functionality and adaptive features of MyAds can be found in Chapters 4, 5 and 6.

Zhou, Chen et al. (2007) suggest a personalised advertisement model that presents advertisements based on; the current behaviour of the users, historical behaviours of users, registration information, the content of publisher's website and the advertiser's webpage as banner advertisements. It does this as described by the diagram in Figure 2.4.

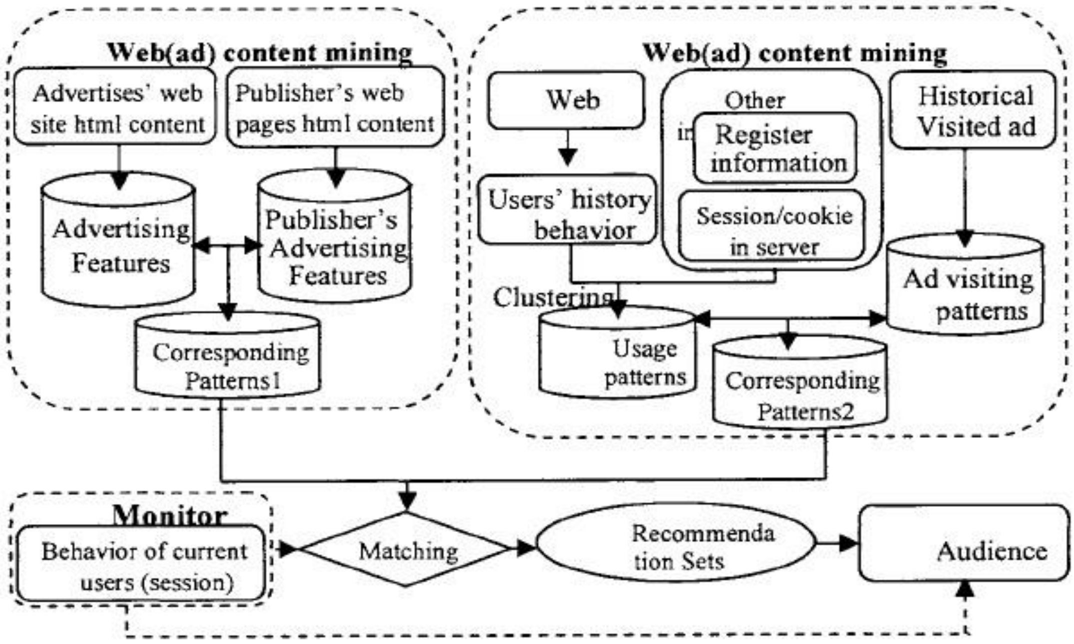

Figure 2.4: Suggested personalised advertising model by [28]

This model bases its main contribution on the idea of clustering the users based on categories – by mapping the advertisement content and the type of user. MyAds, the system presented in this thesis, deals with each case individually as it does not cluster any users.

In the system proposed by Zhou, Chen *et al.*, each user's interest is measured separately from the others. The system then collects previous purchasing history, by analysing the information for the session weblog file and carries out the matching. Personalisation patterns are constructed when the server is idle or off-line.

AdRosa, (Advertising Remote Open Site Agents), is another adaptive personalised advertising model; it aims at generating automatic personalised banner advertising through using content mining techniques and web usage. The main contribution of AdRosa from a research point of view is that of reducing the amount of data input from the user, in order to maintain user privacy [15]. The banner advertisements are generated by using data mining techniques to extract information about the current user's behaviour, combined with the content of the web page being browsed and the previous user session from the browsing history. AdRosa does not store any information about the user for long term use. The Figure below illustrates the main features of AdRosa [15].

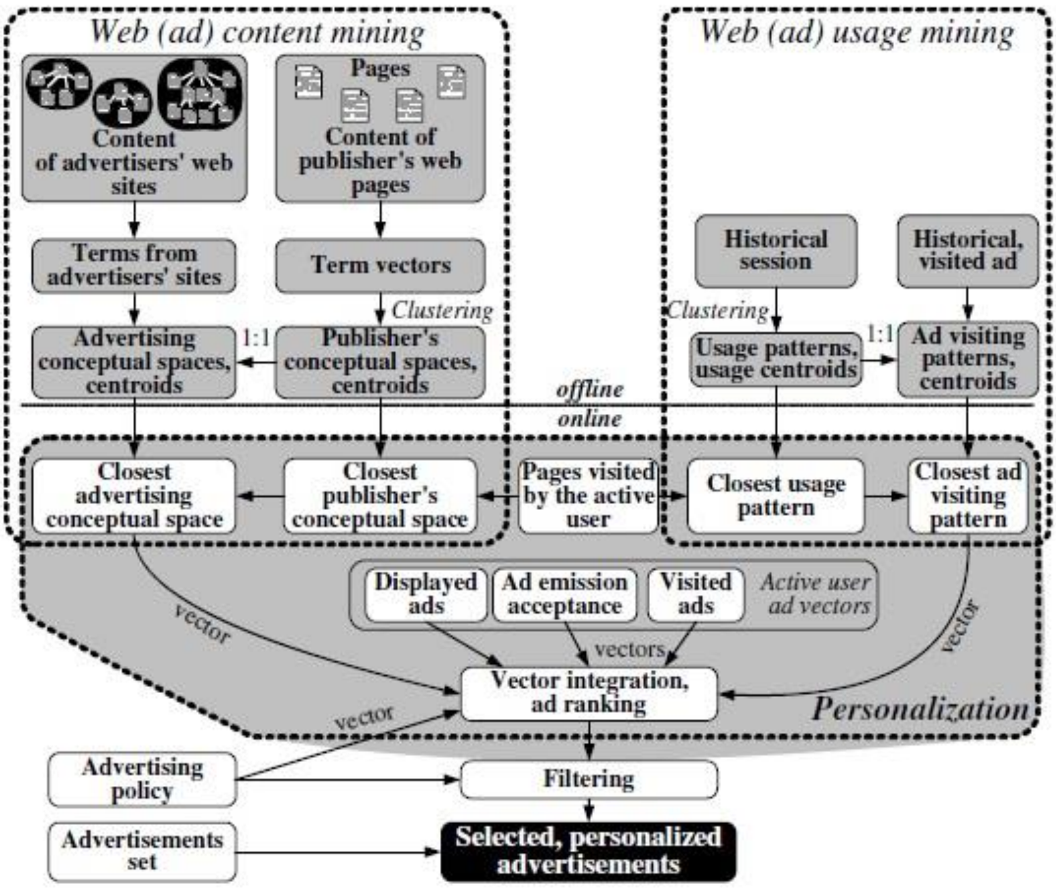

Figure 2.5: AdRosa Overview Method for Adaptive Advertising [15]

The Figure above demonstrates the process of generating personalised banner advertisements in AdRosa. MyAds, the adaptive personalised e-advertisement platform introduced in this thesis functions with a different approach. Although MyAds works as a brokerage system, similar to AdRosa, it does not use banner advertisements. It functions as a standalone system that collects users' information, by asking users direct questions, or via the logging-in option, via social networks, to generally extract whatever public available information can be collected. MyAds uses user modelling and adaptation techniques and provides the personalised recommendations based on a different set of adaptation techniques than those proposed within AdRosa. The model layering in AdRosa comes as one combined process, while MyAds is a layered model that provides adaptation based on the depth of the user's involvement with the system.

Personalised advertising supported by agents is a model that served also as an inspiration to the model for the MyAds system, used in this thesis. This model is a layered model, and it has been used to ensure that the personalised advertisements on web TV that are given to the viewers within program intervals are compatible with viewers' profiles, context and interests [41]. The model used in the MultiMedia Brokerage platform (MMB) stores two types of information; the viewers' profiles and the content of the current TV show being viewed, which are then jointly used to provide niche segmentation for future advertising. This platform operates as an electronic market, which provides an electronic exchange among the advertising agencies and the content providers. What makes this platform interesting is the layered architecture and model it uses, in order to deliver the proper advertisements, as shown below in Figure 2.6[41].

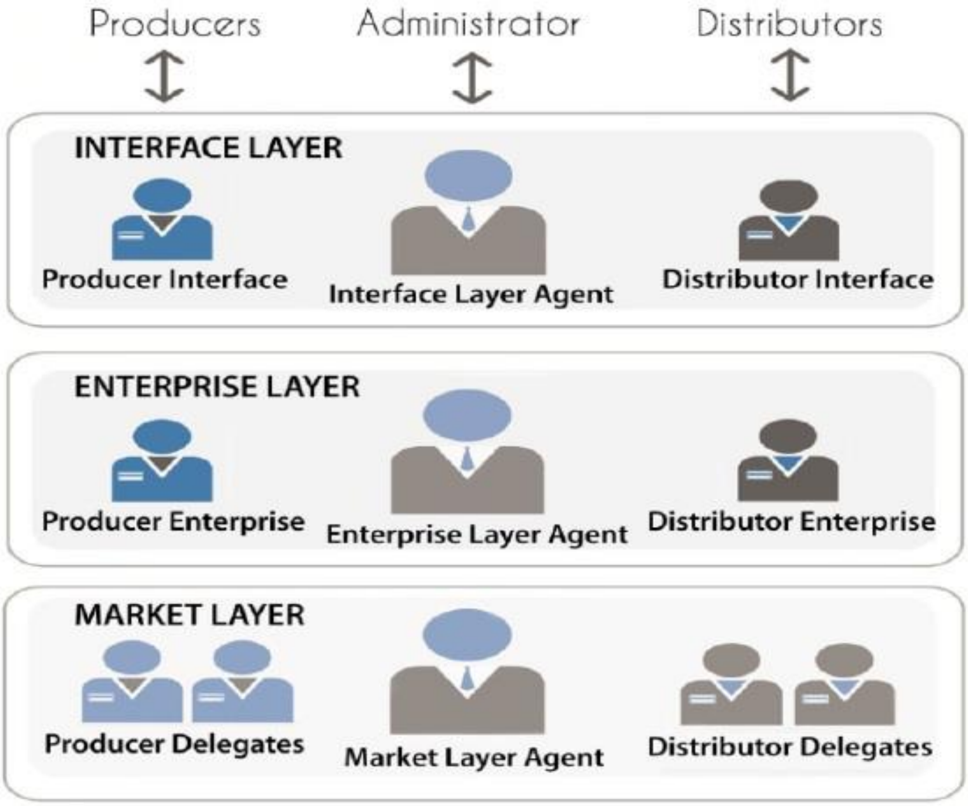

Figure 2.6: The MMB Layered Architecture [41]

The layered architecture above has also inspired the creation of MyAds, which also uses layers as a form of separating functionalities within a homogenous environment.

Sousa, Malheiro *et al.* [42] present a similar platform that is a multi-agent, real time, multi-tier (layer) architecture for personalised advertising for online on-demand TV. This model uses a multi-layer architecture that functions as a brokerage system, where companies' agents and market regulators negotiate and trade the viewers' profiles, based on the market rules. The system stakeholders are the content producers and the content distributors. The content producers are the advertisements agencies that are willing to provide targeted advertisements, while the content distributors are the hosts that provide viewers with on-demand TV. Figure 2.7 illustrates the process within the platform.

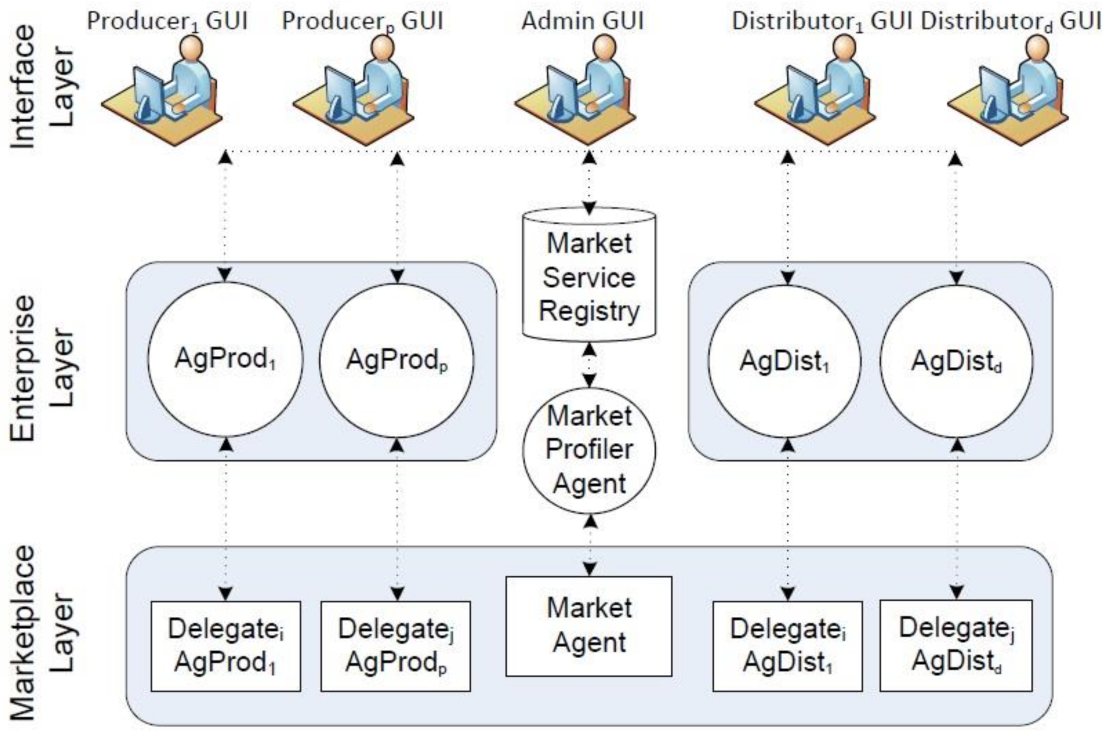

Figure 2.7: Layered Architecture for Advertisements in On Demand TV [42]

The platform above consists of three layers, with the representation of the different stakeholders within each layer. The interface layer with the GUI is presented to the viewers and its content is composed by the agents of the respective company. The enterprise layer is the layer that holds all the related data and information about agencies and enterprises. The last layer, the marketplace layer, is where the automatic negotiation and personalisation between the content and the stakeholders take place [42]. This system has a similar model to the one applied in that of the current thesis; however, the MyAds system, focuses on user modelling and adaptation approaches. The user model in MyAds does not focus on the different stakeholders in the system. It focuses on providing more personalised content by optimising the matching process of the appropriate product to the user model. As for the adaptation techniques, MyAds focuses on the providing the user with a comprehensive experience of personalisation from the sorting of the products to the explanations of recommendations. Detailed descriptions of MyAds features are discussed extensively in Chapter 6.

All the previously mentioned platforms are research-oriented. However, commercial systems such as Google, Amazon and Facebook have invested heavily not only in development, but also in research of which a discussion will follow. Additionally, not all of their methods and mechanisms are known, but this section describes the (comparatively little) published research.

The well-known Google platform provides a personalised e-advertising system called AdSense. This system branches into two domains: AdSense for content and AdSense for search. The AdSense for content is done by inserting a Google search box into the publisher's page (any website that needs a search box). The AdSense for content delivers the advertisements based on the publisher's website, which is analysed to adjust the presentation style to suit the publisher's content. The resulting ads appear in the "Ads by Google" page frame (or 'i-frame'). Using this advertising method ensures that personalised advertisements are also tailored to the publisher's content in the website, which is analysed regularly by Google. Google takes users' interactions with the publisher's site and analyses all the information provided to then provide personalised recommendations. This way, Google encourages publishers to insert the Google search box in their websites. Additionally, Google pays the publisher for each time this box is used.

To complete the cycle of personalisation, Google also provides another service, which is AdWords that functions as a keyword matching technique. This way Google matches the personalised advertisements to the keywords in the users' search. This approach of Google falls under the category of "ephemeral personalisation", as it does not last long and is done per session, or per search [43].

For MyAds, matching key words also happens when the user search or click on a recommendation. The Meta tags associated with the products are matched against the 'bag of words' associated with the product that the user has clicked on or searched for. This will further be weighted as the more frequent the words, the more recommendations will appear. This is similar to the approach used by

Google. The precise details of Google's algorithms are unpublished (for commercial reasons) although a similar principle is achieved in MyAds by using TF-IDF and Jaccard similarity (to be described in Section 2.4).

Other commercial examples are Yahoo Search Marketing (YSM) and Microsoft AdCentre, which use the same technique of keywords matching. The disadvantages of their approach are the limited number of keywords that can be used, being ineffective for reaching a large volume of users, and mismatches between the advertisement and the keyword used [44].

Facebook offers a new model for advertisement, with a viewing percentage of Facebook users of 1 out of 5 (20%). This is relatively high in comparison to the huge number of advertisements ignored every day, and that constitutes one of the reasons to consider using social networks as an advertising tool. There are many ways for business promotion via social networks, by enabling users to post links, videos, pictures, fan pages, groups and even advertisements. Also, businesses can create their own pages, which users can *like* and *share*. Facebook carries out its targeting through looking at users' profiles and collecting all the demographics, gender preferences, location and interests and then displays them on their pages – these are recommendations Facebook uses for targeted segments. Nevertheless, these are all recommender systems, and not adaptive systems. Facebook is a recommender system with social interaction [8].

MyAds also tries to collect as much data about the user as possible. It also tries to capture un-traditional features to associate with events and celebrations. Also, Facebook focuses on segmentation and stereotype user models while in MyAds each case is dealt with separately.

A platform by Hsieh, Liang *et al* [45] recommends advertisements based on the user interests and avatars (pictures) on their blogs. These data are then used to recommend advertisements, by using keyword expansion. In order to get to the final recommendation of advertisements, the system goes through three main stages. The first stage is building the advertisement semantic core vector using two modules; the text-processing module and the query expansion module. In the text-processing module, keywords are extracted from advertisements using a PAT-Tree based algorithm, and then they are filtered (by removing stop words), and the remaining words are stored in the database. The query expansion module uses the expansion mechanism from many webpages and blogs. On the webpages, the content is standard and formally presented; while in blogs it is personal and informal. The second stage is building the user semantic core vector, by studying their behaviour in the system, using the ontology of each element and recording a score, followed by extracting the features of the users' publications on the blogs. Finally, the outcome from the previous step is calculated, to extract similarities and provide a recommendation [45]. This is an approach to recommend advertisements based on social interaction via blogs. The relationship between this system and the current research presented in this thesis is that it looks at ways to extract data from a social platform; this is what the current research also aims to do. It also aims at recommending the appropriate advertisement to the user.

Another approach is that of Amazon.com, one of the most successful e-commerce websites, which functions as a recommender system with a warehouse business model and an advertising platform. Amazon focuses on three main sources of data to recommend products. These sources are: previous browsing history, items related to the ones selected, and other customers' purchasing. It uses two main filtering techniques: *collaborative filtering* and *content-based filtering*. Collaborative filtering is used so that customers can be segmented into groups containing similar customers with the same interests. Content-based filtering is used to recommend related and similar products to the product that is currently being viewed. Amazon is one of the steadiest, most reliable and useable e-commerce systems found online [27]. The system described in this thesis, MyAds, is inspired greatly by the functionality, design, and personalisation of Amazon. However, it relates more to adaptation techniques, and solves the problem of cold start, by building a more sophisticated user model, which could potentially lead to enhanced recommendations. A large scale evaluation of MyAds against popular platforms has been conducted and results are described in Chapter 7.

2.3. Adaptive Hypermedia – Terminologies, Theories, Techniques, User modelling, Architecture and Case studies

Adaptive hypermedia is the backbone of this research due to the fact, that the theoretical framework established later in this research is inspired by the frameworks of adaptive hypermedia. Also the practical design, implementation and evaluation were inspired from the work done in this field of research. This research has also relied on the techniques and case studies explored in AH and the application domain of e-learning to be transferred into the domain of e-commerce and e-advertising. All this is to address the research questions in Chapter 1 (Section 1.3). AH is also used because it is a successful field of research with many solid background theories as well as practical models that makes it the way to personalisation. Furthermore adaptation in terms of the specific use of AH user modelling and adaptation techniques have not been well explored in the domain of e-commerce and e-advertising, so there is little work on this area. This section aims at highlighting the main ideas, theories, taxonomies and case studies that have helped in forming this research.

2.3.1. Terminologies and Theories

Brusilovsky (1996) defines adaptive hypermedia systems as "*systems that reflect some features of the user in the user model and apply this model to adapt various visible aspects of the system to the user.*" Further, adaptive hypermedia is generally defined as the process of tailoring the content of the web-based system, derived from the data such as users' interests, backgrounds, demographics and cognitive abilities, etc. [46]. Adaptive hypermedia works best in applications that have different users with different goals, knowledge and backgrounds. The main use of adaptive hypermedia is to personalise hypermedia. The method adaptive hypermedia follows is to build a model for users' goals, preferences and knowledge and use this throughout their interaction to adapt aspects for their needs.

Adaptive web-based systems have to have a set of requirements, regardless of the application or the domain. These key properties are: having a hypertext or hypermedia system, having a user model, and some adaptation rules based on this model (allowing the system to change appearance and provide different functionally based on different user models) [19]. These are the key principles to consider when forming the idea of the adaptive system to be built, and these were considered for designing the adaptive approach and selecting the controllers for the AH system as discussed further on this thesis.

Adaptive hypermedia has been very well explored in the domain of e-learning. However, this does not limit its applicability to many other domains such as information retrieval, e-commerce and e-libraries [29]. Adaptive hypermedia in e-learning systems usually means that each student will be presented with different content, relevant links and material, based on his or her knowledge of the subject. This has been used in this research approach by considering users demographics, interests and relevant products. Also, adaptive hypermedia can be applied to e-encyclopaedias, where the content of a certain article can be altered, based on the reader's knowledge and interests. Online catalogues or even museum guides can be adapted. based on the user’s preferred path and interests [47].

Adaptive hypermedia was first used in the domain of e-learning. Brusilovsky elaborated about the progress of AH as he suggested that; scholars first focused on intelligent tutoring systems (ITS) which were introduced in the 1980s. These systems paid attention to the user and provided an extended set of user modelling features as well as adaptive features. They also included off-line and stand-alone educational systems. The user models connected to ITSs were usually more complex as they didn't rely on a network and a remote server to process the adaptation. ITS also were usually focussed on a specific educational domain [48].

Adaptive educational hypermedia (AEH) systems that started in the 1990s have tried to be more generic, but had quite primitive user models to begin with (e.g., based only on knowledge). This changed over time, also based on the development of fast Internet and server processing time [49].

On a relatively recent study by Peter Brusilovsky [47], he summarised the work that has been done on adaptive hypermedia and adaptive hypertext in that past decade. He stresses that there are three main components to be found in adaptive systems. These components are the domain model, user model and presentation model. The approaches used within these systems is either structural or non-structural, but these models always appear as the main controllers [47]. Scholars have updated these models to include goal models such as in [50]. A more detailed discussion is presented in Section (2.3.4).

User models will be discussed later in Section 2.3.2, but in brief, they contain (and sometimes process) information about the user. Often, it can be a guessing game about who the target user is, and what information is pertinent to model, in order to achieve a good recommendation or adaptation. The most common attributes considered when constructing the user model are: knowledge, preferences, interests, cognitive/learning styles (particularly important in e-learning), background and navigation history [51].

The *domain model* is one of the essential models in adaptive hypermedia, as it functions as the backbone of the systems by containing all information content in the pages of the adaptive system, and is the basis for further adaptation to take place [47].

The *presentation model* takes into consideration the environmental aspects related to the adaptive systems, such as the browsing device, bandwidth capacity and window size [22] [50]. Figure 2.8 illustrates the main blueprint for adaptive systems [19].

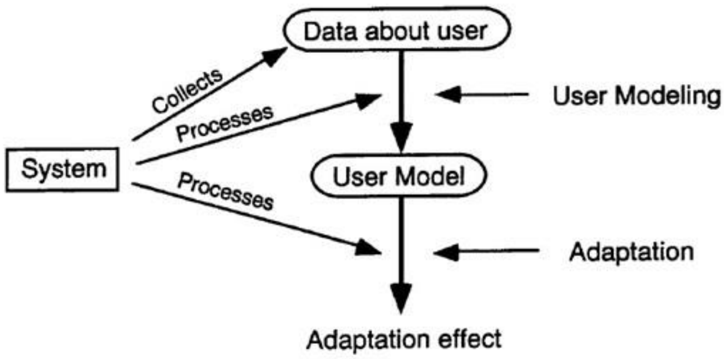

Figure 2.8: Classical loop of User Modelling and Adaptation in Adaptive Systems by [19]

The figure above illustrates a classical approach of adaptive hypermedia, explaining the functioning loop of the adaptation. In terms of the model interaction, the loop functions as follows. The adaptive system collects information about the user, which is used for constructing the user models. The update in the user models determines which information to select from the domain model, based also on the set of well-defined goals or rules (which constitute the goal model). Finally, the content is presented to the user, using a specific presentation model.

The *goal model*, first introduced in [50], is concerned with the reason for using adaptive systems and the added value of using this approach in web-based systems. The goals can be both local and global. The local goals change regularly, based on the user's changing needs, while the global goals are the set rules upon which the system is based [22].

Figure 2.9 presents a generic architecture of adaptive hypermedia systems [52]. It consists of the user model generator, where all the information about the user is processed and the initial and where the updated profiles are constructed. The decision making and personalisation engine is where the actual linkage between the user model and the content occurs. It aims at providing the adaptive content and the actual application interface, as the generated content is presented to the user, adapted to the technological parameters of the environment within which the system functions [52]. This architecture is particularly important for this research as it was used as the basis for the system architectures used to build MyAds. Details about architectures can be found in Sections 5.2 and 6.2.

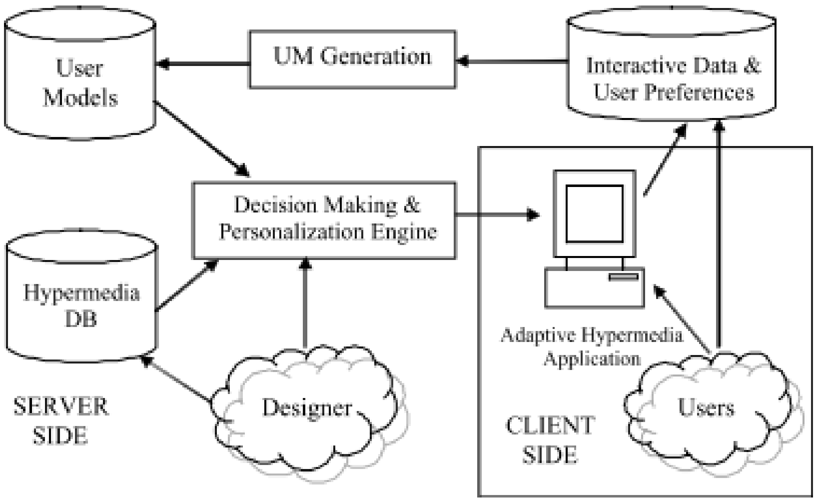

Figure 2.9: Generic architecture of adaptive hypermedia systems [52]

The key purpose of adaptive systems is to provide personalised content to the user, regardless of the application domain. In personalisation, there are two types of personalised systems: systems that are *adaptable*, and systems that are *adaptive*. Adaptable systems are user-tuned systems, while adaptive systems are system-tuned [53, 54]. Adaptive systems use dynamic adaptation, driven by the system itself; the knowledge is contained within the system, and the user needs minimum effort to receive the personalised content. On the other hand, in adaptable systems, users control the process and functionality of the system; the knowledge is extended via the user; it gives the user the sense of control over the system. However, at a certain point, the user needs to do substantial work, as the complexity increases [55]. These seemingly different approaches for adaptation do not need to be used separately, as they can function together within one system. In e-advertisements, the research domain of this work, adaptive hypermedia serves as the structural theoretical foundation and the technical guidance for the delivery of personalised adaptive e-advertisements.

2.3.2. User Modelling – Definition, Variables, Methods and Techniques

User modelling is one of the key aspects of adaptive systems. It is fundamental to understand their purposes, design requirements and suggested architectures. The foremost objective of user modelling is to collect as much relevant data as possible about the user, and then tailor the content according to the users' different needs (or other parameters) [46, 51, 56]. User modelling is defined as "a representation of the user in an information system, in the form of information which the system collects and maintains in order to improve the quality of information access" [46]. The importance of user modelling lies in the fact that, with the large amount of information available online and the need for adequate time to process all this information, only relevant user data is to be considered and processed [18].

Hence, it is necessary to understand the different aspects in user modelling so the decision upon the appropriate approach to be used in this research can be selected. Furthermore, this section explores these different aspects so the justification upon the decisions made on the design, implementation and evaluation of the proposed approach can be clear.

Generic user modelling systems (GUMS) were the first introduction to dedicated user modelling systems. They used simple stereotype hierarchies of users [57]. This has later facilitated the establishment of the "*user model shell systems*". These systems allowed user models to be part of adaptive systems and enhancing these models to become dynamic. The reason for this modification is to allow for the modifiability and reusability within the application, yet separating the user model functionality from the user-adaptive application systems. These types of shell systems have basic characteristics, especially with the application of user-modelling to commercial applications and web personalisation. Such basic characteristics include domain independency, expressiveness, quick adaptation, extensibility, importing of external user related information, distributed information management, open standard support and privacy support and many more. This is important in this part of research so that the main characteristics of user models that are specific to the field of e-commerce can be understood. This is later used in the research to determine how to design such models. With the emerging need to upgrade the systems to function well in the World Wide Web, the need for *user model servers* has emerged. These servers work as the shell systems, but they do not run as part of the application. Rather, they run independently, interacting via communication channels, with a central repository of the users' data. They need to ensure the consistency and coherence of the data, and the privacy and security of these data [57]. MyAds (the tool that has been designed and implemented throughout the research) has adopted the user model shell system approach as the user model controller that runs within the adaptive system. A detailed description of this can be found in Chapter 6.

The adaptation process entails three main stages: *data acquisition*, *data representation* and *application production* in some form, such as recommendations, customised interfaces, or the recommended product/service presentation [57]

Different scholars describe user-modelling in terms of layers. Some divide user models into three main layers: the *content* that is being modelled, the *structure* of this information and its representation, as well as the *modelling approaches* that include the maintenance of different user-models [46]. For a better understanding, the nature of user modelling can be understood as follows. It first selects and prioritises the relevant items, then performs some adaptation (such as manipulating links). The content is then presented adaptively. The user model algorithms constructed in this research follows this pathway of including and excluding parameters based on the user's information. Detailed algorithms can be found in Chapter 6 (Section 6.7).

The approach proposed by [58] divides user profiles into *core* and *extended* user profiles; core user profiles focus on the actual goal of the user interaction with the system and main interests, while extended profiles focus on information related to the user such as demographics, background and abilities to mention some. These two different styles are combined in the proposed research approach. As user profiles are a combination of extended features of the UM, however; users' interests and main goals are defined in the early stages of constructing the model. Details of the initial and extended UM design and implementation are in Chapters 5 and 6.

Constructing user models relies on the variables that are going to be used within the model. These variables are divided into *dependent* and *independent* variables [59]. Dependent and independent variables are summarised by [46, 56, 59] as follows:

1. Dependent Variables

    1.1. Knowledge of the domain presented

This is an important variable that has been used to define the user's needs based on his/her knowledge of the field. It is argued by [19] that one third of the adaptive hypermedia systems adapt their systems based on previous knowledge about the user. This is important in intelligent tutoring systems and student modelling, where often the students' level of knowledge is examined via quizzes and other means, as part of the initial introduction to a course, then adapting material based on the user level.

    1.2. Background experience

This does not refer to knowledge as previously mentioned above. Instead, this variable is used to estimate how comfortable the user is in using these systems, in terms of navigation and information space. It can focus on the users' profession, or work experience.

    1.3. Preferences

This is related to the user's taste and the set of likes and dislikes. It is fed into the system either directly or indirectly. Directly is where the user actually states a preference. Indirectly is where the user chooses to change colours of navigation or fonts. It is usually collected through user feedback, such as checklists and likes and dislikes on Facebook.

1.4. Interests

These are more focused elements; they describe users' long term interests, not only short term ones, which can be changed easily. This can be examined through *navigation monitoring*.

1.5. Individual Traits

These are more concerned with users' very specific type or lifestyle. For example, whether he/she is a shy person or an outgoing person, or whether he/she is conservative or open. These can be summed up in the following features.

1.5.1. User Personality

In order for computers to know how users function, it is very important that they replicate human behaviour, such as having two humans talking with each other rather than just a machine and a human being [60]. This is achieved through comparing the performance of introverted and extroverted users using "extroverted" and "introverted" interfaces. They found that these interfaces actually mimic the actual behaviour of users. Extroverted users tended to like more colours, big fonts and more interaction. While introverted users go for calmer interfaces and are more text-oriented.

1.5.2. Cognitive Style or Learning Style

Cognitive or learning styles refer to a user's information processing behaviour and have an effect on the user's skills and abilities, such as preferred modes of perceiving and processing information, and problem solving. They can be used to personalise the *presentation and organisation of the content, the navigation support, and search results* [61]

1.6. Personal Data

This is related to knowledge acquisition, as users with different ages, languages, cultures and gender tend to like different things.

1.7. Abilities / Disabilities

People with disabilities may find it difficult to use computer-based systems, as they need special consideration when using these systems which, unfortunately, is not always available for them.

1.8. Social Group

Computer Supported Collaborative Learning (CSCL) and groupware applications have been at the focus of educational research lately. Group models are important for collaborative work, since a standard group model should serve as a starting point for interaction for the new member that joins a group [19]. While the new user starts to interact with the system, the user profile can be formed including those characteristics that are in common with, or are different from, the group profile.

To build the group profile, information from users can be acquired using similar techniques to those used for the individual user model: stereotypes, interviews, and monitoring users' behaviour. However, these techniques take into account adaptivity variables, such as mental models, in order to select users for the construction of the group.

2. Independent Variables:

2.1. Goal or Task

This is one of the changeable variables that systems should adapt to. They are the current goals or tasks the user is working on. For example, in information retrieval systems, a user's goal is a search goal; in educational systems it is a learning goal; in testing systems it might be a problem-solving one.

2.2. Environment – Work

This is a very convenient and widely used feature in web-based applications, as many users have different platforms, hardware, software, system performance, system bandwidth, etc. Such adaptation usually involves selecting the type of material and media in which to present the content, for example, still image vs. movie, or text vs. sound.

2.3. Situation Variables

Situation variables that influence user abilities as well as task requirements include time pressure, location in space and presence and location of targets; situation in time; weather conditions; visibility; and vibration and noise.

Studying the various variables that can be considered within the user model contributes to an enhanced understanding of the data sources collected about the users. In the domain and application of this research of e-commerce and e-advertisements, there are many different types of data available about the user. These data sources are much harder to harvest than in educational based systems as the users tend to be exploring more than actually learning. In the application of MyAds, in this thesis, different data sources and variables were collected to analyse the users' behaviour and recommend products based on this analysis. The data collected are both dependent and independent ones. Dependant variables used in MyAds are interests and individual traits. These two variables are crucial for constructing the user models as the users' interests are scaled. Also personal information is used as part of the individual traits so that the appropriate ads can be assigned based on these variables. From the independent variables both the goals and environmental ones are used. Because the goal of the users can change over time, the system monitors the users' behaviour and keeps track of their updated goals. Also environmental factors are included in this research so different aspects such as bandwidth capability, screen size and device type are changed based on the user.

The previously mentioned terminologies, users' variables and processes show that the actual harvesting and allocation of users' data is not a straightforward job. There are five different approaches for user identification and categorisation for the construction of the user model as follows. First, there is *software agents*, which are programs embedded within the users' computer that collect information and share with external servers over the network. The second approach is the *login approach*, which is one of the common ways of collecting data about the users, as they willingly provide such information. The third approach is the *proxy servers* that are connected to certain geographical locations. *Cookies* are another common approach, well used in web-based systems; for websites browsed for the first time, the user will be given an ID, which will be used to track his/her browsing history. A similar approach is the *session ID*s, which temporarily allow for the user to be tracked, but the user ID is not saved [18]. In e-advertisement systems, the common approaches of creating user profiles are based on the less intrusive ones, such as the ones using cookies or session IDs. Tracking the user navigation and browsing history establishes a lightweight pattern of what the user may or may not like.

The research in this thesis uses both intrusive and non-intrusive methods. It uses intrusive methods, such as login, where users do provide information about themselves and the system conducts the modelling, as well as the less intrusive method of storing the session ID for the user and using a more sophisticated set of operations to provide recommendations, which will be discussed in later chapters.

Harvesting information about the users has mainly two fundamental approaches: *implicit* and *explicit* user information collection. The explicit approach relies heavily on information provided by the users themselves over the web. Most of the data collected are demographic data and simple checkbox and feedback information. Big companies such as Yahoo ask their users directly to create personalised profiles by providing personal information, so their profiles can be customised. The main problem with this method is that users are concerned about their privacy, so they tend to give inaccurate information. The other approach is the implicit method. This method does not require any direct intrusion on the user; it collects user information by means of collection techniques such as browser cache, proxy servers or browser agent monitoring browsing activity, desktop agents, web logs, and search logs [18, 28, 29]. This field is particularly important for the research presented in this thesis, as it evaluates the users' different perceptions on adaptive e-advertisements, based on their different sources of information collected, and it also evaluates the accuracy of user model from a user point of view.

The last part to discuss in this sub-section refers to user modelling techniques and representation. User models are usually formed based on weighted keywords or semantic networks or weighted concepts or association rules [18]. User models can also use a set of machine learning and data mining techniques based on the purpose and the expected functionality [62]. The first form of user profiles discussed is the keyword profile. The keyword profile functions by collecting a bag of words. These words are a collection of all the users' behaviour over the system or are provided directly by the users. Each word is then given a weight based on its importance and in some cases its frequency. However, as simple and efficient as this approach may sound, there is a problem of words having multiple meanings. This problem can be solved using another type of user model, the *semantic network profile*. The semantic network profile works with what is called a "corpus", as each word (or node) is connected to a set of related words, and each of them also has a weight and based on these weights, the profiles are then presented. The last type of profile is the *concept profile*. Concept profiles are similar to semantic profiles, but the nodes in the concept profiles are not words and their related ones. Instead, the nodes are abstract topics that are interesting to the user [18]. The research presented in this thesis uses the keyword profiles to construct the models. These profiles rely on the weights of the keywords and Meta tags to define users' needs. It also uses a set of machine learning and data mining techniques to initialise user models. After the user models are initialised, keywords are used, by weighting each word by means of frequency and similarity techniques, of which a detailed discussion will follow in Chapter 5. The reason for using this approach is that it is an applicable method on adaptive e-advertising; all products come with a product description and keywords associated to their categories and information. Using this method makes the process of matching Meta tags of the products to the user profile an easy one.

2.3.3. Adaptation Techniques and Taxonomies

Scholars have explored and discussed adaptation techniques for the web intensively, which led to the development of adaptive hypermedia. This sub-section addresses the main techniques used and their related taxonomies. The main question to answer is "*adapt to what?*" as discussed earlier in relation to the user model and the different variables that can be considered while altering the content, it is crucial to know what to alter in the content. Web pages are a set of hyperlinks, multimedia components, index pages and global maps, etc. [19]. There are two main methods of altering the content; the adaptation of links related to a web page, also known as *adaptive navigation support*; and adaptation of text, pictures, videos and content within the web page, also called *adaptive presentation* [22].

Figure 2.10 illustrates the techniques classified as *adaptive presentation* and *adaptive navigation support*, respectively. The adaptive presentation includes both the adaptation of multimedia presentation and the adaptation of text presentation, while the adaptive navigation support includes the direct guidance, adaptation of links sorting, adaptation of links hiding, adaption of links annotating and map adaptation [19].

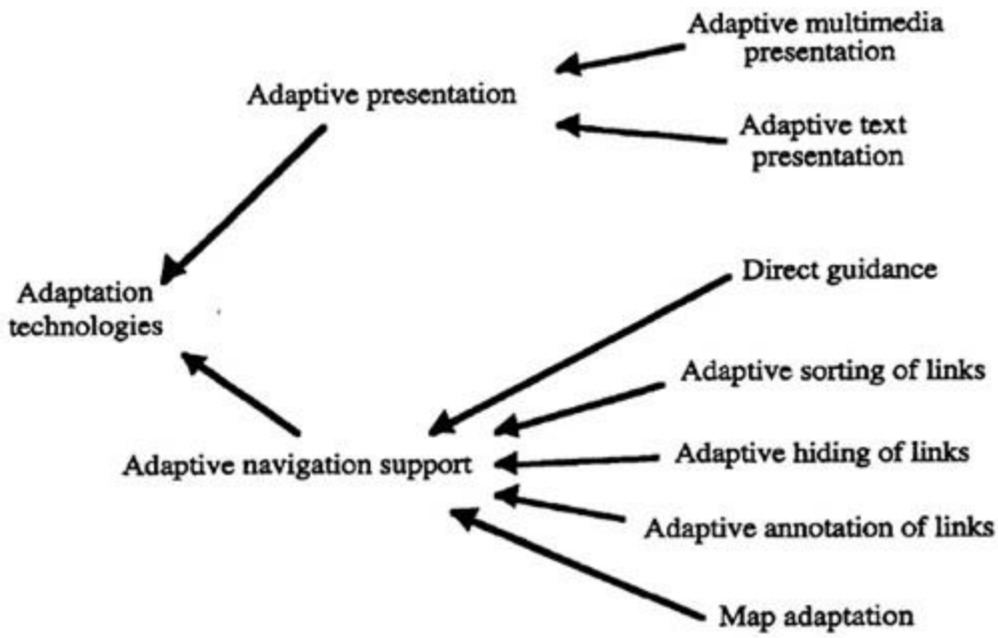

Figure 2.10: Adaptive Hypermedia Techniques by Brusilovsky [19]

In adaptive navigation support, there are five sub-approaches according to [19]; [63]; [47, 64]. A description of each follows below:

Direct guidance is one of the main technological approaches of adaptive navigation support. Direct guidance decides what the "best" node is for the user to visit next, according to the user's goal and other parameters represented in the user model, to provide direct guidance. The problem with direct guidance is that it provides limited support: "follow me or no help". In adaptive e-advertising, direct guidance can hardly be the only form of navigation support, because it does not provide enough support for the users who would not like to follow the system's suggestion. Direct guidance is useful, but it has to be used together with a "more supportive" technology [1]. In MyAds the nodes and buttons have been enhanced to function on differently in different situations. The help provided in MyAds includes both approaches for users that want to follow the system's suggestion and those who do not.

The adaptive sorting or ordering of links is to sort all the links of a particular page according to the user model and to some user-value criteria; the closer to the top, the more relevant the link is. This approach can be a bit un-stable, as it can change every time the user enters the page (i.e. when there are different parameters). This is useful in information retrieval (IR) applications, where there are a lot of links, as it reduces navigation time. In MyAds this approach has been adapted due to the fact that products need to be sorted based on users' preferences.

Hiding adaptive links is popular and widely used in e-learning applications. It works by hiding the links that are not related to the user at this stage. In e-learning, this is very useful, when the link is not related to the user's current goal, or when the user is not yet prepared to look at the link. It protects the user from the complexity of the unrestricted hyperspace and reduces the cognitive overload. It can be used with all web pages types, even with contextual pages, as "hot words" can be transferred into normal text and highlighted later. The links are added incrementally, rather than reordering or removing them.

Adaptive annotation: In this case, the users get to see some comments or messages, when they reach a certain node or link. It explains the nodes behind the current node. This can be presented as text, when hovering around the node; it can also be placed as an icon, or as a different font size, or colour. Even in its simplest form, where the user receives explanations based on visited nodes, it is still useful, as it all depends on the user model. While hiding is only focused on two forms of links – relevant and irrelevant; link annotation is more powerful, as it can support up to six different states. It can also be used for all types of adaptation. It can be used as a "dimming" technique, rather than dividing links simply into relevant and irrelevant.

Map adaptation technology can adapt to the different forms of global and local hypermedia maps presented to the user. In personalised e-advertisements, it is uncommon to use adaptive navigation support technology, so the system introduced by this thesis, MyAds, embeds most of these techniques, to suggest adaptive content to the user and move the field forward, by introducing a more dynamic application.

Adaptation presentation support deals with the actual content of a webpage. Some content is kept hidden from the user, as it is irrelevant to the user at this stage. Some details are also hidden from users as this is too much detail and is not needed as this point. This is not only about the hiding and showing of the content; it is also about the different user needs, based on the category of the user. Two other popular methods are the *prerequisite explanations* and the *comparative explanations*. These two methods change the information presented, based on the user’s knowledge of the related concepts. The first method is based on *prerequisite links between concepts* [46].

The main aim of managing personalised views is to protect the users from the overwhelming and complex hyperspace. This is achieved through offering them a choice based on *goal oriented views*. This is carried out through making a list of views (categories), where each view is a list of all the possible links for the hyper-documents within the particular working goal. This represents the adaptation from the other end (adaptability), where the user can arrange these lists manually. The traditional way of presenting such adaptation is through bookmarks and hotlists. What is required here is to suggest these lists based on user models [46] [63].

The adaptation has been gradually modified by other researchers [23, 58], as in Figure 2.11. Adaptive presentation is further subdivided into text adaptation and multimedia adaptation technologies; adaptive navigation support is further subdivided into link hiding, sorting, annotation, direct guidance, and hypertext map adaptation.

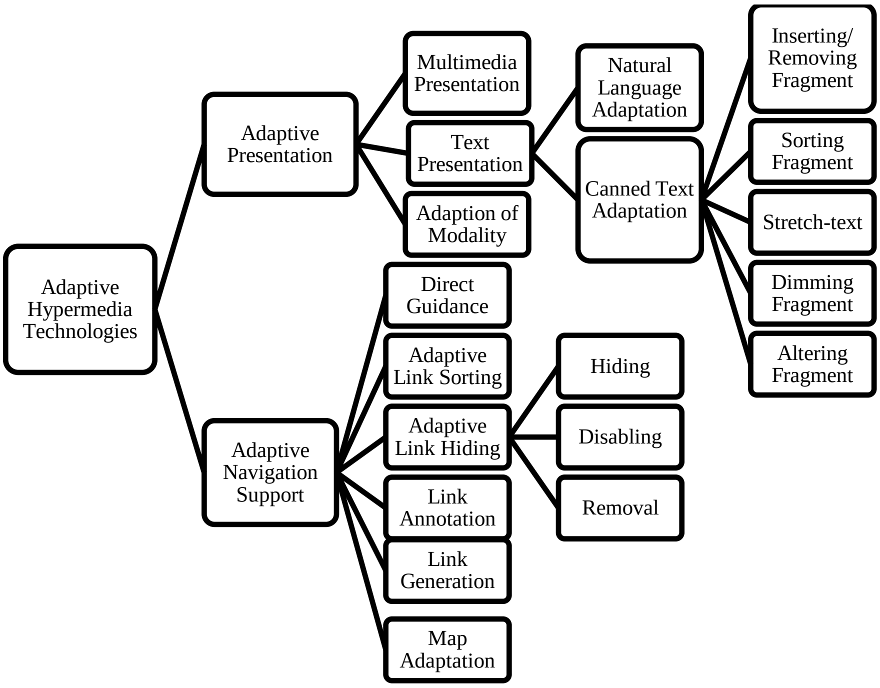

Figure 2.11 : An Updated Taxonomy of Adaptation Techniques and Approaches[23] [22]

2.3.4. Models and Frameworks of Adaptive Systems

Adaptive hypermedia emerged as a technical research field. The research conducted in this applied field is connected to the implementation and evaluation of numerous systems and frameworks for different research applications, mostly in the field of e-learning. This is particularly important for the research presented in this thesis, as it is used as an inspirational framework, to generate an e-advertising adaptive framework and architecture. A set of the famous conceptual models, listed in chronological order are: Dexter [65], the AHAM model [66], the XAHM model [67], the Munich model [68] and finally the LAOS model [50]. What distinguishes these models is that they all use the concept of separation of concerns, by proposing a layered model for adaptation, while all the layers work homogeneously with each other, to eventually propose adaptive content.

The first model to discuss is the Dexter Hypertext Reference model, which works as the foundation model for adaptive hypermedia systems, although when proposed, it addressed only hypertext systems. Dexter divides a hypertext system into three main layers which are: the run-time layer, the storage layer and the component layer which works as an inner layer to the storage. The storage contains the nodes that are connected to links that map a hypertext system. The importance of this layer lies in the fact that it ensures that all the links and nodes are connected with each other properly, best described as a “database”. Within this layer is the component layer, which structures the nodes and links, by calling a number of functions, to generate the appropriate content. The run-time layer presents the content to the user and traces the dynamic and user interaction within the system [65].

An enhanced educational hypermedia system that is based on the Dexter reference model was proposed. It was proposed to address the increased complexity of hypertext systems and demonstrate the techniques and methods for adaptive hypermedia as an extended application to hypertext. This model is called AHAM. The main purpose of the AHAM model is to provide adaptive educational content to students, by focusing on updating the functionality of the storage layer that has been proposed in Dexter and not limiting it to a store of functions. It proposes the following additional sub-models: the domain model (DM) that aims at structuring the information and links together, the user model (UM) that is concerned with the information about the user and what information to keep and what to update. For example, non-volatile information for the purpose of the specific use of the application, such as age, course and gender are permanent, while grades, performance and behaviour on the system may change. The teaching model is where all the connections between the user and the content happen, acting like a connection layer between the domain model and the user model, to then decide on the adaptive content. Finally, the adaptive engine actually generates the adaptive content to the student [66].

With the enhanced performance of the web and the expanded web-based application, multi-dimensions are to be considered when developing these systems. Based on that, the need emerged for a model that takes into consideration dimensions such as user behaviour, technology used and the external environment, this prompted the creation of XAHM, an adaptive hypermedia model based on storing metadata on flexible and data-centric XML files. XAHM uses a logical algorithm at execution time, to support these different dimensions, by integrating both object-oriented semantic description of AH, as well as a graph based description of navigation criteria [67].

MyAds, the proposed delivery system in this research, also uses these different dimensions of the user environment, behaviour, different technological devices, and bandwidth, etc..

The Munich reference model also bases its structure and functionality upon the Dexter model and is closely related to AHAM; however, what sets it apart is the use of the unified modelling language (UML), to generate object-oriented specifications to address both the abstraction of the earlier models and providing the appropriate visualization. The system focuses on enhancing the adaptation functionality, by expanding the storage layer to contain both the user model and the adaptation model, so that a dynamic user modelling and dynamic role-based adaption can happen at run-time. Although it has the same layers of the Dexter model, it separates the functionality of adaptive hypermedia systems – such as authoring operations, retrieval operations, and finally adaptation operations [68].

The last model to discuss is LAOS, an authoring model that was found to address the dynamicity of AH systems. LAOS is based on AHAM, but adds to the previously introduced models the goal and constraints model (GM) that falls between the domain model and the user model. This added layer works in two ways: the first part is within the goal aspect that aims at giving precise presentation related to the goals of the user; the second is the constraints dimension that focuses on limiting the space of the searched content, so well refined content is presented to the user [50]. The research in this thesis proposes a layered model that addresses the e-advertising applications, by also using the sub-models of the domain model, user model and adaptation model, as well as the “presentation model”.

2.4. Information Retrieval in Adaptive Recommendation systems

Research about information retrieval is particularly important for this thesis's research, as the aim is to deliver personalised e-advertisement recommendations to the user.

2.4.1. Personalised Information Retrieval Systems PIR – Definitions and Approaches

Personalised IR (PIR) systems are defined as systems that provide the user with a list of results, based on both the query and the user's data and behaviour. The key feature in PIR is keeping track of the information needs of the users, in order to personalise the service [69].

This has been interesting for the commercial sector, as it provides system loyalty, effectiveness and user satisfaction. However, the mechanism of this personalisation is quite challenging in terms of obtaining the user's information (through explicit or implicit methods), and the storing, presenting and use of the information. Therefore, there are many approaches to address these issues, from information gathering to information representation and finally information implementation and execution [69].

In commercial platforms, recommender systems are considered key, because of their functionalities of providing the user with the appropriate recommendations. The primary reason to use recommender systems technology in e-commerce and its related fields is that they contribute to an increase of sales (and therefore the number of items sold). This is due to the fact that they address the user's needs and desires for e-advertisements, so they increase the click-through rate and the viewing of ads [70]. They also provide more diverse items that can be sold, as usually users are recommended items according to their query, not just popular or common ones; also, it enhances users' satisfaction and loyalty, as mentioned before [70].

As there are many classifications of IR systems, this research will take into consideration only the individualised personalisation, as it is the one of significant relevance. *Individualised personalisation* is when the system's adaptive decisions are taken according to the information about each individual user, as exhibited in his/her user model [71].

It is important to distinguish between information retrieval and information filtering. In *information filtering*, the aim of the system is to keep a continuous stream of analysis of the user's behaviour in the system, like news and feeds. While in the IR systems, and the PIR systems, the aim is to provide the best (available) experience to the user and enhance user satisfaction, while providing the results to the current query, as well as enhancing the search process [69].

The first step in PIR is to gather information about the user. In order to do that, the appropriate information gathering approach should be selected. The approaches to collect such information can be either *explicit* or *implicit*. Explicit collection proposes users input information about themselves directly into the system. The well-known methods for this type of information harvesting are via filling forms (such as registration forms), replying to surveys and answering quizzes. The main issue with this approach is that the user may not be willing to give this amount of information and spend time and effort [72]. The second approach is the implicit information harvesting approach, which collects information about the user, without the actual obstruction of the user. Common approaches include harvesting and analysing browsing history, queries, clicks [29], and the hot topic of harvesting information from social networks, such as blogs, tweets, likes, tags and interests [73]. The reason for implicit information gathering is that with the explicit approach users may be reluctant to provide information about themselves; implicit information gathering generates masses of information and can give the same outcome as the explicit information [74].

The second step in PIR is what information to collect about the user. This includes information about the users themselves (such as demographic, education, languages, religion, interests, favourite colours and personal information). It also contains information about the users' usage of the system by tracking their behaviour. This can encompass any interaction between the user and the system, such as browsing history, bookmarks, search queries, tags and tweets [69].

The third step in PIR is to understand the source of information: whether the information is harvested from the server side or the client side. This raises some privacy issues that are not the focus of this research; however, it is worth understanding the different sources of information [69].
Information representation is a key element in personalised IR systems. It is crucial that the user's information is kept and his/her long-term and short-term interests are stored. User modelling constructing takes into account two dimensions: the *data structure* and the *content*. The data

structure dimension is concerned with the underlying storage mechanism used to represent interest terms in the model. This can either be a *vector-based model*, or a *semantic network-based model*. The content dimension is concerned with the nature of the terms maintained in the user model. The terms either can be words that are freely mined from user/usage information, or conceptual (categorical) terms that are drawn from some sort of knowledge source [18].

A vector-based user model is made up of a feature vector, which is a vector of terms and associated weights. The weights can be determined, for example, using a term weighting scheme such as TF or TF-IDF [75]. One way to represent the terms in the model is by using words or phrases that are freely mined from the user or their usage information.

An example of how words or phrases are harvested from the search history and how they are used to populate a vector-based user model was illustrated in [76]. The system builds a vector-based user model, which comprises multiple vectors of interest. The terms in the vectors are weighted using the TF-IDF method. Interest terms are extracted from documents, which the user has explicitly marked as relevant, where each vector in the model corresponds to important keywords obtained from a single document. The full text of the document is not actually used for term extraction; only the terms that are in the query's context. The system has a threshold concerning the number of vectors to be maintained in the model (i.e., a maximum of N clusters of interest). Furthermore, the system also has a threshold for the number of terms stored in a vector (i.e., a maximum of M interest terms per cluster) [76].

If the threshold of N vectors was reached, and a new vector comes in, then all the vectors in the user model – in addition to the incoming vector – are textually compared to each other, using cosine similarity [75]. The two most similar vectors are then combined together in one vector. This is done by grouping together the terms from the two vectors, sorted in descending order of weights, and then keeping only the top M-terms. The benefit of this approach is that, over time, terms that commonly appear in topics that were repeatedly searched for by the user will tend to cluster together in the model.

Based on the previous properties of the vector based model, MyAds uses this approach. User profiles are kept in arrays because this type of data structure can hold different types of data. The similarity between these words is collected, so the next recommendations will be similar to the items the user navigated, based on the Jaccard similarity.

The two types of user modelling are the *static* and *dynamic* user models as follows;

- Static user models do not change over time and have a set of information that is most likely to be non-changeable over time, such as demographics, personal characteristics and background. This type of information allows PIR to have a high level of personalisation, such as special features in the GUI and recommendation based on location.
- Dynamic user models keep changing over time. For example, models that maintain *short-term user interests* are usually created *on-the-fly* and are *updated frequently* over the span of the user's search session. Long-term interests can be considered as dynamic information as well, if the system has a revision or update mechanism for them in place (e.g., increasing or decreasing the weights of the interests on a periodic basis, or adding new interests). More user-focused personalisation decisions can be made when the system maintains dynamic information [69].

The three aspects to be considered when implementing PIR are:

- The type of service provided; which is adaptive e-advertisements in the case of this research.
- The scope of personalisation; the work in this thesis uses individual personalisation, as each user is considered a distinct case.
- The approach of personalisation; which can be a query, or result adaptation.

In the research in this thesis, all three approaches are used, as the search features – as well as the system – are adapting to the results of the user behaviour.

Some of the types that can be used in information retrieval effectiveness can be quantitatively measured in a number of ways, using well-known metrics in the IR community [75] [77]:

- *Precision*, which is the number of retrieved relevant documents over the total number of retrieved documents;
- *Recall*, which is the number of relevant documents that are retrieved over the total number of known relevant documents in the document collection [69].

2.4.2. Definitions, Approaches in Data Mining

The reason for exploring different data mining techniques for system recommendation is that, in order to identify the appropriate item, ad or recommendation to give, the system needs to *predict* or *compare* the importance of the suitable next recommendation [70].

Data mining is used in the research presented in this thesis, for constructing the user model for each user. The design of the user model requires scaling users' interests and calculating how far they are from a certain point. Also sorting the links and products based on these interests requires a classification algorithm to perform the job. Machine learning and data mining are the fields that contain well structured, applicable, extensively researched and well explored techniques and equations to solve such problems [78]. It has been used in two stages; the first stage is the initiation of the user model, to calculate how close (or far) a user is from a certain interest, and the second stage is to track the user's behaviour over the system, so that the system can automatically provide the appropriate recommendations. A review of common data mining approaches is discussed in this subsection, to create a general understanding of them – particularly the selection of the current ones used within this research.

Recommender systems are usually associated with other intersecting disciplines, such as human computer interaction (HCI) and data mining (DM). The sequential steps in data mining are: *data processing*, followed by *data analysis*, and finally *results interpretation and understanding*. Data processing usually includes *distance measures*, *sampling*, and *dimension reduction*. The research presented in this thesis focuses on distance measures. Data analysis is divided between prediction and description, and this research is concerned with classification using *K Nearest Neighbour*

(kNN). Most classification and filtering techniques rely heavily on the similarity measures and then the associated kNN classifiers data mining approach [79] [80].

One of the techniques that is simple, common and reliable is the *Euclidian Distance*. This technique calculates how far a certain point is from another one. This is commonly used in e-commerce applications, to measure how far a certain item is from a pre-defined value of an attribute [79]. The formal equation of the common *Euclidean Distance* is shown below:

$$\mathrm{d}(\mathrm{x},\mathrm{y}) = \sqrt{\sum_{k=1}^{n}(\mathrm{x}_k - \mathrm{y}_k)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Equation 1: Euclidean Distance Equation

where n refers to the dimensions in a given space and x_k and y_k are the k^{th} attribute of the features of data objects x and y, respectively [80].

The *Euclidian Distance* measure has been intensively used in the domain of data mining in web applications, as well as being used in the filtering techniques of collaborative filtering and content based filtering. The main contribution of this method is that it works well with similarity measures and helps in constructing models from given information [81]. The *Euclidean Distance* approach can also work as a basis for enhanced filtering and personalised recommendations that can then be used to build more advanced techniques to generate personalised recommendations [82].

There are many other distance measures, like, for instance, the *Minkowski Distance* and the *Mahalanobis Distance* that are not targeted in this research. This is because the *Minkowski Distance* is a more generalised approach of the *Euclidean Distance,* as it focuses on the value of the exponent under the square root. In this form of distance, the exponent can be any number, whether it is larger or smaller than 1. In the case of this research the minimum value of the attribute (interest) to be calculated is zero, so there is no need to use this equation. Also, the *Minkowski Distance* does not work best with the classification method used in this research which is *kNN* as scholars such as Kantardzic proposed [78]. *Mahalanobis Distance* measures the distance between a certain point and the distribution of other points to be used within multidimensional categories [78]. The scope of this research does not require this type of calculations.

The *Euclidean Distance* equation has been used for the initiation of the user modelling in the system defined in this research, MyAds. Each user interest is calculated by how far he/she is from the maximum value of 10.

In web applications that save data in an *n*-vector dimension space or data structure, the similarity between certain patterns can be calculated. The similarity measures aim at making a prediction and reaching an understanding of the users' behaviour in the system and are also considered part of the distance measure [62]. Some of the commonly used similarity measures are the *cosine similarity* and *Pearson correction* to indicate how similar certain attributes are and measure the linear relationship between them with continuous values [79]. However, if the there is a need to measure the similarity between certain values that happen to be binary or discrete values, a set of similarity measures, such as the *simple matching coefficient*, *Jaccard coefficient* and the *Extended Jaccard coefficient* has been proposed for both continuous and discrete values [80].

In the research presented in this thesis, the *Jaccard Similarity* method has been used in the user modelling updates, as the system generates dynamic user models based on the users' behaviour in the system, after constructing the initial user models. This is achieved through counting the frequent words used by each user. For each recommendation the user clicks on there are Meta tags, these are combined with the words that the user uses to make a certain query, and added into the bag of words. Then the similarity between these words is calculated by applying the *Jaccard Similarity* method. If the similarity of these words is higher than a certain threshold, then the user is given a recommendation related to the most frequent words.

Hence, the main reason of using *Jaccard Similarity* is due to the fact that this form of measure does indeed help in describing textual documents and can calculate the similarity between the respective bags of frequent words [80] [62]. The formal definition of the *Jaccard Similarity* is:

$$J(A,B) = \frac{|A \bigcap B|}{|A \bigcup B|} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Equation 2: *Jaccard* Similarity

(If *A* and *B* are both empty, $J(A,B) = 1$.)

$0 \leq J(\mathrm{A},\mathrm{B}) \leq 1$

If $x = (x_1, x_2, \ldots\ldots, x_n)$ and $y = (y_1, \mathrm{y}_2, \ldots\ldots, \mathrm{y}_n)$ are two vectors with all real $x_i, \mathrm{y}_i \geq 0$ their Jaccard similarity coefficient is defined as

$$J(\mathrm{x},\mathrm{y}) = \frac{\sum_i \min(\mathrm{x}_i, \mathrm{y}_i)}{\sum_i \max(\mathrm{x}_i, \mathrm{y}_i)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Equation 3: *Jaccard* similarity coefficient

In MyAds, the classification of these interests is then accomplished via a classification method that aims at mapping the interest with a label space and a set of items, for the initialisation of the user model, using the *K-nearest neighbour* approach.

When using the classification methods, two types emerge: the *supervised classification*, where pre-determined values are set in what is called a “training set”, and the *unsupervised classification* that relies on the fact that there are no pre-determined values and some method is used to organise the values [79].

The *K-nearest neighbour* classifier is a common, simple and intuitive algorithm. It is widely used to design and operate recommender systems, as they function well with filtering techniques. Furthermore, this approach has been proven to indeed generate accurate results, and it is flexible enough to be amended for further improvements. The *k*NN classifier searches for the *k* closest points (*nearest neighbours*) from the training records, in the case presented in this research from the interests values, and then it labels this value with the class that it belongs to, based on the preset value of k [62, 79]. For the purpose of the research presented in this thesis, the initiation of the explicit user model takes place in two phases; the first phase, discussed above, calculates the *Euclidean Distance* between the user's interest and the maximum value of 10. If this value is equal to or higher than 5, in this case $k \geq 5$, which is the threshold being set, the system automatically assigns this interest to the user and later suggests a recommendation for the user based on this calculation. This approach is a lazy learner approach [83], which is only used for the initiation of the user model, because it is not dynamic enough to keep updating the users' profiles, based on their behaviour.

2.5. Gaps in the Literature Review

The extensive research conducted in this chapter aimed at exploring the state of art in the field of adaptive personalised e-advertisements. The main gaps highlighted during this review of research are as follows:

- Personalised e-advertisements do not utilise adaptive content, and therefore does not use adaptive hypermedia techniques, such as adaptive navigation support or adaptive presentation.
- Personalised e-advertisements base user profiling upon traditional approaches (such as harvesting previous purchasing history, or using cookies). It therefore cannot construct rich user models that reflect upon the users' needs and interests through implicit or explicit user models.
- Most of the research focuses on banner advertisements as the most common approach for e-advertising, neglecting other types of e-advertisements such as classified ads. Only commercial platforms, such as Craigslist, Gumtree and Groupon, have explored this model, albeit with minimum personalisation.
- Information Retrieval (IR) literature provides a concrete theoretical and technical basis for this research as the framework researched relies on different approaches for design, implementation and evaluation of IR. However, still the root into personalised e-advertisement is not well explored and these techniques have not been applied on this field.

In conclusion, this Chapter has highlighted the main research areas that have been explored in order to explain the wider context of the research performed in this thesis. This Chapter has also fulfilled research **Objective 1** that stated; "*Conduct an extensive theoretical background study, to investigate the area of research that needs further exploring, by extracting the main gaps found in the literature and focusing on the contribution on this area*".

The research presented in this thesis has investigated a less explored area of classified ads, where users access a standalone system, to explore products that they need. However, these products are personalised via rich user models that this research has been building. The system built based on the research presented in this thesis also aims at presenting the appropriate products for the user, by using appropriate adaptive methods.

Chapter 3

3. Methodology

One of the fundamental parts of any research is to choose the appropriate methodology. A methodology is defined as a guideline to solve a certain problem using the appropriate tools, techniques and tasks [84].

As introduced earlier in Chapter 1 Section 1.2 in the problem statement and motivation, this research is *interdisciplinary*. Within this research, e-advertisements models and properties, user-centred design and evaluation, user modelling and adaptation are targeted. As a result, a good balance between these different intersecting areas is necessary. The research should be described at an appropriate granularity level, with the ultimate goal of delivering a comprehensive outcome.

Overall, in this research, the target is *users' acceptance* of the proposed solution (adaptive e-advertising), *in terms of usability, usefulness;* and, in some specific evaluations, *in terms of their needs and desires*. This work is thus user-driven, because the central research question aims at measuring users' acceptance with the proposed research. As a result, a *user-centred research methodology* has been embraced throughout the practice of design and validation. This methodology functions as the umbrella that guides a set of other methods, to target certain design and validation issues.

Thus, the user-centric methodology for design and evaluation has been used within all the experiments conducted in this thesis. It has been used to outline experiment procedures. Other research-based methodologies have been used to investigate the proposed design and evaluation of the research, together with the guiding principles inherited from the user-centric methodology, as will be discussed in details later in the chapter.

In relation to this research, this chapter aims at addressing research Objective 6 as follows;

Objective 6: *Ensure that each step of the research is conducted based on established research methodology.*

Outcomes of this chapter: this chapter works as a general guideline for the whole research approach adopted within this thesis. It explores the approaches, techniques and methods used during the research, and thus give useful pointers and suggestions to other researchers who want to embark on follow-up or similar type of research. Moreover, it discusses the quantitative and qualitative analysis methods that are used in the analysis of the results generated from experiments. This should provide a comprehensive understanding of the methodology applied to approach the proposed research questions in Chapter 1.

In order to create a coherent understanding of the methodology and its application within this research, it has been grouped as follows.

Section 3.1 discusses, at a generic level, the various methodological approaches used within the thesis. These approaches include the literature review, user centric methodology for both design and evaluations and the iterative system cycle implementation.

Section 3.2 discusses generalities of the user centric methodology. Section 3.3 discusses in more details the user centric methodology from a design perspective. In this section, the application of the methodology with the help of other approaches and techniques is explained. The aim of using the methodology in the design phase is to help in generating a requirement list to be used in further implementations of the system.

Section 3.4 discusses in more details the user centric methodology from an evaluation perspective. In this section, various evaluation measures are explored, as well as different acceptance evaluation models. The aim of the section is to highlight and justify the use of the user centric methodology for evaluation purposes.

Section 3.5 discusses the use of the user centric methodology in this thesis and specifically how it was applied in the conducting of the design and practical experiments. Section 3.6 discusses how the methodological approach used implies a certain ideal sample size. Furthermore, it discusses the limitations of the results in relation to different sample sizes and approaches, including the approaches taken by similar researches; in this light it reflects on decisions taken in the current research. Section 3.7 discusses the analysis of the results generated from the practical experiments, and how numerical and textual data has been processed. The final section is the summary, comprising final discussions and conclusions.

3.1. Overview of the Main Methodological Approaches

This section presents the main methodological approaches deployed through the thesis, as follow;

- ***Literature Review***

The literature review is the backbone of the research development. It was the starting point, as it served as guidance on what has been researched and what has not, in the area of adaptive e-advertisement. Work on it, of which part of it is reflected in Chapter 2, commenced in 2011, and has continued until the date of the thesis submission, to ensure that the work is up to date. Important gaps in e-advertising, recommender systems, adaptation and user modelling were identified within the literature. The gaps in the literature have been discussed in Chapter 2, Section 2.5.

The aim of including the literature review within the methodology is to ensure that the research content is updated with the available development of the state of the art. Also, it is described to highlight that this approach has been used throughout the thesis and has helped in the decisions on follow-up work.

- ***User-Centred Design***

The goal of this research is to measure users' acceptance of e-advertisements, as per research Question 1 found in Chapter 1 Section 1.3. As the users are the central focus of this research, the *user-centred design methodology* (UCD) is used throughout the research in design specific experiments, to extract their needs, requirements and constraints [85]. This approach has been used in the early stages of the research, combined with the *six thinking hats* method [86] and the *brain-*

storming method [87] to initialise the first prototype of the personalised e-advertising platform. This user-centred design methodology is used as part of the research methodology in many researches involving application-oriented research in general, and, more importantly, users (e.g., [88], [89] and [90]).

This provided the users with the opportunity to express their perceptions on what is considered appropriate for e-advertisements. It has also been used again in the form of *focus group* [91], at a later stage of the research, when further improvement of the first prototype was needed, as it allowed more focused ideas (including comparisons between other famous commercial platforms). This approach facilitates the users' participation, allowing them to express their feelings and achieve a high-level experience in relation to the system's design, usability and functionality. Further descriptions on the user-centred design applied in this thesis can be found in Section 3.3. The user-centric design approach has been specifically applied in experiment 1 – the exploratory system design, found later in Chapter 4 and in the revisited system design experiment 2, found in Chapter 6.

- ***Iterative System Implementation***

The features generated from the research had to be evaluated through users actually experimenting directly with these features, so the necessity for an implemented system emerged. The implemented system serves as an evaluation tool for the user-centred design, user modelling and adaptation features. The implementation of the system is not a straightforward process, as it is an iterative process following the iterative and incremental model [92], based on the Spiral Model [93]; each system prototype is an enhancement of the previous version – addressing the weak points and enhancing the stronger features. For this research, the personalised system developed is called MyAds and has gone through two main iterations of enhancements and development. Further descriptions on the iterative system implementation applied in this thesis can be found in Chapters 4, 5, 6 and 7.

- ***User-centred Evaluation through Experiments and Case Studies***

Several experiments were conducted, to collect users' opinions of the proposed research and their reflections of the implemented system. Users were asked to work with the system, as they are presented personalised advertisements. During the process of browsing, log files were stored and user interactions were frequently updated in the database, to track the users' behaviour on the system. By the end of each experiment, users were asked to fill in a questionnaire, to provide feedback on the system, as well as their overall experience. Furthermore, qualitative feedback was collected, as part of the discussions that were shown with the users who were interested in giving additional recommendations. Further information on the experiments and case studies performed in this work can be found in Chapters 4, 5, 6 and 7.

The literature is rich with many different definitions, design and evaluation methods for user-centric applications. In this research, the user has been the key focus in both design and evaluation. Users have participated in the initial suggestion on the system design, using the user centric methodology presented in [94]. They have also used thinking techniques, such as brainstorming [95] and the 'Six Thinking Hats' method presented in [96]. They have evaluated the system, participated in the second version design, using the focus group methodology [97] and evaluated the updated version of the system as well.

3.2. Generalities on the User Centric Methodology applied to Experiment Execution

Gill (1991) defines human-centeredness as "a new technological tradition which places human need, skill, creativity and potentiality at the centre of the activities of technological systems" [98].

As mentioned above, the *user centric methodology* works as the main guideline for the experimental design and execution throughout the thesis, and is a part of the overall research methodology, used in many researches involving users (e.g., [88], [89] and [90]). It is defined as the "the active involvement of users for a clear understanding of user and task requirements, iterative design and evaluation and a multi-disciplinary approach" [99].

The main advantages of using the user-centred methodology are summarised in the following [100]:

1. It helps to create a better understanding of the factors that affect the user whilst they use the designed system, as the users are involved at every stage of the design process. This is practically important for this research as users' acceptance is the main measure to be evaluated.
2. It gives a sense of assurance that the final system will be suitable for the users, since they had a say in the design.
3. It ensures the creation of more effective, efficient and safe outcome.
4. It has a central impact on system designers and system analysts, as it gives them an idea about the expectations of users.
5. It helps in dealing with any problems in an early stage of system development, rather than waiting for the final testing of the system. This has been explored through this research as revisited system design was needed after the first practical evaluation.

However, there are a number of disadvantages in using the user-centred methodology [101], some of these disadvantages are:

1. The process is costly and time consuming. In this research, two design experiments were needed to ensure that the design actually meets users' requirements.
2. It may require the involvement of a large team of designers. In this research, the teams have been kept small out of time and location restraints.
3. Some requirements may be difficult to fulfil. This has been faced in the first exploratory design experiment detailed in Chapter 4.
4. The requirements may be too general or too specific. This may lead to failure of the experiment. For this reason, this research has involved an iterative process, with two design experiments, and further evaluations of the finished product.

The two parts of Figure 3.1 below illustrate the stages that the people go through in an experiment involving user-centred methodology. This process has three stages, which intersect with each other, to produce the final product [94].

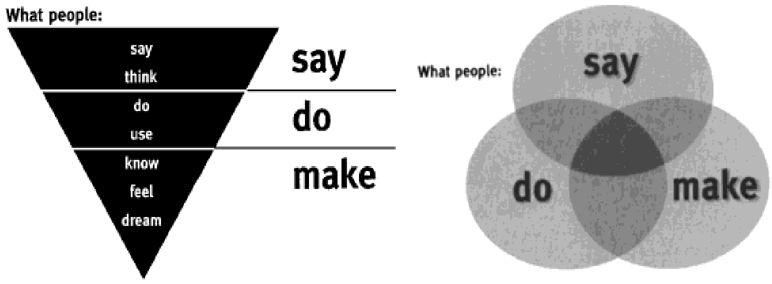

Figure 3.1: The user-centred methodology

There are a number of techniques to be used with users that are involved in an experiment, based on the stage of the research, whether it's' the design or the validating of the proposed approach [101].

The methodology suggests that users go through three main stages of (say – do – think). The *Say stage* includes users' projections on what can be said and what do they think. The *Do stage* includes how they actually use and manipulate the suggested problem or research idea. The *Make stage* is where their actual involvement with the problem or research area arises. In this stage, they can contribute with their knowledge, feelings and ideas. The stages are intersecting with each other, and the order of the execution can be based on the needs of the experiment [101].

However, during the research there have been a number of other methodological approaches adopted. As the user centric methodology has its limitations, other methodological approaches were needed. These approaches addressed the specific needs of the work. These methodological approaches are discussed in their respective context.

3.3. The User Centric Design Approach

Making this research user-centric involved users being part of the design process. From the overreaching requisite to collect the proper set of requirements for system development, the method of a participatory design has emerged. *Participatory Design* is an approach that focuses on the role of the users, by engaging them in the process of system design [94]. Users engaged in the process of system requirements extraction can then be also used in the design process, and then finally can be involved with testing the implementation of the system [94].

Some of the main techniques that have been used in experiments are: *questionnaires*, *focus groups* and *role playing walk-through simulations*. In this research, questionnaires, as well as focus groups, were used as they are one of the appropriate types of information gathered, eliciting responses about the desires of the users, as well as their requirements with respect to personalised advertising.

For the focus group, two different thinking techniques were used throughout the research, the *brainstorming technique* and the *six thinking hats technique*.

This *brainstorming technique* is a supervised thinking approach, which is a very popular thinking technique, introduced in [95]. The technique suggests that people or individuals tackle a certain problem by discussing all the possible situations and then conclude on a problem solution. The reason for using this technique is to collect as much data as possible about a certain problem, then classifying and summarising the problem into main points to be further investigated and solved, producing so called "spider diagrams" [102]. Due to its popularity, ease of use, speed of producing results, and the fact that this technique deals well with well-defined search spaces, this technique has been selected for the experiment described in Chapter 4 (Section 4.2). Figure 3.2 is an example of a spider diagram. Spider diagrams are a representation of the thinking approach, by centring the main idea then dividing it into sub-ideas, then dividing the sub-ideas into even further detailed descriptions, to create a set of links connected to a central node. This therefore helps in organising the ideas as they get larger and more detailed [102].

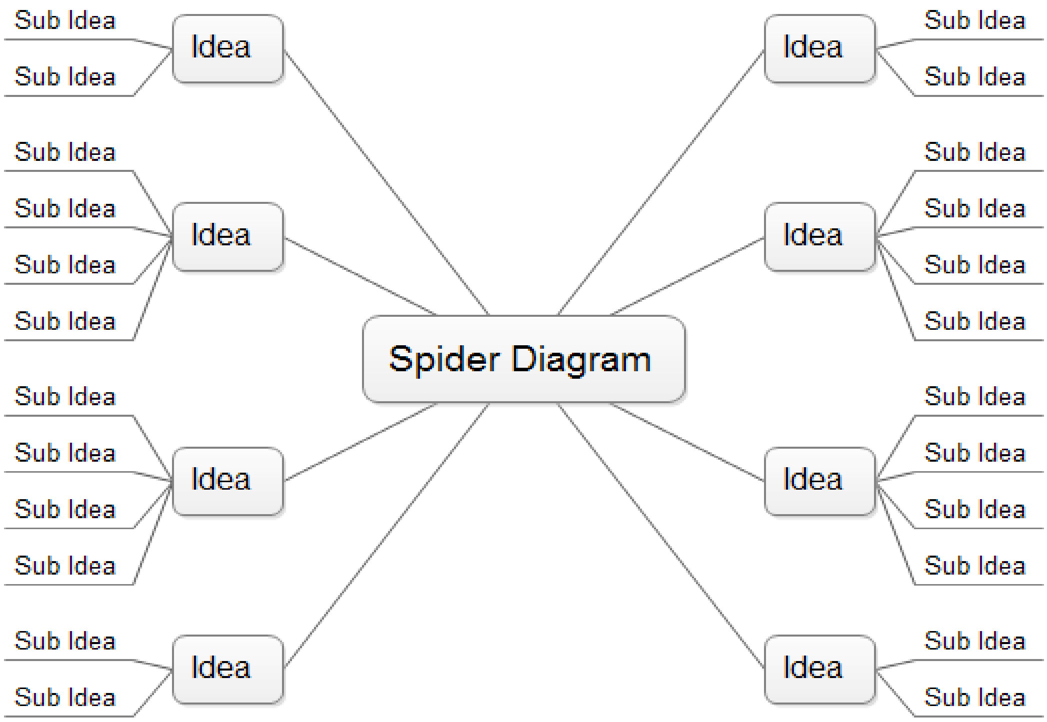

Figure 3.2: Spider Diagram

Another thinking technique – slightly less frequently used, but quite useful and able to generate rich information is the *six thinking hats* technique [96]. The main aim of this technique is that each person in the group actively and purposefully thinks differently from the other people (thus wearing a different hat), so a full analysis from all perspectives can be covered. This technique is useful with a small number of participants and guarantees that important aspects of a design process are not omitted, thus ensuring that users really consider all angles, having already discussed their preferred one using the brainstorming technique. Of course, here it should be considered that in some cases users may not be capable of successfully and completely understanding, and thus exploring, some aspects. For instance, the system administrator's perspective may not be as clear to the average user.

The research obliged for more precise ideas about the new system design. The *focus group* has been defined as a part of a qualitative research method that has been used for a long time, in order to collect solid observations on (for instance) products, services, advertisements or ideas. Focus groups are conducted via an interactive group setting, where the session leader asks questions which are then discussed by the group, to collect the various perceptions and attitudes [103]. It is a form of *participatory design*, as customers or potential users become part of the solution [104]. It represents a mixture between a personal experience, where individuals express their personal observations and a collective experience of the group ideas [105]. Moreover, if the experiments are conducted in a socially relaxed environment for both the participants and the moderators it can generate good outcomes [106]. Although the experiments can be performed in a relaxed and interactive environment, it does not omit the fact that the discussions can be oriented to answer the questions proposed by the researcher [107]. It is also a rather challenging approach of data collection, as the session moderator (usually the researcher) has to ensure that ideas are being discussed thoroughly and the general atmosphere is engaging for the participants and within the context of the research [108].

The reason for using this approach is because there was a requisite for a more concrete interaction with the participants, with a larger amount and range of answers, and more focused responses. Another reason the focus group approach has been used within this experiment, is due to the fact that it provides a complete cycle of understanding the participants' points of view. This allows for justifying the reasons for certain participants to have certain opinions, eliminating the abstract forms of information collected from questionnaires and surveys [109]. Another reason is that focus groups are useful in research that is oriented towards understanding customers' behaviours and patterns [97]. However, focus groups also add extra complications in terms of ethical and personal considerations, and require the researcher to have special inter-personal skills. Researchers have to be very conscious about participants' personal ideas and maintain a very professional attitude [109].

There has been extensive research in the area of user-centric design methodologies. Different approaches have been used as part of different socio-technical views. The reason to use such approaches is to balance the abstraction of the "systems", with the interactivity of "humans", in order to create systems that will eventually be used by humans [110]. Some of the frequently used user centric methodologies include the *traditional IS design approaches*, the *prototyping and* *participatory design*, the *interactive design*, *UML and use case* and the *agile software development* [110]. Each approach has a number of strengths and weaknesses, as summarised in Table 3.1 below.

Table 3.1: Different methodologies for human centric IS design, as described in [110]

Approach	**Intended Focus**	**Actual Focus**
Traditional IS design approaches	The structuring of ill-structured problems: goal-driven decomposition.	Explicit (management) focus is goal-driven and decompositional. Implicit strategies are opportunistic, to deal with goal-emergence.
Prototyping and participatory design	Negotiation and exploration of ill-structured problems.	Iterative and cyclical process of stakeholder involvement, limited by political selection of user-representatives and technology-centered requirements focus.
Interaction design	Exploration of IT-supported user work-processes.	Technology-centered, individual user focus. Assumes consensus among system users, with well-understood IS goals.
UML and Use-Cases	Modeling of business processes and user-interactions with intended IT system.	Models formal information-processing (business processing rules). Technology-centered and decompositional (so no opportunity to redefine goals as these emerge through design process).
Agile Software Development	Adaptation of an evolving system design, based on user interaction and scenario generation.	Technology centered prototyping, accomplished by the development of individual user-scenarios.

The approaches discussed above do not vary radically from the actual methods used within this research. However, different approaches can be used based on factors such as the nature of the application, number of participants included and the targeted outcomes of users' involvement. For instance, from a software development point of view, an iterative implementation method, based on the Spiral Model [93]- where objectives, development, testing, planning were iterated - was preferred to Agile Software Development, which is more appropriate for systems in constant use, with potentially multiple contributors to the development. Participatory design was directly applied in this research, as mentioned in Chapter 4 Section 4.2. UML and Use-Cases were used in the design stages. Interaction design and exploration of the user work processes was accomplished during the experiments, as described in Chapter 5 Section 5.4.

Other methodologies for designing information systems that do not involve the users within the design process, but rather make it system analyst and designers jobs, include the *bottom up*, *top down*, *meet in the middle* and *platform methodologies* [111]. These methods are not within the scope of this research, as they are not user-focused, and are not further detailed here.

3.4. The User Centric Evaluation Approach

Evaluating user centric systems can be an arduous job, especially in the domain of e-commerce. It is a highly subjective field, because there are many parameters to take into consideration. Firstly, there is a subjective evaluation assessment based on users' responses to questionnaires and interviews [112]. Secondly, there is an objective evaluation assessment through the study of log files of data acquired through the actual usage of the applications [69].

The user centric evaluation (UCE) is considered as one of the common and well-accepted approaches to evaluating user experiences. It covers the subjective perceptions of users' acceptance and their opinions on the quality of the service provided. It also functions well with experimental systems and applications evaluations – see [113] and [114].

The evaluation measures for systems can be classified into the categories of *usability*, *usefulness*, *credibility* and *accessibility*, as well as the system being *findable*, *desirable* and *valuable* [115]. However, within adaptive systems, other measures have been proposed, e.g. of evaluating *user performance*, *satisfaction*, *comprehensibility*, *re-use*, *appreciation* and the *adaptation appropriateness* [114]. Other research has recommended adding the aspects of *flow*, *acceptance*, *performance gains*, *technology adoption* and *empirical behaviours* [116].

The previously mentioned measures do not necessarily all need to be evaluated. The measures can be selected based on the research questions, aspects and objectives to be achieved by the researcher. However, since the focus of this research is to measure users' acceptance, it was necessary to understand what does acceptance imply? And what supporting measures can be used to evaluate acceptance. The set of following definitions establish a theoretical understanding of what to evaluate when examining acceptance, as follows.

Acceptance is defined as the "demonstrable willingness within a user group to employ information technology for the tasks it is designed to support" [20]. Moreover, usability is strongly connected with acceptance as an evaluation measure as it is considered a pre-requisite of acceptance [20].

The standard quality assurance definitions of ISO 9241-210 and ISO 9241-11 are explored, which acknowledge that usability measures are to be used for the user-related experiences within computer applications [117].

Usability is defined as “the extent to which a product can be used by specified users to achieve specified goals in a specified context of use” [21].

For the purposes of this research, the measures of acceptance adopted throughout the thesis focused on usability, as one of the evaluation measures to consider when examining acceptance.

Usability as a measure is not enough to reflect upon acceptance as the definition of acceptance includes “employ[ing] information technology for the tasks”, which indicate the use of a measure to actually examine the functionality of the proposed application. For the sake of understanding what other measures to be included to be used to measure acceptance, some of the well-known models of acceptance are discussed.

One of the commonly used and explored models of acceptance is the Technology Acceptance Model (TAM) [118, 119]. This model focuses centrally on acceptance, in terms of two main factors: the perceived usefulness and perceived ease of use. Perceived *usefulness* is defined as the degree to which a user believes that using the system will change in a positive way his or her performance. It is also suggested that these two factors have a significant implication on the users’ perceptions towards accepting the system, adding to that it has been explored that usefulness is the most important predictor of use [20]. Since the perceived usefulness is actually one of the fundamental measures that reflect upon acceptance, this measure is also used within this research. Perceived ease of use is defined as "the degree to which a person believes that using a particular system would be free from effort" [119]. It has also been explored earlier that usability is considered a pre-requisite to acceptance and therefore it is to be included within this research. The usability and usefulness issues were explored in the early stages of the research found in Chapter 4. Then, a large scale evaluation can be found in Chapter 7.

Additionally, this research, for some specific evaluations, additionally gathered data about users' satisfaction and needs. Doll and Torkzadeh suggest that it is important to evaluate users' satisfaction when using end-user computing, especially in relation to their needs, and not only the perceived ease of use and usefulness [120]. Satisfaction and needs are used in this research in relation to the direct user models, as is discussed in Chapter 7.

The *user centric evaluation model* discussed earlier bases its evaluation on both subjective and objective feedback from a user experience. The user experience is connected with the type of application platform on which the system is being tested. In each case, the defining parameters do differ, based on the final output expected from the system. The UCE can be used in any application domain, as long as the evaluation measures that are connected to the application domain are justified [114]. This methodological approach is used to set the evaluation atmosphere and set the guidelines for both the facilitator and the users, when conducting the experiment. The application of the methodology within the evaluation experiments is discussed in Section 3.4.

The *technology acceptance model* (TAM) is one of the successful platforms in predicting information technology acceptance and usage, as it focuses on two main measures of usability and usefulness only [10]. This model is the basis of the evaluation measures of this research, as this approach is simple and easy to use. However, it still limits its validation to perceived ease of use and usefulness, giving very little flexibility over other measurements to be used, including objective measures. This approach remains the backbone of evaluation models used in this research. In some cases, there has been an expansion for the evaluations towards using objective evaluations [10] and expanding the measures of acceptance to include needs and desires.

The *unified theory of acceptance and use of technology model* (UTAUT) increases the number of variables that are used to measure the acceptance of an information system, to include four different measures of performance: expectancy, effort expectancy, social influence and facilitating conditions. All these measures are related to the user's personal traits, and connects them to the behavioural intention and usage behaviours [121]. This model may seem wide, as it covers many aspects to be considered within the evaluations. However, it does not actually address the requirements of this specific research. It has more measures than TAM, but it still limits them to these four measures, excluding other measures. Moreover, the research presented in this thesis is not as focused on issues related to social interactions. Whilst the influence of social interactions was considered in the start of the research, the overall focus of the finally emerging piece of work was about *user's individual perceptions*. Furthermore, the UTAUT model does not specifically include usability and usefulness, which are two of the main variables that are promoted by all the other models, and which were considered vital to include in the research presented in this thesis.

Thus, the user centric methodology has been used within the research, informing the different methods and techniques used for the evaluations. For the purpose of the evaluation, these models as above have been considered, and some employed, including the *user centric evaluation* (UCE) as a guideline for conducting evaluation experiments, the *technology acceptance model* TAM, as a methodological approach of evaluation measures, and the *unified theory of acceptance and use of technology model* (UTAUT), as a potential alternative, which was not directly employed in this research.

3.5. The Methodological Approaches for Experiments within the Thesis

The application of the different methodological approaches was conducted as follows;

- ***Exploratory study – design experiment***: the first experiment was a design targeted towards generating an initial requirement list, to be further used for implementation. Generating the initial system requirements was a tricky job. The exploratory study adopted, as said, the user centric design methodology, to conduct the experiment and set the general atmosphere for it. The experiment was divided into three main phases to imitate the *say – do – make* method. The users first expressed their opinions *(say)* about the current e-commerce and e-adaptive system by answering a questionnaire covering different aspects of e-commerce personalisation. Then the users started exploring *(do)* different e-commerce and e-advertisement websites and experiencing different platforms through a seminar that has been given to the users to understand how different platform functions and their type of personalisation used. The final stage was the *(make)* stage where the users started designing their own personalised e-advertisement platforms exploring different features and technologies. Because this final stage is quite intense, the users used the six thinking hats and the brainstorming technique to help them generate ideas so the final requirement list can be generated. The requirement list generated from this experiment was then used for the first practical development of the system. Details of the experiment can be found in Chapter 4.

- ***The first practical experiment – introduction of MyAds***: this experiment was conducted to evaluate the first iteration of the developed system, called MyAds. This system was built based on the requirements list generated in the previous experiment, as well as the selection of the appropriate features found in literature. The users also validated the system, using the user centric evaluation methodology that worked as the guideline for setting up the experiment stages. Firstly, users started by the *(do)* phase examining other systems, so a fair comparison between MyAds and other well-known systems could be conducted. At this stage, users actually started exploring other platforms, and the researcher also introduced the research area to them. The second stage was when they started using MyAds the adaptive delivery system, which reflects on the *(making)* stage in the user centric methodology. In this stage, users were involved in manipulating the system and making their own profiles and preferred selections. The final stage was the *(say)* stage, as the users expressed their perceptions on the system and evaluated it through answering a questionnaire, to evaluate the different features within the system. Details of the experiment can be found in Chapter 5. The results from the first live system evaluation indicated that there are number of features that should be additionally included and an improvement of the system usability was also required, so another re-visited design had to be conducted. A focus group experiment was performed, as explained next.
- ***Focus group design experiment: after the first system*** iteration experiment was finished, the focus group experiment was conducted. The aim of the experiment was to enrich the requirements list and address the issues raised in the practical experiment. The focus group experiment followed the same approach as in the exploratory study, and a list of requirements

was generated. Details of the experiment can be found in Chapter 6. The detailed list of requirement was then implemented and aimed at being evaluated as in second and third practical experiments, as explained next.

- ***The second practical experiment – second iteration adaptive delivery system MyAds:*** after the rich requirement list was generated in the second design experiment, the requirement list was then used to implement the second iteration of the adaptive delivery system MyAds. The methodological approach adopted was exactly the same as in the first practical experiment. However, the system had two main issues; the first issue was that the login token via Facebook was not active, so no implicit data could be collected. The second issue was that there have been some features that existed in the system, but were not evaluated. So these features had to be evaluated via another experiment, as below. Details of the second practical experiment can be found in Chapter 7.
- ***Third system iteration experiment***: This experiment covered the missing aspects in the previous one, e.g., by introducing the Facebook login. This experiment addressed all research questions, as the system was finalised enough to allow for this. The evaluation questionnaire covered all the missing issues that have not been covered before. The experiment followed exactly the same setting of the methodological approach that was used in the first and second system iteration experiments. The details of this experiment can be found in Chapter 7.

3.6. Sample Size, Generalisability and Limitations

The methodological approaches used within the thesis are highly user-focused. Since users do take action in determining the confirmation or refuting of the proposed approaches, it is crucial to understand the various aspects of the samples selected. Sample size is a feature of an experiment or a study design that has an influence upon the detection of different evaluation measures significant differences. In experiments, one of the focal issues is to determine the intended sample size to be investigated. The question that is usually posed is “what number is reflective to the actual population?”. This question cannot be answered or determined by a number only. The common factors include the aim of the study, the population size and the sampling error [122]. Moreover, from a formal perspective, factors to determine the sample size should include the level of precision, level of confidence and the degree of variability attributes [123].

The *level of precision* is defined as "the range in which the true value of the population is estimated to be. This range is often expressed in percentage points, (e.g., ± 5 Percent)", the *level of confidence* is defines as "the average value of the attribute obtained by those samples", "equal to the true population value" and the *degree of variability* in the attributes being measured is defined as "the distribution of attributes in the population" [123].

Determining the sample size can be obtained using one of these various four strategies. These strategies include: using a census for small population, for example population size of 200 or less. Another strategy includes using the same sample size as used in similar research, by imitating the same sample size decisions. The third strategy suggests using numbers suggested by published tables for a given set of criteria. The final approach is via using the formal method of calculating the sample size if the level of precision, confidence and variability may change [122].

With regards to the generalisability of the research, the results generated from the research, besides being influenced by their actual values and nature, are also influenced by the sample size involved. Holton and Burnett discuss that determining the sample size in quantitative survey design is important. They explain that within quantitative methods, the use of smaller groups can make inferences about larger groups [124]. Another aspect that should be taken into consideration is the numbers to be used within data analysis. If the research is highly focused on descriptive statistics, such as mean values and frequencies sample, almost any sample size can be used with careful attention to the significant claiming [122]. Moreover, for any analysis that needs further statistical significance analysis, a sample size between 200 and 500 qualifies as a good one [122]. Additionally, Gay and Diehl add that the number of participants in an experiment, or the sample size, can be determined by the type of research involved. For descriptive research, the sample size should be within 10% of the total population. However, if the population is quite small, 20% is required. If the type of research aims at finding correlations between different evaluation measures, within experimental research, 30 subjects per group is the usually accepted norm [125].

Another prospect that should be considered when considering the sample size is the type of group selected. The more homogenous the population, the smaller the sample size needed. If the true variability of the group is large, indicating a heterogeneous population, a larger and more representative sample size should be considered [122].

The previous discussed approaches do deliberate about the ideal way of selecting and generalising the sample size. However, the reality within the research poses a number of limitations. These limitations can lead to researchers using a less than ideal sample size, because of the practical constraints. Limitations include time, budget and resource limitations [126]. Another constraint is the accuracy of the prediction of the actual population that can be used to then determine the appropriate sample size. In other words, determining who is actually a representative of the research questions posed and if their feedback is adequate enough to generate results based on this feedback [127].

Within this research, sample size has been given due to the previously mentioned consideration. The application falls within the domain of e-commerce and e-advertisements, which qualifies any internet user as an appropriate user. However, the domain of research is narrow in terms of adaptation and personalisation. Although any user can qualify for the task of evaluating an e-commerce/ e-advertisement application, the limitations of having the actual reflective sample size are numerous. The first limitation is that this is a prototype system, so the actual evaluation should be conducted within a monitored environment, to ensure that any bugs or issues can be dealt with on the spot. The second reason that the evaluations aimed to be as controlled as possible, so the experiments also needed to be monitored. Moreover, there are limitations to the number of users who are willing to take part in the experiments, and if the numbers is to be expanded, an extended amount of time and budget have to be allocated to collect more users. For instance, a currently popular way of acquiring more users is to use some of the online surveying services, such as Amazon Turk[1] or Crowdflower[2], where participants have to be paid for taking part of the study.

Being aware of these limitations in user study, potentially affecting the research, the following decisions were made, to try to overcome these difficulties as follows:

- To overcome the problem with technical issues, all the experiments were conducted within monitored labs, with the presence of the key person responsible for the experiment.
- To overcome the controlled experiment problem, all the evaluations were conducted within a controlled environment, as explained in the previous section.
- Finding a sufficiently large number of users has been a pressing issue from the beginning of this research. To overcome this problem, as well as the budgeting problem, the solution was to involve students as users. The reasons for using students were manifold. Not only were they available, and easy to monitor as above in controlled settings, they are also highly aware of the different technological advances and they are extensively web users [128]. However, when aiming at getting as many users as possible, the number of users in the University of Warwick that can help within the evaluations is limited. Additionally there were cultural aspects that affected their availability, such as that students in the western world and UK tend to have a more relaxed relationship with their monitors, as the hierarchy is less emphasised, and hence are less likely to participate in large scale experiments [129]. The other places that the researcher had access to and could benefit from the users were the University of Jordan in Amman, Jordan and the University "Politehnica" of Bucharest, Romania. The students in the University of Politehnica have only participated in one experiment out of five in the beginning of the work; the details are in Chapter 4. Other useful factors include the fact that all courses taught in the university are in English, students take advanced courses on web development, and web-based systems and e-commerce systems. Additionally, the numbers of students are in the

[1] https://www.mturk.com
[2] http://www.crowdflower.com/

University of Jordan much higher than the ones in the UK, with courses with more than 300 students per course – even for final year courses.

After these factors and limitations were considered, different sizes of user population were involved in the different experiments. For qualitative experiments, which were gathering initial ideas and pointers for the research, smaller scale populations were used, in order to keep the process manageable (e.g. brainstorming cannot function appropriately with a large number of participants) as well as to keep the costs low. For the large scale evaluation of the final system, which evaluated all research questions, the sample size was calculated based on the formal formula. The population that was used to base the calculation on was the number of internet users in Jordan, which is 5,700,000 users in 2015, which represents more than 86.1% of the population [3]. The calculation was based on a 95% confidence level, a 5 confidence interval and the previous population [130]. The number resulting was 384, which is the recommended sample size. So the aim of the research was to collect 384 users for the large scale evaluation. This number was not achieved, however, with 221 participants taking part in the experiment and another 46 for in a follow-up experiment, summing up the total to 267.

This number is still considered a reasonable number for a research-based evaluation, as other case studies report on a close or a lower number of participants in similar cases. For example, in a case study that reports on an evaluation of a web-based business to consumer e-commerce applications to reflect on users satisfaction, 56 users was the sample size [131]. Another case study, investigating the business to consumer website quality, reported on 213 users as the sample size, also using students as evaluators [132]. A case study reporting on the application of the Task-Technology Fit Model to structure and evaluate the Adoption of E-Books by Academics, a population of 4,383 was initially approached, but this resulted only in 434 responses, with only 361 valid ones [133]. Another case study incorporating the social aspect with a recommender mechanism for e-commerce reports on an initial approach of 1075 participants, to return only 424 [134]. From this point of view, the return in the work in this thesis was much higher in percentage when compared with the latter two studies.

3.7. Qualitative and Quantitative Analysis of Results

As can be seen in the list in Section 3.5, this research introduces five different experiments. In each experiment, results have been generated. These results were dealt with based on their nature of either being *quantitative* or *qualitative*. In order to create a better understanding of how these results have been produced and analysed, the methods applied, such as statistical tests and analysis, are briefly described.

Throughout this thesis, *descriptive statistics* was conducted to analyse quantitative answers. Additionally, especially in the initial exploratory experiments, open questions were asked, and open discussions were held. Those were more oriented towards discussing the pros and cons of adaptive features and what can be suggested in terms of technology, features, user and user models, than actually confirming or rejecting a hypothesis.

The outcome of the design experiments was mainly qualitative. In order to analyse the qualitative feedback collected, the *qualitative content analysis* method was used. The qualitative content analysis method is defined as "subjective interpretation of the content of text data through the systematic classification process of coding and identifying themes or patterns" [135]. The approach includes three different types of analysis, including conventional, directed and summative. The approach to be used is the summative approach, as it focuses on collecting keywords that hold the main answers for the open questions posed. These keywords are collected from the raw data generated by the users and is interpreted within the underlying context [135]. Details on the use of this method are found in Chapter 4, which analyses the outcomes of the exploratory study, and Chapter 6, which provides a re-visited design for the proposed system.

For the numerical results, *questionnaires* were used. The questionnaires were filled by the users, using a Likert scale between 1 to 5 (with 1 meaning strongly disagree, and 5 meaning strongly agree). The questionnaires' answers were mapped on a Likert scale, due to the fact that this form of scaling can help researchers in understanding, expanding and predicting the behaviour and perspectives of the respondents [136]. As Likert scales vary, the presence of a midpoint can be tricky; however, it is believed that it can cause a balance of the obvious negative against the obvious positive opinions that can lead to getting validation and reliability out of responses [137].

More importantly, the midpoint pulls in genuinely unbiased/unconcerned respondents from one viewpoint and irresolute respondents from the other [138]. Hesitant respondents, who are forced to take sides, tend to react negatively [139]. Results within the midpoints are tested to be increasing the Net Acquiescence Response Style (NARS) that can lead to them being more on the positive side of the argument [136].

In this thesis, in order to be somewhat stricter in the analysis, being beyond the midpoint itself (3, on a 1-5 Likert scale) was not considered enough. Instead, to be surer of the result outcomes, the results were compared, by considering that any value that is equal or larger than 3.5 was positive, taking into consideration the standard deviation and the mode value, to normalise the result.

In order to analyse the results, the following statistical test were conducted:

1. *Descriptive statistics*: these tests included all the descriptive ones of Mean, Mode, Standard deviations that addresses to the central tendency theorem. These tests were conducted mainly in Chapters 5, and 7. The mean values and percentages were used in Chapter 4 & 6.
    - *The mean*: In probability and statistics, mean and expected value are used synonymously, to refer to one measure of the central tendency either of a probability distribution or of the random variable characterized by that distribution [140].
    - *The mode*: The mode is the value that appears most often in a set of data. The mode of a discrete probability distribution is the value x at which its probability mass function takes its maximum value. In other words, it is the value that is most likely to be sampled [140].
    - *The standard deviation*: is a measure that is used to quantify the amount of variation or dispersion of a set of data values. A standard deviation close to 0 indicates that the data points tend to be very close to the mean (also called the expected value) of the set, while a high standard deviation indicates that the data points are spread out over a wider range of values. [140]

2. *T-test for significance*: It can be used to determine if two sets of data are significantly different from each other. In this research, the obtained values have been compared against the neutral value of 3. The tests conducted are two-tailed, to see both the negative and positive side of the arguments. The significance level used is the frequently used one of 0.05, so any probability value lower than this value is considered significant [140]. This test was conducted in Chapters 5 and 7.
3. *Wilcoxon signed-rank test*: which is a non-parametric statistical hypothesis test used when comparing *two related samples*, matched samples, or repeated measurements on a single sample to assess whether their population mean ranks differ (i.e. it is a paired difference test). It can be used as an alternative to the paired Student's t-test, *t*-test for matched pairs, or the *t*-test for dependent samples, when the population cannot be assumed to be normally distributed. Based on the data collected from the descriptive statistics, in this research, the results are not normally distributed, as they tend to be skewed to the right, as most of the values for the questions' answers are between 3 and 5. So the need for a non-parametric test to examine the significance against the median value of 3 has emerged [140]. This test is conducted to support the results achieved earlier in the descriptive statistics, to prove the results are on the positive side of the argument. This test was conducted in Chapters 5 and 7.
4. *Mann–Whitney U test* is a nonparametric test of the null hypothesis that two samples come from the same population against an alternative hypothesis, especially that a particular population tends to have larger values than the other [140]. Here, the responses on the questionnaire were one sample and the other sample was the neutral value of 3. This test was conducted in Chapters 5 and 7.
5. *Cronbach's alpha* test is used as a (lower-bound) estimate of the reliability of a psychometric test [141]. The aim of the test is to find out how correlated and reliable the questions presented in the questionnaire are. In this way, the final results from these questionnaires can be justified, based on reliable questions to start with. Table 3.2 describes the *Cronbach's α* value for a specified scale of items. This test was conducted in Chapter 7.

Table 3.2: Cronbach's alpha scale for reliability values

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

3.8. Summary and Discussion

This chapter aimed at exploring the appropriate methodological approach to be used within the thesis. The methodology is one of the main and essential parts of any research, as it draws the path the research will follow.

For the purpose of this research, the user centric methodology was selected throughout, in both the design and evaluation. In the design experiments, other techniques were used, to simulate the users to provide more ideas, such as the brainstorming, six thinking hats and the focus groups techniques. In the practical experiments, the actual stages suggested by the user centric evaluation methodology were followed, so a comprehensive outcome can be achieved. This chapter also discussed the evaluation measures selected in this research, and reflected upon the overall research, and works as a blueprint of the design and validation of the proposed research.

Chapter 4

4. Concept of Adaptive E-advertising and Initial Theoretical Framework

4.1. Introduction

This chapter aims at defining the concept of adaptive e-advertising and partially addressing the following research objectives:

Objective 2: *Conduct a series of experiments that investigate the appropriate approach and features to design adaptive e-advertisements, and then test the practical development of these features in an adaptive e-advertising system, addressing the acceptance of this form of ads in the targeted evaluations.*

Outcomes of this chapter: This chapter addresses the first part of the objective "Conduct a series of experiments that investigate the appropriate approach and features to design adaptive e-advertisements" by describing the first iteration of the system design, and establishing the concept of adaptive e-advertisements in relation to this research.

Objective 3: *Propose a suitable (new or extended) theoretical framework/model for the adaptive features necessary in advertising, such as a layered model.*

Outcomes of this chapter: This chapter addresses the first part of the objective that proposes the initial "new theoretical framework/model for the adaptive features necessary in advertising such as a layered model". The chapter defines the initial theoretical framework, as derived from the layered models proposed in the literature, as well as explains the exploratory study conducted.

Objective 6: *Ensure that each step of the research is conducted based on established research methodology.*

Outcomes of this chapter: In this chapter, the first exploratory study is conducted. The user centric design methodology was used in the experiment. Later, the qualitative results generated from the experiment are analysed, using the qualitative content analysis method described earlier in Chapter 3.

Researchers can be knowledgeable about research needs and techniques. However, this may not be the same with respect to the users' expectations and requirements. They may have different requirements from the system, which the researcher may not be aware of, so the importance of engaging the users in the design and evaluation has emerged [142]. Another angle to be considered is the fact that the actual involvement of users' can help in decreasing the time, effort and cost of redesigns, especially in the case of research, where researchers need to improve and update their system iteration [143]. Users or customers do play a significant role on the design of personalised systems as it influences their interaction strategies. This indicates that engaging users in the design of personalised e-commerce web systems can help designers to specify the design features. These features can be built into the application and then the way they affect the application be evaluated [24].

It is clear that due to the huge availability of information about products, and the loss of trust in traditional advertising, businesses need to rethink their advertisement strategies [144]. For this reason, the research presented in this thesis starts with users from the very beginning, via an exploratory study. The aim of the study is to gather system requirements and design know-how for an e-advertisement adaptive hypermedia system. The idea of conducting this experiment was derived from to the perspective of understanding different customers' perceptions. These perceptions are imperative in designing a system that fulfils their requirements, and involving them from the very beginning can improve the chances of system's acceptance [101].

4.2. Experiment

Fortuitously, when it comes to online advertising, any web user qualifies as a user of e-adverts. Certainly in the Western world, with a close second in numbers in Eastern Europe, the great majority of the population is a web user, with more than 2 billion users in the world and 518.6 million users in Europe [145].

It is a well-known fact that consumers usually ignore adverts [146]. The overall research aims to find a way in which e- advertising can be provided, in such a way that it is not intrusive to users, that it is smoothly integrated into the general purpose of the website which the users are visiting (so that it does not clash with the users' expectations). Most importantly, the users should be drawn to the advert and actually visit it (and hopefully end up buying the product). Thus, research questions to be investigated are:

- Q1: Can adaptive e-advertising lead to users' acceptance in terms of being usable and useful from a user perspective?
    - Q1.1: What features from adaptive hypermedia users would want to have in adaptive advertising and how they are related to users' acceptance?
    - Q1.2: How can user modelling contribute to users' acceptance of the e-advertising experience?
    - Q1.3: What are the main sources of user information that can be explored for adaptive e-advertising?
- Q2: How can adaptive e-advertising be generated theoretically?
- Q3: What technology is acceptable for e-advertising?

These research questions are being explored in this experiment. They are answered partially as part of the continuous process to research for the final conclusive answer. Moreover, this experiment is the starting point for the applied research. One of the main intended outcomes of this experiment is a requirements list. The focus of this experiment is more qualitative than quantitative. The answers to these research questions will be obtained from the requirement list generated, rather than the quantified results.

In order to be able to perform a controlled experiment, and as the experiment organisers are involved in teaching at university level, it was decided that the experiment was to be conducted with the help of university students. The students were a class of 3rd year students enrolled in the Computer Science degree, Faculty of Engineering Sciences in Foreign Languages, at the University

“Politehnica” of Bucharest, Romania. They were studying a course entitled ‘Web Application and Development’. The overall student population was of around 35. However, as this experiment was not a direct part of their curriculum, and could not be marked in any way, we could only ask for volunteers. As a result, out of the 35 participants, only 12 participants agreed to participate in this experiment. The positive effect of this process was that participants were actively engaged and determined to help, instead of being coerced in any way. Also, the relatively small size of the sample ensured that the whole experiment was relatively easy to coordinate, that all opinions could be properly listened to, discussed and recorded, and that the overall atmosphere could be kept quite informal, and thus conducive to honest and straightforward discussions. It is to be said here that students enrolled in Romanian education have, unlike their British, Dutch or Western European peers, a more hierarchical view of the education process, where teacher and student keep their distance [129]. Thus, it is less likely for students to express impulsive ideas in front of their teacher or even peers, for fear of looking bad and perhaps lowering the chances of a good grade. For this reason, it was crucial to create this cooperative, informal atmosphere. However, since this experiment involved a limited number of participants, the results shown cannot claim statistical significance. As discussed earlier in Chapter 3, the involvement of users helps the researchers to accomplish a comprehensive idea about what are users’ expectations. Although, the sample size here is small and no generalisability can be assumed, the outcome from this experiment is then further investigated to extend and/or update the available state-of-the-art, and expand the researcher ideas.

The experiment lasted slightly over two hours, based on the natural flow of the interactions and (monitored) discussion. In these two hours, the methodology of the *user-centred design* was applied; please refer to Chapter 3 for details, based on the two thinking techniques, the *brainstorming technique* and the *six thinking hats technique*. The experiment was conducted over three main phases, as follows.

In the *first phase*, a questionnaire was given to the participants, to examine their current level of knowledge on the topics of e-commerce, e-advertising and adaptive hypermedia. It also covered their general expectations and requirements from such e-commerce and advertisement system. This part of the experiment lasted for 20 minutes.

The *second phase* was conducted in the form of a short seminar, lasting for around half an hour, introducing participants to the experiment and the framework that was used.

The *third phase* was the most labour-intensive for the participants, as it comprised the system requirements gathering stage, as well as the participants' involvement in the design process. This phase lasted the longest, for over an hour, as participants were encouraged to discuss their ideas in full.

Phase 1: The questionnaire

The first step of the experiment was to help participants express what they think. At the beginning of the experiment, the participants were not sure about what they were expected to deliver. So the questionnaire was the tool to make them express their ideas, by examining their current level of their understanding in relation to the expected outcomes of the experiment. The questionnaires' questions were formed in such a way that they should be rather simple, direct and to the point, in order for the questions not to confuse the participants. Here it has to be added that the whole process took place in English even though the participants were Romanians, due to several reasons. First and foremost, English was the language the experiment organisers and participants had in common (for both sides, English represented a second language). This was less of a problem, considering that the degree the students were following had all classes in English and not Romanian, and the experiment organisers were familiar with teaching in English in the UK. Nevertheless, the questionnaire design took into account that English was only the second language for these participants.

Questions were also designed in such a way as to be neutral. For instance, instead of asking a positively loaded question, such as 'Do you like the advertisement that you see online?' the question used was phrased as: 'What do you think of the advertisement you see online?' (With answers from 'Useless; Useful; It does not make any difference; Other; Please specify'). Moreover, as can be seen from this example question, participants were additionally asked to comment, where necessary, on their answers for the researchers to better understand the reasons behind it. The questions are in Table 4.1.

Table 4.1: Questionnaire questions and answer range

Questions	Answer range
Q1: What do you think of the advertisements you see online?	(Useless, Useful, It does not make any difference , Other)
Q2: When you come across an online advertisement what do you do?	(Ignore it; Look at it; It depends on the advertisement; Please Explain)
Q3: Do you prefer personalised e-advertisement for your needs?	(Yes, No) If yes, choose the properties that you would like to have (Customised profile – name, location, age , Products that satisfies your needs, Recommendation for products)
Q4: If you had the opportunity to design an e-advertising tool, would you consider using adaptive techniques?	(e.g., showing specific content customised to users, change content based on user change of preference) (Yes/No/Please explain)
Q5: If you use an e-advertisement tool, what would you prefer it to do?	(Change content by itself, Change content based on parameters set by the user)
Q6: If you have used online advertising before, from where did you click to reach the product website?	(Facebook, Twitter, Google, Google+, LinkedIn, Other, Please specify)
Q7: Did any of the websites you have used offer any type of personalisation	(e.g., customised name, products and recommendations?) (Yes , No)
Q8: What factors affect you when using an e-commerce website?	(Popularity, Reliability, Privacy, Security, Other, Please specify)
Q9: Choose from three usability and functionality properties that you would want to see within a personalised e-advertisement application?	Usability: Ease of use, Simple and noncomplex interfaces and well integrated features Usefulness: Rich features, features aligned with users' expectations and dynamic updating of recommendations

Phase 2: The seminar

The questionnaire established the baseline, the ideas and requirements of the participants, based on their own prior knowledge. Phase 2 was dedicated to expanding this knowledge. The seminar was the second stage of the experiment, where the participants needed to become familiar with related systems, via a lecture-like process, as well as via hands-on experience [100]. The seminar was conducted in just over half an hour. During the session, participants interacted via discussions, as they familiarised themselves with the examples displayed, building on their own experiences and knowledge. The seminar discussed e-commerce platforms and their importance as well as the models derived from these platforms – such as online stores, online-auctioning and online advertisements. It also expanded upon targeted advertisement delivered on Social Networks, such as Facebook. Part of the allocated time was spent on the topic of adaptive hypermedia systems, their application and some case studies of online advertisements in adaptive hypermedia. The presentation also mentioned the well-known commercial system, AdSence by Google [43], as well as a research-based system called AdRosa, created by Kazienko and Adamski [15].

The final part of the seminar introduced the thinking techniques that were going to be used in the next phase, since some of the participants were not familiar with *brainstorming* and the *six thinking hats technique*.

Phase 3: The design session

Participants were encouraged to start designing their own version of the system by setting up a list of requirements that they wanted to see fulfilled by their desired system. This stage lasted over an hour and was divided into two main sub-phases. There were twelve participants who were divided into two groups, each group containing 6 people. Participants were allowed to select which group to participate by themselves, as some of them felt more comfortable working in a certain group rather than the others. In this stage, the participants were supervised by two facilitators. The first facilitator, who was an expert on e-commerce systems and a PhD candidate at the University of Warwick, helped to ensure that the participants were deploying the appropriate knowledge, without any direct intervention or influence on the design ideas from her side. The second facilitator was an expert on monitoring experiments and a PhD candidate at Nottingham University, and was there to provide feedback, as well as maintain an appropriate experimental atmosphere and time frame.

The participants started the process by firstly using the brainstorming thinking technique. At this stage, they created spider diagrams [102], dividing their ideas into *main ideas*, then *sub-ideas*, etc., until they arrived at the detailed requirements.

Next, the participants started using the *six thinking hats* technique, where they were encouraged to express intense statements, using their emotions, and attempt to think outside the box. In this phase, they raised and listed usability-related issues, which they predicted may be encountered, whereas in the previous stage they had mainly suggested functionality-oriented problems.

By the end of this session, participants had a clearer understanding and a set of expectations of an adaptive online system for e-commerce. They presented their work to each other and to the facilitators in a semi-formal presentation and received feedback from both the other participants and the facilitators. They created, beside the set of requirements, designs of systems that were based on their expectations. They also created visual representations of the modules required for the design of their ideal systems. The feedback resulted in a set of recommendations that are presented in the result Section, and discussed further on.

4.3. Results

The results were derived from two sources: the questionnaire conducted in the beginning of the experiment and the design session. These two sets of results are described below. As previously stated, since this experiment involved a limited number of participants, the results shown cannot claim statistical significance. However, the results do represent an exploratory and idea-generating study.

4.3.1. Questionnaire Results

The questionnaire included 9 questions covering different aspects about e-advertisements found online. Additionally, it covered expectations about the new tool to be developed. When the participants were asked about their opinion of e-advertisements they see on the web, 40% claimed that “it does not make any difference”, 60% claimed that they are “useful” and 0% found it “useless”. This is a good starting point from a research point of view that e-advertisements are actually noticeable by online users and can be useful for them.

Then their reaction to these noticeable e-advertisements was also further explored. Thus, they were asked about what they do when they come across these e-advertisements, and 16% indicated that they “ignore it”, 15% indicated that they “look at it”, and 69% indicated that “it depends on the advertisements”. This question has created an important opportunity for our research, as it showed that almost two thirds of the participants indicated that the click on the advertisement depends on what it presents. These results point to the potential that if users do actually find something interesting, they are willing to click through and view the advertisement. The next question after that, completing the cycle of exploring the importance for personalised e-advertisements, was: do you prefer personalised e-advertisements for your needs? The answers were that 83% of them do prefer personalised e-advertisements, while only 17% indicated they do not. From these 83% of the users, 47% of them wanted personalised recommendations, 41% wanted products connected to their needs, and 12% of them wanted customised profiles. To further investigate the personalisation expectations and aspects, another question was posed, asking: if you had the opportunity to design an e-advertising tool, would you consider using adaptive techniques? The answer for this question was overwhelmingly promising: 91% of the student answered with “yes”, while only “9%” answered with “no”. Another question was posed to see what type of adaptation they preferred. 92% claimed that they would prefer “the content changed, based on the parameters set by the users” and 8% indicated that “the system should change the content by itself”.

The other aspect to be explored within this exploratory experiment is which of the famous platforms with targeted ads can be used as an inspirational platform. The reason for that was that sound solutions should be further promoted, and the aim was to extend the current state-of-the-art, not to reiterate it. The participants were asked about if they have used online advertising before through Facebook, Google or other websites; at this point the research was exploratory towards using Social Networks as a blueprint so Facebook was suggested. Additionally, they were asked from which platform they clicked to reach to the product website? The answers were 45% for

Facebook, 25% for Google and the remaining 30% scattered between others. After that, a question followed this up, by asking if any of these platforms did offer any type of personalisation: 75% claimed it did, and 25% did not. The type of personalisation perceived consisted mainly of recommendations based on the previous browsing history. The question following was concerned with the factors that affect the users, when using the currently available e-commerce websites. The results were split as follows: 32% mentioned personalisation (personal recommendations), 27% popularity, 27% reliability and 14% security upon purchases. The final question was concerned with the usability and usefulness issues that the participants find important. The usability issues raised were: ease of use 40%, well integrated features 25%, and simple (noncomplex) interfaces 35%. The usefulness issues raised were: rich features 38%, features aligned with users' information 44% and dynamic updating of recommendations 28%.

4.3.2. Qualitative Results and the Requirements List

One of the main outcomes of this experiment was to generate a requirement list that is used later to build and implement the prototype system. The requirements list should also address the research questions imposed to match the needed outcomes of the research. In order to ensure that the discussions and ideas generated are kept within the scope of the research, the researcher kept monitoring the discussions and the process continued, as follows.

As the participants continued with the seminar, and afterwards proceeded towards designing their own system, they firstly started this process by verbally expressing their own ideas and perceptions. They then finally crystallised these initial ideas into a set of requirements that they would consider necessary (and, in most cases, sufficient) in their ideal systems.

Their ideas were structured as a spider diagram. After that, they started the exercise of the six thinking hats and recorded their ideas. The six thinking hats suggest that user participant wears a different thinking hat that is represented in a colour. Some hats like the green hat suggest thinking very creatively and "out of the box", this may have been extended by the participants to start going out of scope. Figure 4.1 shows the raw data generated by participants, before further analysis, which included the following ideas:

- A stand-alone system or portal to be used to generate the advertisements.
- A system could include social interaction capabilities, where users can comment on ads, rate, have group discussions, suggestions, and a newsletter and can exchange personal messages.
- Vocal recognition, where they can give and receive commands vocally.
- Extend the system to also include trading capabilities of selling, buying and auctioning.
- The proper use of logistics, such as supply, delivery and payment.
- Policies of security, privacy and warranty to be introduced.
- Educational portals to be included within the system.
- Data about the users to be collected from social networks and forms.
- Personalisation of both appearance and content.
    - Appearance: themes, displays
    - Content: age, location, gender, type of products, languages

All these raw data provided from the users do form a rather unstructured requirement list. Moreover, not all that participants suggested does actually address the research questions posed by the researcher, so further analysis of the data and selecting which requirements are, was necessary. The resulting analysis is to address the research questions and ensure that the selected requirements fall within the scope of the research.

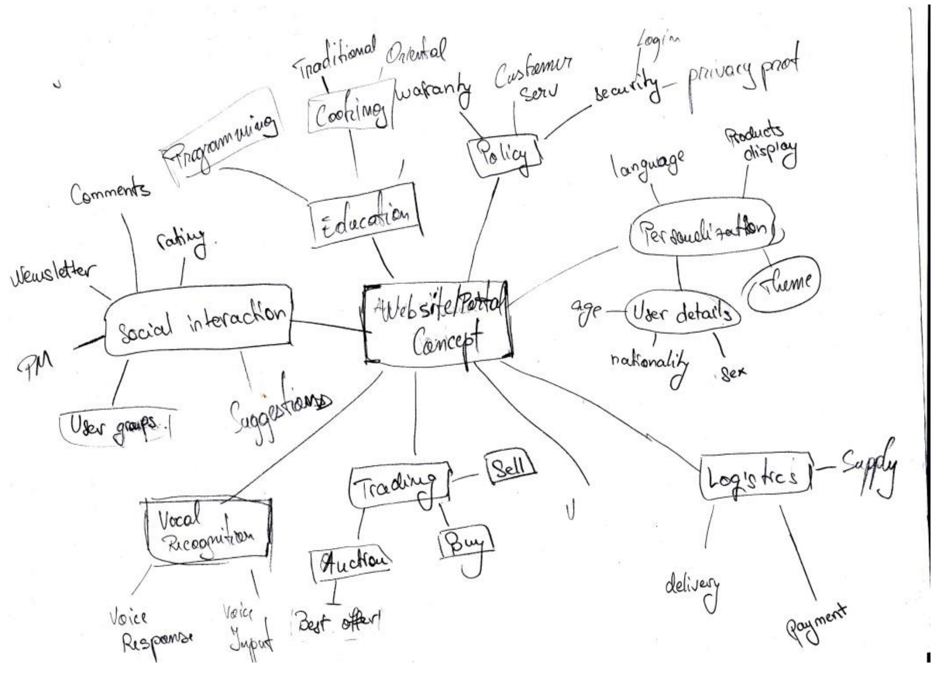

Figure 4.1: A snapshot of the spider diagrams produced by the participants to design their systems

Most of the data collected from the participants are text data, as they firstly interacted verbally, as part of the discussion, and then recorded. Additionally, as this is the actual content generated by the users, the qualitative content analysis method [135] needed to be applied to analyse the requirements. The method depends on collecting key words that can be then further explored. Details of this method were described earlier in Chapter 3.

The keywords collected from the discussion included: personalisation, stand-alone, social interaction, vocal recognition, logistics, security and appearance. Not all the keywords are directly related to the research questions and scope, so the unrelated words were omitted from the requirements list, an only the ones within the context were used as described below.

The requirement list that was further modified and can be used as a starting point for the adaptive system includes the following:

1. A stand-alone system or portal that provides the users with the advertisements.
2. Data about the users to be collected from Social Networks and registration forms.
3. The system to collect data about the user including:
    a. Demographics, such as age, gender and location

    b. Interests data

4. The system to provide personalised content by
    a. Allowing different appearances and themes
    b. The content to be personalised, based on the data collected about the user, such as age, location, gender, type of products and languages.

4.4. Early Stages of the Proposed Theoretical Model

The proposed model is an early stage theoretical framework that has been derived from the results obtained from the exploratory study. It has also been used mapped into the gaps found in the related work and the basis of the theoretical background.

The experiment provided both qualitative and quantitative data that helped in forming an initial understanding about the model and its requirements and addressed the research Objective 3 "*Propose a suitable (new or extended) theoretical framework/model for the adaptive features necessary in advertising, such as a layered model".* From this experiment the generated features have been extracted and integrated into the initial framework as discussed further in the Figure 4.2.

The framework presented in Figure 4.2 is divided into three main stages. These stages have been derived from the requirements list and the results obtained from the exploratory study. The first stage includes the data harvesting about the users. In this stage, only the data related to the users was considered, and the main source was from Social Networks, as the participants requested via their generated requirement list, found in Section 4.3.2. The second stage is when the actual adaptation takes place and the system automatically generates the adaptive content to be delivered in the final and third stage of the framework.

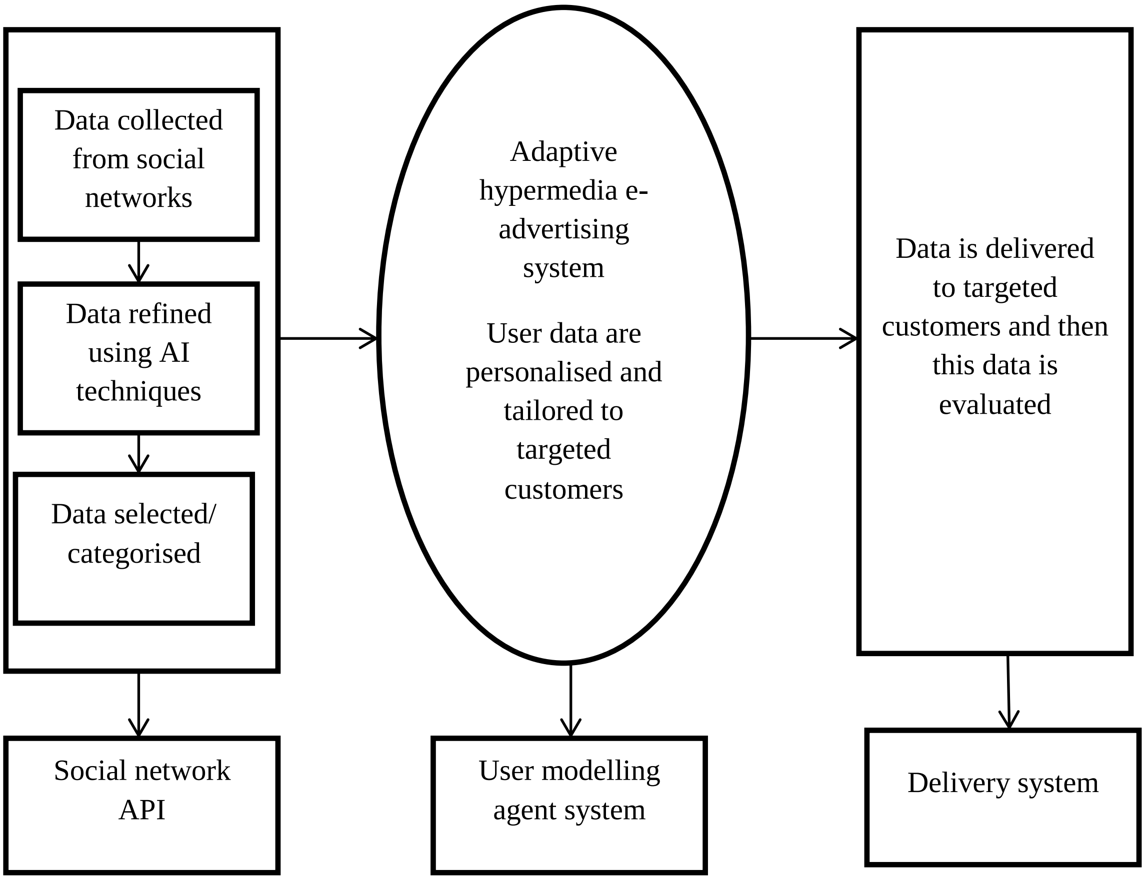

Figure 4.2: Early Stage of the theoretical framework

4.5. Discussion

The main aim of the experiment was to create an understanding of users' requirements regarding personalised advertisement systems, using different data sources such as Social Networks and registration forms. There are many tools and systems on the web offering different types of targeted advertisements to users. The experiment explored ideas from the end-users' perspective, regarding their perceptions of an adapted system, taking their ideas and requirements into consideration. The main important outcome of the experiment showed the participants' interest in personalised advertisements.

The results also highlighted that the participants, like many users in fact, did not have a clear understanding of what adaptation means and how content can be automatically adapted. They looked at adaptation as a tool, and not as the main approach of system delivery. Therefore, their level of understanding was not reliable enough to detail the system design of the adaptive process and give a detailed description of the system requirements.

The experimental data points to the fact that the main two aspects to be explored have been achieved. The first aspect was the *users' current knowledge and perceptions of personalised e-advertisements*. The second aspect is their *expectations from a personalised e-advertisement platform*. The first aspect aimed at exploring what can be used as a motivational platform, to use within the proposed adaptive delivery system; as well as what these platforms offer, to ensure users' acceptance of them. The second aspect aimed at exploring features and functionalities that are to be used within the proposed adaptive delivery system. Moreover, the likely impact of these features upon users' acceptance.

The results were generated from both the questionnaires and the design session. The results from the questionnaires were quantified, and suggested that e-advertisements can be useful. This is in particular true when they contain some personalisation, which can lead to the customised experience users are looking for. Participants also indicated that famous platforms, such as Facebook and Google, do perform some personalisation. These websites were heavily focused on the data harvested from previous browsing history.

To define the future expectations of the adaptive delivery system, information was collected both quantitative and qualitative. From the answers collected from the questionnaires, the participants indicated that personalisation is one of the important factors to be included. Personalisation was divided between usability and usefulness. Usability concerns were: ease of use, integration and simplicity. Usefulness issues included richness, connecting with users' information and dynamic updating of recommendations.

The discussion session resulted in a rich set of features proposed by the users. Some of these features were out of the scope of this research, so the requirement list was further refined to address the research questions posed in the beginning of the chapter.

4.6. Suggested Theoretical Framework

The proposed processing framework was established, based on two main resources. The first one is building upon previous literature and filling in the gaps by incorporating the social aspect that has not been introduced before in advertising. The second resource is the set of requirements proposed, based on the outcomes from the conducted preliminary study. The model presented in this Section is a modified version of the one that has been proposed in Section 4.4. The earlier model was more of an abstract representation of the exploratory experiment outcomes. However, the framework presented in this Section has incorporated and merged the ideas from the theoretical adaptive education system SLAOS that adds the social component to the traditional adaptive educational systems [147].A layered model has been derived, in order to understand the proposed framework - see

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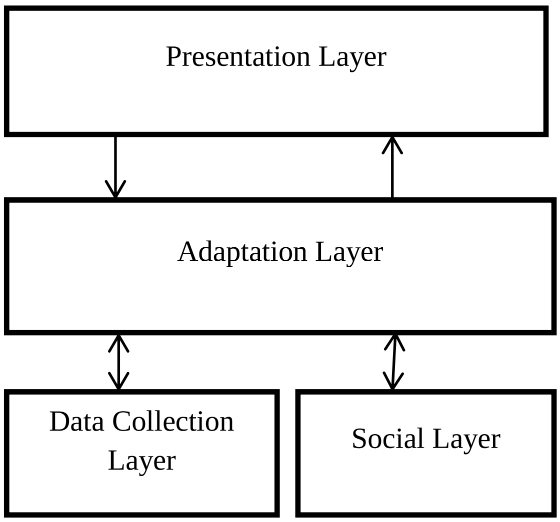

Figure 4.3: MyAds layered processing framework

The layered model proposes three layers that work interactively with each other. The first layer essentially represents two sub-layers working simultaneously, which are the *data collection layer* and the *social layer*. Each layer works separately to perform a different task. The data collection layer is responsible for collecting the data related to online advertisements (to be stored later in databases) and users' information that will be used later for building the user model. The social layer is responsible for aspects related to social networks (SN) and any social interaction to be conducted. The *adaptation layer* is the layer that performs the personalisation and adaptation by taking the data collected from both the data collection layer and social layer to build the user model appropriate for each user. The *presentation layer* is responsible for presenting the adaptive content to users where users interact with this content.

The architecture of the system based on the above processing framework is further built upon the *model, view and control design pattern* (MVC), where it uses the three tier architecture [148]. In the architecture there are five main controllers to establish the functionality of the system (as explained below). The proposed system is web-based and is divided into the client side and the server side. In the client side MyAds web services and In the web services Section three main controllers work together so the adaptation can be performed and then presented on the interface (as shown in Figure 4.4).

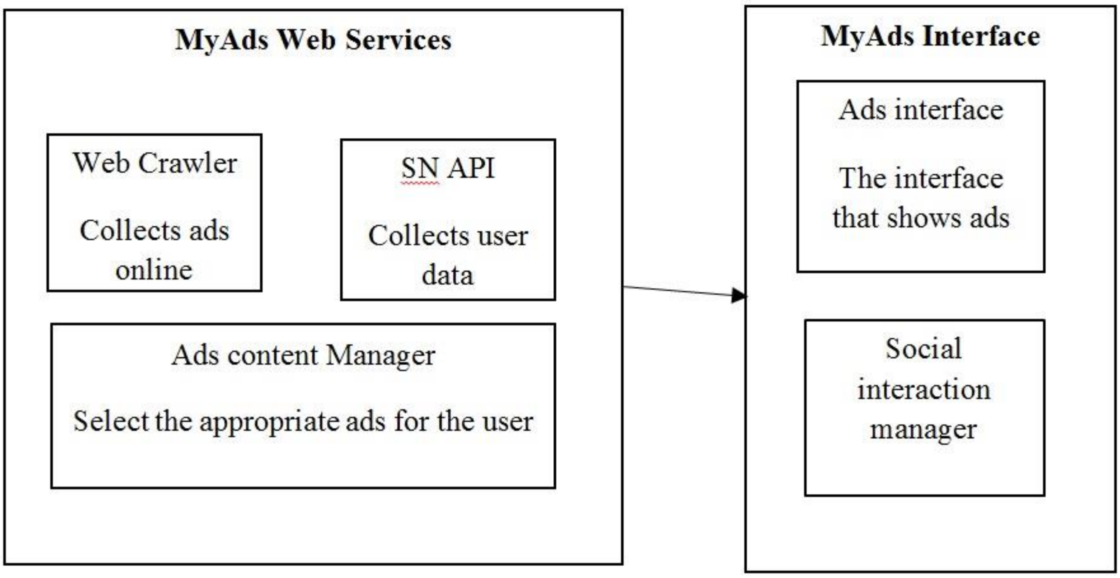

Figure 4.4: MyAds Architecture

The layered framework ensures the separation of functions, reusability and flexibility to create a dynamic web application. The system architecture fulfils what the framework proposes by creating different controllers. Each controller has a different functionality that works, as follows:

Web Crawler: the web crawler is responsible for crawling the web for all the ads available. These ads will be refined and mined based on specific parameters that are going to be defined based on the user model for each user. All the ads will be saved in a database to be retrieved later. The reason for using the web crawler at this stage is to collect as many ads as possible, to ensure that there is enough data to be used.

SN Application: the social network application is built on top of the social networking platform. The main aim is to collect all the relevant data related to users such as age, gender, interest and background to mention some. These data will be used later on, to build an individualised user model for each user.

Ads Content Manager: in this part of the system, the user model is built for each user, taking the information collected from the SN application and connecting it with the appropriate ad(s) collected from the crawler. This operation is performed by mining data from both the crawler and the SN application, then suggesting the most appropriate ad to the user and then preparing it for presentation to the user.

Interface of the system: in the interface of the system, the ad that has been adapted to the user will be displayed.

Social interaction manager: in the interface of the system, a live social interaction bar is located. In this section, the users will get to comment, chat, share blogs and rate ads. This has been added based on the suggestions of the participants in the preliminary study, who would want to be able to more comprehensively interact with the given ads. This would also be part of what we believe will further encourage and motivate users to use this system.

The system should take into consideration accessibility issues and have a simple but coherent design. Figure 4.5 is a mock-up screenshot of how the suggested system's main page would look.

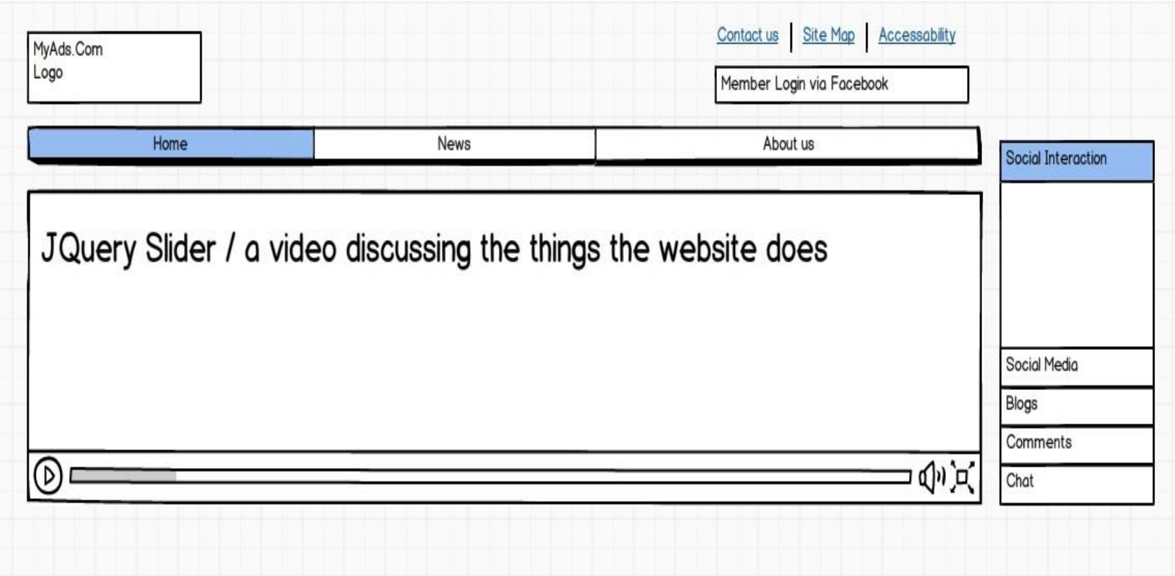

Figure 4.5: Suggested Home Page of MyAds

One of the main sources of data about users is the applications built on top of existing social networks, as well as the user's browsing history. In order to be able to collect this data, users should use MyAds direct them to log into the social network. This may lead to issues – such as the fact that users who do not have a social network profile cannot use the system, as well as potential privacy considerations. These need to be further explored during the system evaluation, besides the evaluation of the main functionality and usability. The system evaluation results and updated needs are further discussed in Chapter 5. The privacy issue was not considered as for further investigation because it does not connect to the research questions.

4.7. Suggested Evaluations

Since the proposed framework is a research-based system, the actual return on investment cannot be measured, because there will not be any actual buying of products/services or companies paying to display advertisements within the system. So there is a need for the development of another evaluation technique.

There are two ways of collecting data for evaluation purposes; the first one is via direct answers from users, which can be performed via direct questionnaires given to them to evaluate the system as soon as they finish trying it. The second way is via measuring usage data such as tracking the type and number of clicks they have performed; for instance, did they click on the advertisements that are supposed to match their expectations? Additionally, the viewing time of ads can be taken into consideration, as well as the users' social interaction actions, such as commenting, chatting and rating.

The system was implemented and then evaluated as planned using questionnaires, which provide qualitative as well as quantitative information, because questionnaires can collect enough data in a standard fashion and at the same time give an adequate insight about the perceptions of participants [149]. The system went as planned, through two iterations, allowing the system to be evaluated, to ensure that it satisfies the requirements of the theoretical framework. The detailed implementation and evaluation for iteration one can be found in Chapter 5 and for iteration two in Chapters 6 and 7.

4.8. Discussion

The initial path of research into developing the concept of adaptive e-advertising was performed through suggesting a new layered processing framework for adaptive online advertising using Social Networks as a source of information to build user models. The framework has been transformed into an initial architecture proposal, leading to a stand-alone web-based system. The system relies on a SN application to collect data related to users by making the access to the system via a single sign-in connected to the SN application. It also uses the registration forms as a log-in approach. The architecture of the system is based on the MVC pattern design, since it is well known for its usefulness in interactive web based systems.

This system design and perceptions on implementation have come with challenges; one of the major issues is that if users do not want to use their SN profile they will not be able to use the system, which is a limitation since many users may have reservations to share their personal profiles, and thus the issue of privacy could be a major concern to users. Another limitation is the evaluation of the system. Since this is a research-based system, the return on investment cannot be measured in terms of money so the actual evaluation for this kind of systems has to be measured in a different way.

Although there are a number of limitations using the suggested system, there was also great potential for future work. As discussed before, the suggested framework was a result of research of the literature and trying to fill the gaps in adaptive e-advertising systems. Moreover, the framework was based on an exploratory study that was conducted to include actual users in the design of the system and record their perceptions and requirements.

The results of both the literature and the exploratory study were used to design a layered processing framework that includes three main layers. The first layer is divided into the data collection layer and the social layer. The second layer is the adaptive layer where all the adaptation and the building of the user model take place. The last layer is the presentation layer where different presentations will be displayed depending on the different users' preferences. Based on the layered processing framework, the three tier architecture was presented and the main controllers were defined. The main evaluation tools were chosen to be questionnaires and studying the log file of users to track the number of clicks.

4.9. Conclusions

This chapter aimed at describing and narrowing down the concept of adaptive e-advertising and explaining the work beneath the final approach adopted by this research. The initial approach was to gather enough information about users' needs and perceptions about personalised advertisements. In order to fulfil this objective, an exploratory study using participatory design was carried out. The experiment generated a requirements list, in which one of the key aspects was the establishment of a standalone system, as this area had not previously been well explored, instead of the traditional approach of banner advertisements and floating ads.

The experiment was conducted as a part of an on-going research to explore a new approach of creating and delivering adaptive advertisements. The experiment was conducted in the University "Politehnica" of Bucharest, with the help of students studying Web Application and Development. Their background and experience helped in delivering the experiment as it was designed.

The experiment went through three main stages. In each stage, the participants explored and used different thinking and cognitive techniques. In the first stage, they answered a questionnaire, which was followed by a short seminar to introduce the experiment to them, and finally a design session, where they further explored their own ideas and were asked to design their desired system according to their own requirements and functionality requests.

The main outcomes from the experiment were that participants were greatly interested in personalised advertisement.

Some of the main drawbacks of the experiment are that the participants were not really aware of concepts such as adaptation. They wanted their systems to have 'everything', without actually realising the processes involved. This, of course, presented a follow-up challenge for the designer, who needed to further refine the initial set of requirements, together with more adaptation-savvy researchers.

Nevertheless, the experiment was successful in highlighting the end-users point of view of what the system should include. The experiment also gave an understanding about what should not be included in the system.

The exploratory study, as well as the work in the literature, has inspired the definition of the *initial theoretical framework*. The framework addressed the domain model, user model and adaptation model used in adaptive systems. The system architecture generated five main controllers, divided between the client side and the server side. The overall outcomes of this chapter do suggest some initial answers to the research questions, as follows:

Q1: Can adaptive e-advertising lead to users’ acceptance in terms of being usable and useful from a user perspective? *Adaptive e-advertising is found in general a good way forward. Acceptance can be addressed through the process described in this chapter, of exploring what makes platforms exciting and accepted by the users. The specific setup can be further investigated by answering the sub-questions, as follows;*

- Q1.1: What features from adaptive hypermedia users would want to have in adaptive advertising to reflect upon their acceptance? *Initial answers to this* *question were in the form of users answering the questionnaires, as well as the requirements list generated.*

- Q1.2: How can user modelling contribute to users' acceptance of the e-advertising experience? *An initial answer came from users stating that they want their recommendations connected to their needs and information, as well as other parameters of their choice. This is reflected in the requirements list.*

- Q1.3: What are the main sources of user information needed for adaptive advertising? *This question is addressed by the participants' answers, indicating that they want their information to be harvested from Social Networks, as well as registration forms.*

This work also suggests a first answer to research question Q2: How can adaptive e-advertising be generated theoretically? *As a result of the experiment, and further literature study, an early stages of the theoretical framework has been proposed.*

Finally, this work also explores initial answers for research question Q3: What technology is acceptable for e-advertising? *An initial answer was that users requested a standalone system, instead of the traditional type of banner e-advertisements.*

The detailed set of research questions can be found in Chapter 1 and the final answers for these questions can be found in Chapter 8.

Chapter 5

5. Initial Approach towards Personalised Adaptive E-advertisements

5.1. Introduction

Online businesses are facing the challenge of keeping up with the increasing competition every day, enforcing businesses to ensure they sustain a competitive advantage over others [150].

MyAds, the system built and used for evaluation of the theoretical developments in this thesis, had to propose a new approach of addressing e-advertisements. E-advertisement is defined as the process of delivering a marketing message through different media [27]. The marketing message thus needed to be delivered according to the specific user models and adaptation features.

MyAds was initially aimed at being an adaptive system for e-advertising and its main goal was to explore how to make online ads acceptable by the users. In order to achieve such a goal, various technologies and techniques were used. The system was implemented, and a pilot experiment was conducted to validate the initial personalisation features within the system.

The initial delivery of the system was specifically planned to include the following:

- Classical adaptation and user modelling.
- Standalone capabilities to provide personalised advertisements.

The classical adaptation and user modelling involves building user models for each user, and then matching the information harvested about these users with the appropriate products that match their interests. The standalone system aims to get the user to the product's advertisement, instead of forcing it into the user's screen, to achieve users' acceptance of advertisements.

This chapter describes this initial implementation and evaluation of the suggested framework, architecture and design that were described in Chapter 4. It represents a step in the iterative cycle, specifically addressing the research objectives as follows:

Objective 2: *Conduct a series of experiments that investigate the appropriate approach and features to design adaptive e-advertisements, and then test the practical development of these features in an adaptive e-advertising system, addressing the acceptance of this form of ads in the targeted evaluations.*

Outcomes of this chapter: This chapter addresses the second part of the objective "test the practical development of these features in an adaptive e-advertising system, addressing the acceptance of this form of ads in the targeted evaluations", as the first iteration of system implementation and evaluation, to create an understanding of applying adaptation on e-advertisements.

Objective 3: *Propose a suitable (new or extended) theoretical framework/model for the adaptive features necessary in advertising, such as a layered model.*

Outcomes of this chapter: This chapter addresses the second part of the objective: "test theoretically to what extent this new framework addresses the features that are necessary for adaptive e-advertising".

The implemented system features and functionally are built upon the theoretical framework and the designed evaluations focus on the original features introduced by the theoretical framework.

Objective 4: *Design, implement and update a dedicated system for testing the adaptive advertisement and measure the level of acceptance from the end users through the evaluation of their subjective and objective feedback.*

Outcomes of this chapter: This is the first iteration of system implementation and evaluation. Thus, the results from this evaluation are a first indication of the potential of adaptive e-advertisements and work as the starting point for more advanced solutions (and therefore more evaluations).

Objective 5: *Ensure that each research question is represented in the framework and in the delivery system.*

Outcomes of the chapter: The system proposed and used as an evaluation tool in this chapter includes basic adaptation and user modelling features. These features do connect to the earlier design, and aim at evaluating users' acceptance. Log files are also examined, to see if the results do match the ones achieved from the subjective feedback collected from the questionnaires.

Objective 6: *Ensure that each step of the research is conducted based on established research methodology.*

Outcomes of the chapter: In this chapter, the first pilot practical study is conducted. The user centric evaluation methodology is used in the experiment. The numerical values are justified and interpreted, as described earlier in Chapter 3.

The remainder of the chapter is structured as follows. It firstly introduces the updated theoretical framework and user architecture, followed by the initial scenarios. The next section represents the technical representation of the system and the related algorithm, process breakdown and use case. The fifth section discusses the experiment, and the related results. The chapter then concludes with the discussions and conclusions section.

5.2. Updated Theoretical Framework and Architecture

The initial attempts to implement the first version of MyAds showed that the theoretical framework needs to be more specific. Thus, the theoretical framework was revisited, with specific focus, amongst others, on the data collection and representation. This resulted in a modified framework being created, as described below.

5.2.1. Theoretical Framework

In Chapter 4 (Section 4.6), the theoretical framework was formed. It was constructed based on the requirement list generated from the exploratory experiment and the gaps from the current state-of-the- art.

Modified framework

The practical reflection of the framework on the system architecture and then the implemented system was not carried out. This is due to difficulties identified with the practicality of the initial framework, which was divided into a social layer and a data collection layer. These layers didn't interact with each other and any social interaction (proposed earlier and described in Chapter 4) will not be connected to the associated users. So the necessity to re-design the framework has emerged.

Returning to the literature and reviewing the different existing e-commerce and adaptation frameworks has made it possible to reflect the requirement list upon the framework. At this level, it has been decided that social interaction will be limited to the purposes of evaluation only, since designing and implementing a social adaptive e-advertising system was out of the scope of this research and the research questions. Additionally, the social based systems address different frameworks and technologies that are not in the scope of the research at this stage and it is therefore, considered part of the proposed future work.

The change upon the new framework included a better fragmentation of the layers. The data collection layer consists of the crawlers and data from social networks (SN). The user modelling layer caters for the different types of users and stakeholders, the adaptation and presentation layers both remain the same. A new layer was added, which is the evaluation layer, to address the research evaluations that are necessary, including tracking the users' behaviour within the system, rather than simply evaluating their subjective answers to questionnaires and interviews. The theoretical framework presented in this research should be further refined and developed to accommodate the extended research requirements. This flexibility has been considered as a key aspect in the contribution of this research and has been the focus of the researcher. Figure 5.1 represents the updated theoretical framework.

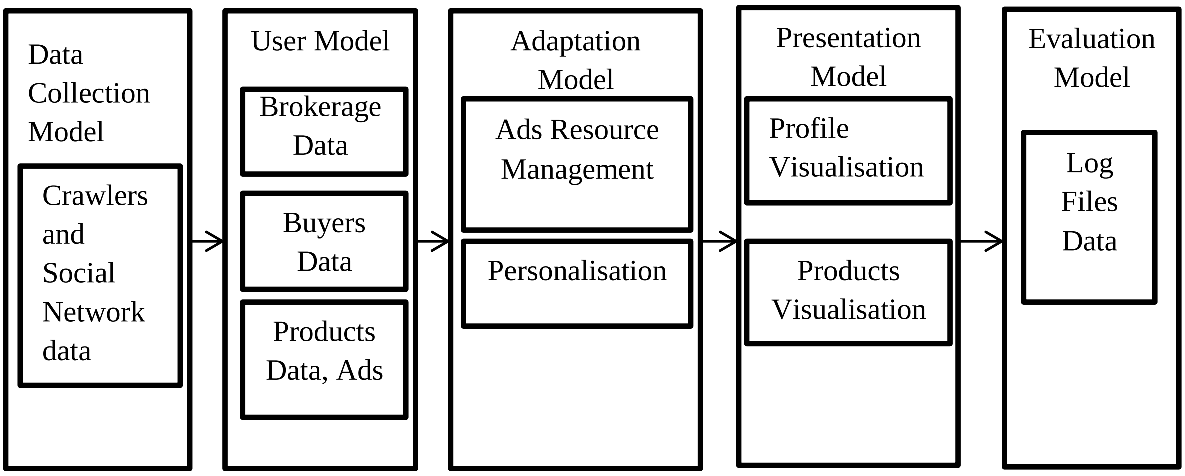

Figure 5.1: Proposed theoretical framework

The framework is divided into five main layers. The main reason for separating the layers is to ensure flexibility as well as to maintain homogenous interaction within the whole (between layers) [148].

The first layer is the *Data Collection Layer;* this layer is the gateway for all the data. Data sources vary; there are data related to advertisements, users, data collected from social networks and data entered directly from the user during the registration process. This layer is a new layer that has not been introduced in the earlier version of the framework. Traditional frameworks look at this layer as a contained or internal layer of the user model layer. However, because this is layer is quite rich and e-advertisements data are usually rich, it was decided that separating the layer will be easier to reflect upon the practical development of the system and the actual architecture.

The second layer is the *User Model Layer*; this layer is where all the distinct user profiles are established and differentiated. Each user will have their own distinct representation, in order to use these data for further adaptation and personalisation. Also, in this layer, the different stakeholders are represented differently. The main ones are the buyers and the brokers, whose data is collected earlier from the data collection layer. This layer is one of the classical adaptation layers that can be found in almost all adaptive frameworks, as the users are key aspects in personalisation [46], [64] and [51]. The initial framework did propose a data model layer but did not specify the different users connected to it.

In the *Adaptation Layer*, the appropriate advertisement is mapped to the user based on the previously defined user model. The personalisation is obtained and specified in this layer. All the 'intelligent processing' happens in this layer, in term of applying the adaptive hypermedia algorithms and data mining techniques. This is also considered a classical adaptation layer and is presented in most of the adaptation frameworks such as the Munich Model, AHAM and XAHM as in [68], [66], [67] respectively. This layer was also defined in the previous framework as it is one of the main layers that should exist in adaptive systems.

The *Presentation Layer* is the layer that describes the direct interaction and contact with user. The profile visualisation, the text and advertisement representation, are displayed in this layer. It also takes into consideration different environmental aspects such as the bandwidth and different devices used for browsing [22]. This layer also has been presented in the earlier version of the framework.

The final layer is the *Evaluation Layer*, which collects the interactions on the system and saves them as log data, to be evaluated again and studied, to be used for further modifications of the user model and adaptation. This layer is a new layer that has not been introduced in the previous framework. It addresses Objective 5 that focuses on the evaluation of all the proposed layers. In order to achieve this objective, evaluation data from the system which is the data generated by this layer should be harvested and analysed.

The theoretical framework represents the basis for the system architecture, and it is used to specify the main system components.

5.2.2. Architecture

The architecture of the system based on the above processing framework is further built upon the model, view and control (MVC) design pattern, using a three tier architecture [148]. The architecture should address the different theoretical layers introduced earlier. Accordingly, the architecture is designed in a flexible manner and also considers the separation of functionality whilst maintaining a homogenous outcome.

Initial architecture

In the proposed architecture, five main controllers establish the functionality of the system. Three controllers work on the server side and two controllers work on the client side.

Figure *5.2* shows the initial system architecture and the specified controllers.

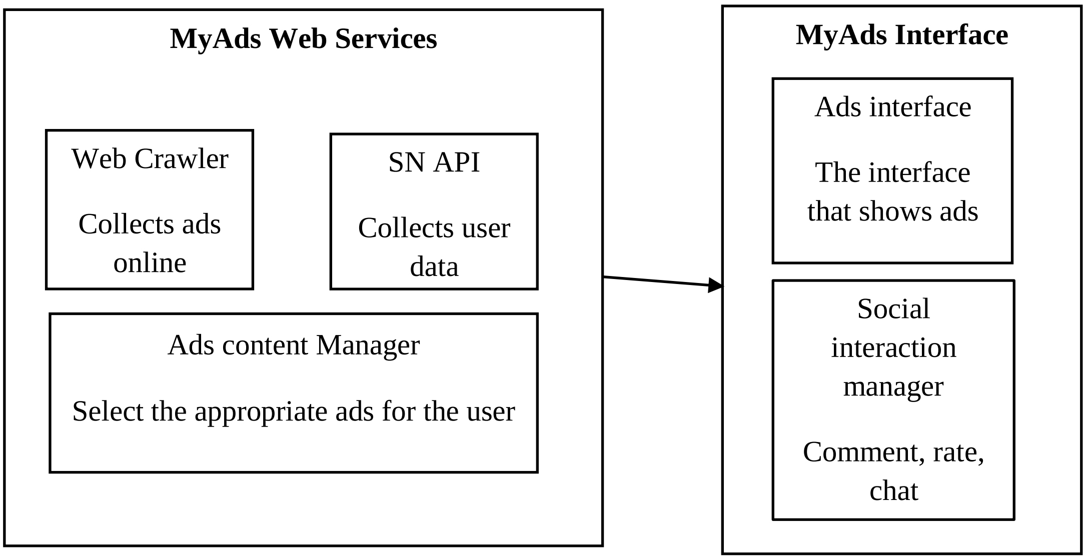

Figure 5.2: Initial Architecture for MyAds

The layered framework proposes the layers in order to ensure the separation of functions, reusability, flexibility and creating a dynamic web application [151], [152]. The system architecture fulfils what the framework proposed by creating different controllers. Each controller has a different functionality and works as follows.

Web Crawler: the web crawler is responsible for crawling the web for all the ads available. These ads will be refined and mined, based on specific parameters that are going to be defined by the distinct user's models. All the ads will be saved in a database so that they can be retrieved later. The reason for using the web crawler at this stage is to collect as many ads as possible, to ensure that there is a large enough amount of data to be used. This controller works as part of the first data collection layer in the theoretical framework.

SN Application: the social networking application is connected with the social network platform. The main aim is to collect all the relevant data related to users: for example, data such as age, gender, interest and background. These data will be used later on, to build the individualised user model for each user. The controller is also part of the first data collection layer proposed earlier in the theoretical framework.

Ads Content Manager: in this part of the system, the user model is built for each user, taking the information collected from the SN application and connecting it with the appropriate ad(s) collected from the crawler. This operation is performed by mining the data from both the crawler and the SN application and then suggesting the most appropriate ad to the user and preparing it to be presented to the user. This controller is connected with both the user model layer and the adaptation layer, as the controller contacts the UM and then performs the needed adaptation.

Interface of the system: here, the ad that has been adapted to the user will be displayed. This controller also takes into consideration the different devices used and changes the display properties and bandwidth loading based on these devices. It also tests the bandwidth capacity. This controller reflects the presentation layer in the theoretical framework.

Social interaction Manager: a live social interaction bar is to be located in the system interface. In this section, the users will be able to comment, chat and rate ads. This has been added based on the suggestions of the students in the preliminary study found in Chapter 4 (Section 4.3), who wanted to be able to more comprehensively interact with the given ads. Thus, it was considered that adding such functionality would encourage users to use this system. The theoretical framework is reflected by this controller in the evaluation layer, which stores the users' behaviour on the system to generate more objective evaluations.

The system needed to take into consideration accessibility issues and have a simple but coherent design. However, the initial architecture introduced above actually corresponds to the initial framework. A modified architecture needed to be proposed for the modified framework, as described in the following section.

5.3. Initial Scenarios

In order to better contextualise users' requirements, these two initial scenarios were created, to ground the system design and implementation. These scenarios were based on the requirement list generated in Chapter 4.

Scenario 1: Introducing a new product, based on a friend's network

Anna is reading her favourite fashion magazine online. She is now reading an article about the latest trends in summer 2012 in beach clothes. Anna has recently registered with the adaptive advertising system MyAds. From Facebook, the system has gathered that Anna's favourite colour is blue, and that Anna is 22 years old, so young fashion would be appropriate for her. The system also knows that Anna's friend Dana (as per friend-of-a-friend FOAF network) [153] has purchased recently a large beach bag. The system also knows that Anna possibly likes cloth bags, as she has marked that fact on Facebook, on a page displaying bags. Thus, the system recommends to Anna a blue cloth beach bag from a company whose products Anna usually likes (as per her Facebook markers).

Scenario 2: Introducing a new company, based on personalisation:

Julia has marked as '*liked'* pages in Facebook that show shoes, and she has shared this page on her Facebook wall. Julia has registered with the adaptive advertising system MyAds. A shoe selling company 'ShoesForYou' has also registered with MyAds some time ago. New products have been coming in for the summer collection from this company. The system thus recommends to Julia summer shoes from ShoesForYou, for older people (thus with sturdier soles), as it has retrieved Julia's age as 69, from Facebook. It also recommends to her one of the stores of the ShoesForYou chain in her city, Coventry, as older people often like to see things before buying.

5.4. MyAds: Proposed Technical Approach and Implementation

The first step of the system implementation was the design of process break-down diagrams and use cases, to imitate the scenarios and what the user would experience within the system. The following set of requirements is to be implemented;

- User profiling via matching user interest and gender with products.
- Social capability to interact, chat and add comments about the system, which is used for evaluation.
- Multiple advertisements based on the user's stated interests.

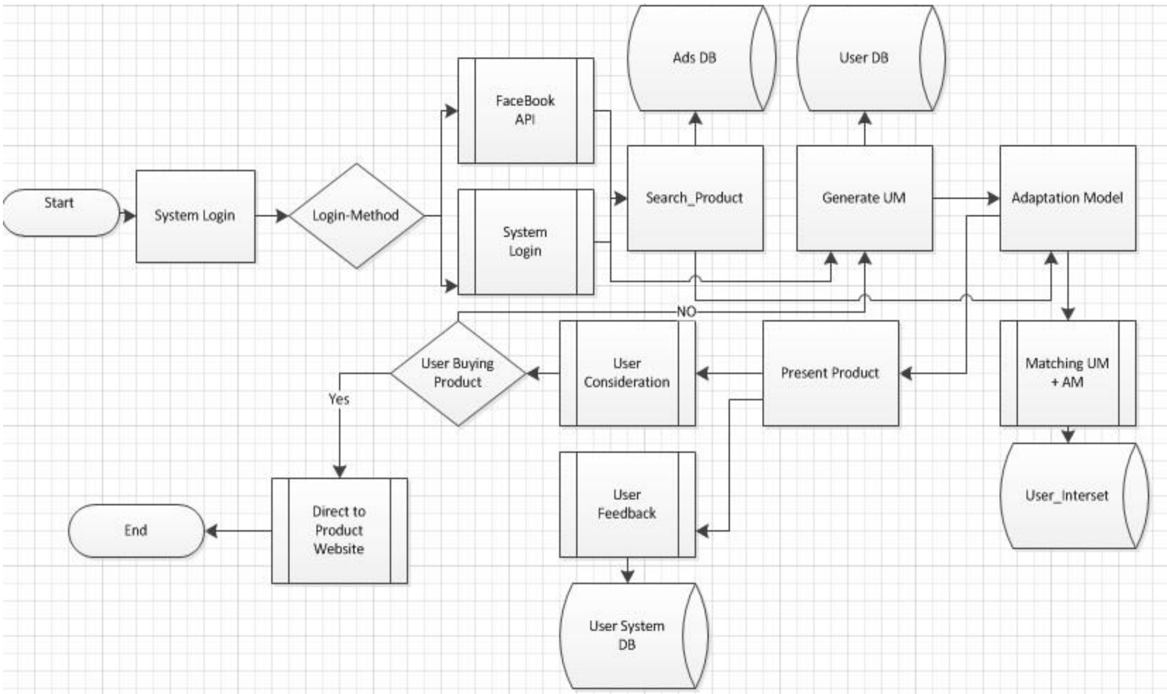

Figure 5.3: Process break down diagram for MyAds

Figure 5.3 illustrates the processes that occur in the system, which are:

1. *System Login* – in this process, the users have two options: either log in via system registration, where they manually insert all their details (so appropriate user models can be generated), or log in via their Facebook account.

2. *Search Product* – the users can search for whatever products they want – this search is directed to an advertisement database, from which the advertisements will be retrieved later on.
3. *Generate User Model* – as soon as the user logs in, a user model is generated.
4. *Adaptation Model* – where the connection between the user model and the appropriate advertisement is established.
5. *Presentation Model* – where the personalised advertisement is displayed to the users.
6. *User Feedback (Consideration)* – where the users should state if they will consider buying the product or not. If yes, the users will be shown a link directing them to the product website. If not, the new information will be used to update the user model and recommend another advertisement.

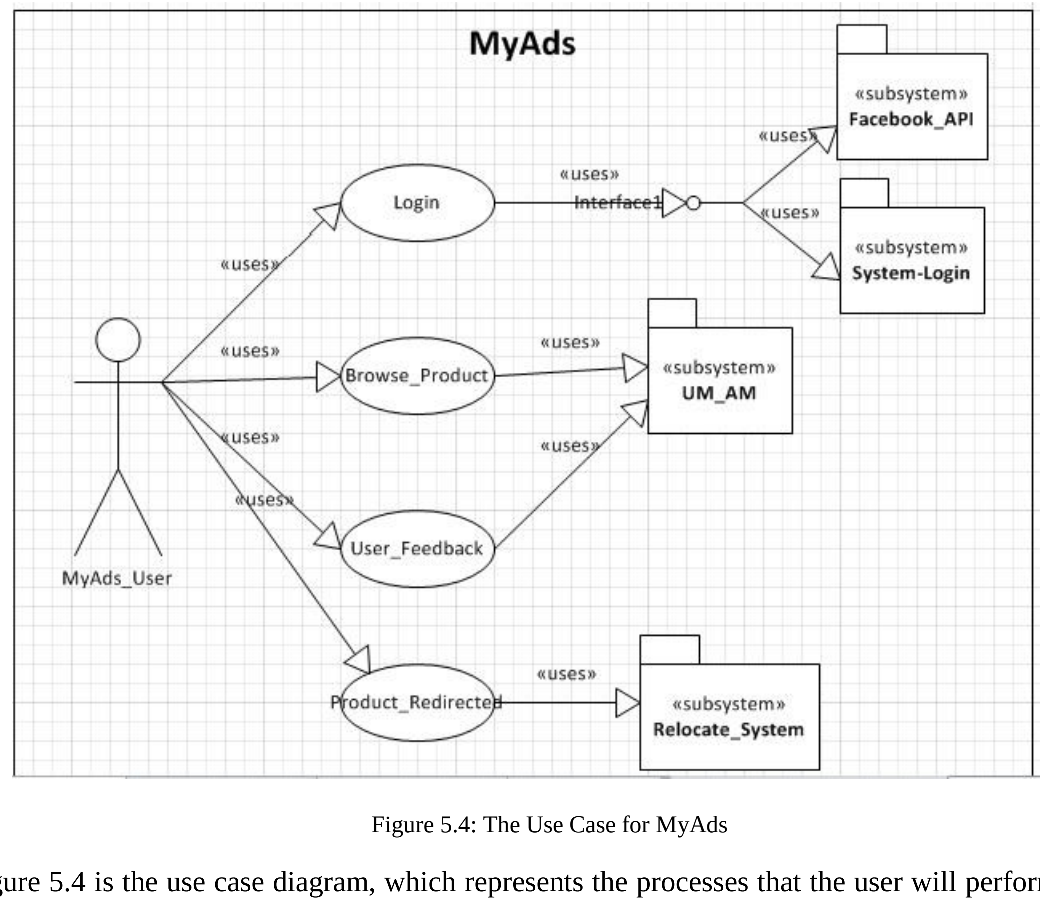

Figure 5.4: The Use Case for MyAds

Figure 5.4 is the use case diagram, which represents the processes that the user will perform in the system, and what sub-systems are involved. The users will log in via one of two sub-systems: either the Facebook API, or via system registration. They can also browse products and feedback about the system, by using user model and the adaptation sub-systems. If they choose to buy the product, they will be relocated to the product website.

The following algorithm in pseudo code illustrates the adaptation process within MyAds, as follows. The users indicate their gender and interests in the registration form. Based on the users' interest, a set of products are recommended to the user via a slider. The users then feedback if the product generated is personalised for them or not, by selecting this from a drop-down list. If they indicated that this item is not personalised, the item will be removed from the list for that particular user.

Algorithm 5.1: Creating a storyline

Algorithm #1. *Create Storyline*

```
Input: a set of all user information from the UM.
Output: procedure creates storyline for users
 if user == Female Exclude [male categories] else
If user == male  Exclude [female categories]
  Foreach user= n get user interest // the interests indicated
in the registration phase will be collected
  Launch function = SetAdaptation { //setting up the function
for adaptation
 Foreach item = i Foreach interest = j // interests can be
fashion, sport, technology, etc.
  if interest == j get i j
             End if }
     S == Get SetAdaptation
    Print  S
     if feedback == yes
              Get  i
             Else [Exclude i ] }
  end procedure
```

The first iteration of the system development has taken place by implementing a web-based application called MyAds. The system was written in Java and used MySQL to create databases. For the interfaces design, Dreamweaver was used. The system aimed to produce personalised advertisements to the user by matching their interests with the advertisements. A Facebook API was added to the system, so that users have an alternative to login into the system using their Facebook account (by using a single sign-in OAuth method) as the regular system registration process may be more time consuming. The actual system implementation is pretty straightforward for an online application and was outsourced; hence it is not further discussed here.

Figure 5.5 displays the home page for MyAds, where the users log in via the system. The MyAds logo shows people from different cultures and backgrounds holding the name of the system to indicate that there is something for everyone and that everyone can get the customised experience that they are looking for. The look and feel also is additionally reflecting principles of simplicity [70] and user-centred approach [154]: by displaying children, the underlying message given is that the whole process is child-play. The colour scheme used is neutral.

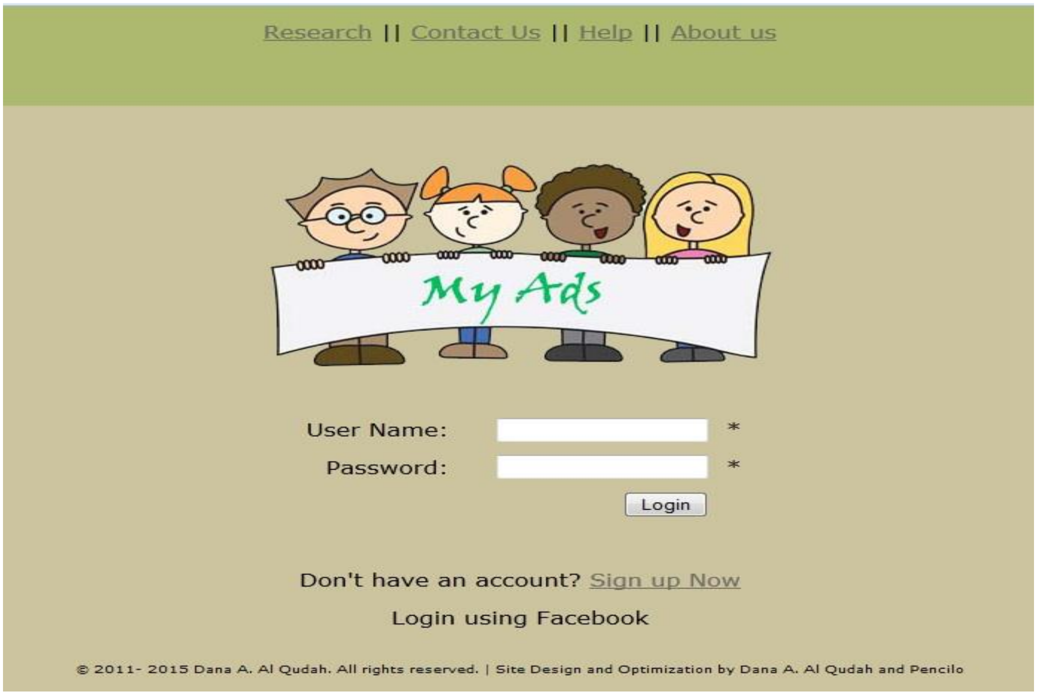

Figure 5.5: Home Page for MyAds

Figure 5.6 displays a sample customised advertisement page. In this example, the user is a female who is interested in fashion, so the system displays fashion-related items. The system also has the properties of feedback, rating and commenting. Users are offered different types of interactions in the system, to address the social interaction need extracted from the first user-driven design phase, as described in Chapter 4 (Section 4.3.2).

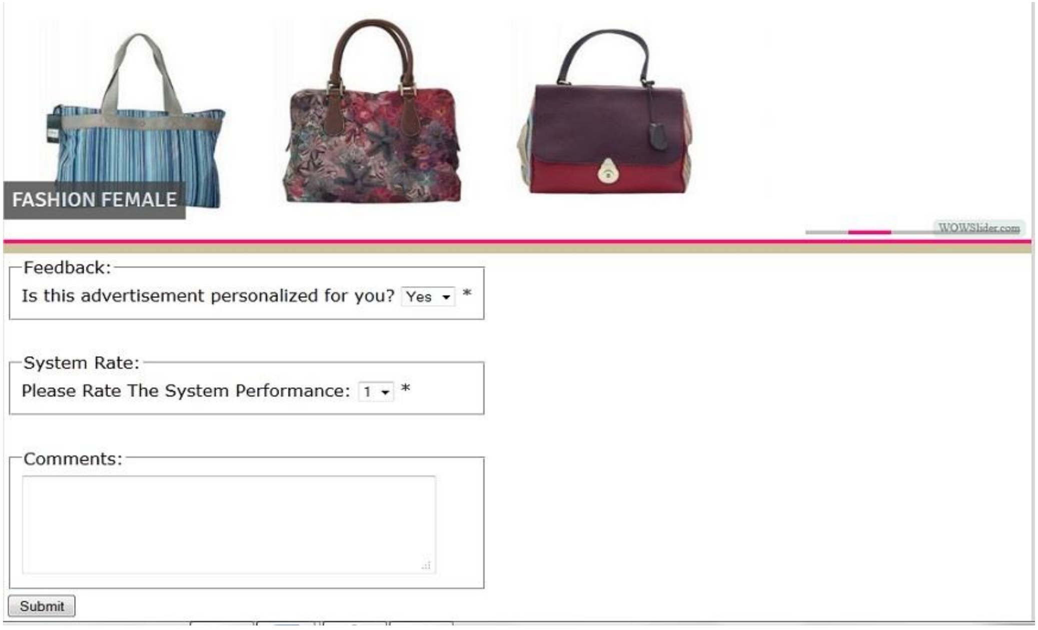

Figure 5.6: A Personalised Advertisement for a Female who is interested in Fashion

5.5. Experiment

After the system implementation was conducted, a pilot experiment took place that had an exploratory nature. The main goal of the experiment was to test the implemented system in relation to the related research questions.

5.5.1. Experiment Participants

The experiment was conducted in the University of Jordan, with the help of 4^{th} year Business Information Technology students studying a "Network Simulation" Class. The total number of participants was 47. This sample size is not ideal, as discussed in Chapter 3, Section 3.6; however, other researchers exploring similar areas [131] and [155] have built their proposals around similar number of users. Moreover, as this is mainly an exploratory experiment, it is useful to explore initial perceptions. They were divided into two different classes, with 23 and 24 students respectively in each class. The experiment was conducted over two hours for each class. They are all within an age group between 20 – 22 years old. The domination of female students was evident, with a percentage of 70% female and 30% male.

5.5.2. Experimental Process

The experiment was divided into three main phases, using the user-centric methodology approach [154], which has been adopted throughout the research in this thesis; please refer to Chapter 3 for more details.

Phase one represented the students becoming familiar with the concept of personalised advertisements. Students were asked if they have any prior knowledge of e-commerce and e-advertisements and their websites. In order for the students to take part in the experiment, they had to have prior knowledge of e-commerce and e-advertisements platforms. This was because the adaptive delivery system MyAds is to be compared against other popular platforms so prior knowledge is mandatory. As the students were senior students, they were familiar with e-commerce, e-advertisements and related websites, as they had studied previous courses specialised on e-business and e-commerce. The participation was voluntary and all the students approved in taking part in the experiment with a participation rate of 100%.

Phase two started with the researcher introducing the MyAds system and the background research. After this, the students started logging in (via the system registration process) and different advertisements were shown to them, based on the information they had entered earlier in the registration process. After the advertisements were displayed, they each interacted with the system by giving feedback, rating and commenting on the advertisements received.

Phase three represented the collection of the students' explicit feedback on the system. Before the end of each session (class), the students were given questionnaires, to evaluate the system in a more formal way. The whole experiment was conducted in English, as the students are taught their courses in English. However, in order to ensure the questionnaire was as straightforward as possible (since English is not the first language for these students), the questions were designed in such a way to be as simple, direct, and to the point as possible. Moreover, according to good design principles for questionnaires [107], the questions were posed in a neutral way, instead of asking positively or negatively loaded questions.

5.5.3.Research Questions for Investigation

After the system was implemented, it was necessary to evaluate the users' experience, to understand their acceptance level of the recommended advertisements, and explore the pros and cons of the current approach and then to consider the next steps, in terms of system development and enhancement. The evaluations are in relation to the research questions below, as well as the research objectives discussed earlier in Section 5.1.

The questionnaire contained 8 questions and used the Likert scale for evaluation. The answers ranged from *strongly disagree* to *strongly agree*.

The research questions to be investigated were the detailed set of research questions in relation to the user modelling and adaptation capabilities, as follows:

Q1.1. What features from adaptive hypermedia users would want to have in adaptive advertising to reflect upon their acceptance?

Q1.2. How can user modelling contribute to users' acceptance of the e-advertising experience?

Q1.3. What are the main sources of user information needed for adaptive advertising?

Q3: What technology is acceptable for e-advertising?

Table 5.1 introduces the set of questions used to evaluate and reflect upon the proposed research questions.

Questions and answer range	**Related research questions**
Q1: System registration is considered a good way for system login (Strongly agree, agree, neither, disagree, Strongly Disagree)	Q 1.2, Q 1.3, Q3
Q2: System registration is a time consuming process (Strongly agree, agree, neither, disagree, Strongly Disagree)	Q1.2
Q3: The advertisement slider suggested advertisements that were personalised according to my interest (Strongly agree, agree, neither, disagree, Strongly Disagree)	Q1.2
Q4: The advertisement within the slider made the advertisement more acceptable than what I usually get from other e-commerce websites (Strongly agree, agree, neither, disagree, Strongly Disagree)	Q1.1
Q5: The feature of selecting if "the advertisement was personalised for you" made the system friendlier than what I usually get from other e-commerce websites (Strongly agree, agree, neither, disagree, Strongly Disagree)	Q1.1, Q3
Q6: *The feature of "rating the system/slider" made the system more personal than what I usually get from other e-commerce websites* (Strongly agree, agree, neither, disagree, Strongly Disagree)	Q3
Q7: The feature of "reviewing the system/slider" made the system more personal than what I usually get from other e-commerce websites (Strongly agree, agree, neither, disagree, Strongly Disagree)	Q3
Q8: The system contained enough information to make it easy to use (Strongly agree, agree, neither, disagree, Strongly Disagree)	Q1.3

The questions presented in the questionnaire have an exploratory nature; the connection with the research questions is established as follows.

Research Question 1.1 explores the features from adaptive hypermedia that can achieve users' acceptance. The questions from the questionnaire to address to this research question include Question 4 &5. These questions explore the adaptive visualisations of links, texts and multimedia.

These are connected to adaptive navigation support and adaptive presentation support that will be explored extensively in Chapter 7.

Research Question 1.2 discusses the role of user modelling upon users' acceptance. The questions from the questionnaire to tackle this question are Questions 1, 2 & 3. The questions are focused on the login approach and its' applicability. Moreover, the questions discuss the customisation of data collected within the user model and their final reflection on the recommendations presented to the user.

Research Question 1.3 investigates the different sources of data that can be used to build user models. The questions to address this question are Questions 1 & 8. The questions explore the approach for data collection such as the registration form; they also tackle the amount of data collected from this type of data collection approach, and its usability within the system.

Research Question 3 explores the (relatively) uncommon technological approach of a standalone system for adaptive advertisements. The questions to explore this research question are Question 1, 5, 6, &7. The questions address if the login approach is acceptable by the users, they also explored if this system is friendlier and more personal from than what they usually encounter. Moreover, it explores the social aspect in adaptive advertisements, which was something users recommended in a previous exploratory experiment in Section 4.3.

5.5.4. Results

The results of this experiment were obtained from two sources. The first source was from explicit feedback provided by the students in forms of answers to the questionnaire. The second source was the implicit feedback that was traced from the students' behaviour over the system. The feedback was saved in log files in the database. Another source of data was through the evaluation of the social features, such as the commenting, rating and feedback functionality that captured immediate feedback while the students were using the system. Also, this incorporates the social aspect within the system from an evaluation perspective. No qualitative feedback was collected from the users in this experiment initially. However; when analysing the log files one issue was quite unclear as it did not confirm to the results collected from the questionnaire. Users misinterpreted the rating scheme, so follow up interviews were conducted to address this issue.

This is a research-based system, hence it is not possible to trace if the user is actually going to buy the proposed product or not, so another way to evaluate the user's consideration of a certain product has emerged. This was achieved by directly asking the students if the product was personalised for them. The question was "Is this product personalised for you?" (Please refer to Figure 5.6 and the results discussed in the log files section). The results generated from the questionnaires are discussed next.

Results from Questionnaires

The statistical tests discussed earlier in Chapter 3 Section 3.7, have been conducted, and the following results have been generated.

Table 5.1: Results from descriptive statistics and significant tests

Question	Mean	Mode	Std	t-test	Mann-Whitney	Wilcoxon
Q1: System registration is considered a good way for system login.	3.7	4	0.91	0.00	0.00	0.00
Q2: System registration is a time consuming process.	2.9	2	1.15	0.52	0.54	0.51
Q3: The advertisement slider suggested advertisements that were personalised according to my interest.	4.0	4	0.80	0.00	0.00	0.00
Q4: The advertisement within the slider made the advertisement more acceptable than what I usually get from other e-commerce websites.	3.9	4	0.94	0.00	0.00	0.00
Q5: The feature of selecting if "the advertisement was personalised for you" made the system friendlier than what I usually get from other e-commerce websites.	3.8	4	0.94	0.00	0.00	0.00
Q6: *The feature of "rating the system/slider" made the system more personal than what I usually get from other e-commerce websites.*	3.8	4	0.97	0.00	0.00	0.00
Q7: The feature of "reviewing the system/slider" made the system more personal than what I usually get from other e-commerce websites.	3.5	4	0.97	0.00	0.00	0.00
Q8: The system contained enough information to make it easy to use.	3.7	4	1.16	0.00	0.00	0.00

The results from the descriptive statistics aimed at exploring where most of the answers tend to be. From the table above, all (bar one) of the answers have a mean value above 3.5, indicating a positive side of the argument. The mode value is also on the positive side of the argument, as in all the questions, the most frequent answer was "agree", with the value of 4. The only exception to this Question 2, which was originally posed as a negative question, and whose mean and mode were corrected for easier comparison in the table above (*correction used = 6 - answer*), and which is further analysed below.

In order to examine further the significance of the answers for the given sample size[3] – (two-tailed) t-test, the Mann-Whitney and the Wilcoxon tests were conducted. Beside the parametric t-test, non-parametric tests are used to prune out some more of the significance values for the questions, and to ensure that the remaining results are statistically significant.

Again, the results from all the significance tests match the results collected before. All the results are statically significant, with the exception of Question 2, which has a probability value larger than 0.05.The problem raised by the answers to Question 2, with its highest frequency of the answers within the agreeing range, is that it indicates that the registration process was considered time consuming for the users. From a statistical significance angle, Question 2 is the only one that has no statistical significance: the probability value is (0.52), much larger than the acceptable threshold of 0.05. Nevertheless, it's clear that some users found the registration cumbersome.

For research question Q1.1 that investigates adaptive hypermedia features that reflect on users' acceptance, questions Q4 and Q5 examined the adaptive features presented in MyAds. The features presented in this version of MyAds were relatively simple and basic ones. The Introduction of a storyline-like visualisation feature, with the advertisement slider, addressed in Q4, aimed at investigating if this feature can lead to users' acceptance. The mean value of the answers was (3.9 ± 0.76) indicating that the users were mostly positive about this statement. Moreover, the mean value is higher than the selected threshold of 3.5, discussed earlier in Chapter 3. Additionally, the mode value of 4 and the significance of the statistical tests, points to the possibility that this feature is acceptable to users. For Q5, investigating if asking for direct feedback from the users and allowing them to reflect upon the recommendations they received from the dynamic adaptation system aims to increase the system's understanding of users' requests, as well as the users' understanding of the recommendations - both aimed at ultimately achieving users' acceptance. The mean value of the answers was (3.8 ± 0.94), indicating that the users were positive about this statement, taking into consideration the mean value that is higher than 3.5, and the relatively small

[3] As said, the given sample size is relatively low, but it is comparable with other researches on e-commerce, such as 131. Lu, J., *A model for evaluating e-commerce based on cost/benefit and customer satisfaction.* Information Systems Frontiers, 2003. **5**(3): p. 265-277.

standard deviation. Moreover, the mode value of 4 and the significance of the statistical test points to the possibility that this feature is one of the good features to be used. So both adaption features of storyline as well as dynamic adaption can contribute to users' acceptance of this form of e-advertisements.

For research question Q1.2 that investigates how user modelling can contribute to users' acceptance of the e-advertising experience, questions Q1, 2 and 3 are posed. The aim of these questions is to see if the system collected appropriate information about them, if the process of collecting this information is adequate and if the actual constructed user model did meet their interests. For Q1, the mean value of (3.7 ± 0.91) indicates that the users were positive about the login approach, with a mean value higher than the accepted threshold of 3.5. Additionally, the mode value of 4, and the significance of the statistical tests, shows that this approach of collecting data, which then can be used to build the appropriate users' model, is potentially acceptable to users. Moreover, for the results from Q3 posed to investigate if the system did actually build appropriate user models that were aligned with their interests, the mean value is (4.0 ± 0.8), indicating that users have been more on the positive side of the argument; with a mode value of 4 and the significance of the statistical test shows this as one of the favourite features of users. However, Q2 pinpoints a problematic issue with the system, with regard to the fact that, although the approach can be accepted by the users, it is still time consuming to start: with a mean value of (3.1 ± 1.16) and a mode value of 4. The question was; however, not statistically significant, indicating that the results were not different from the middle value of 3, showing that users were indecisive about this question.

Research Question 1.3 investigates what are the data sources used for adaptive hypermedia. For the purpose of this experiment, only the data from the registration form was used. Question Q1 explores the data sources, by examining if the registration approach is a good way to collect data. Also, Q8 explores if the system collected enough data, using the registration approach. For Q1, this has been discussed before in relation to research Question 1.2, the mean value of (3.7 ± 0.91) indicates that the users were mostly positive about the login approach. Furthermore, the mean value is larger than 3.5, indicating a positive result. The mode value of 4, and the significance of the statistical tests, points to conclude that this may be a good approach for data collection, in terms of user acceptance. For Q8, indicating that the system contained enough information that lead to it being usable, the mean value of (3.7 ± 1.16) indicates that the users were either positive or indecisive about the amount of information collected using the login approach. The mode value of 4 and the significance of the statistical tests allow assuming that this may be good way for data collection, in terms of user acceptance.

For research question Q3, investigating if the current technological form of a standalone system is appropriate Q1, 5, 6 and 7 were posed. These questions examined the system as whole, rather than looking at separate features. Q1 and Q5 have been discussed before in relation to research question Q1.1 and Q1.2 and both of them can be claimed to be positive. For Q6, the mean value of (3.8 ± 0.87) indicates that the users were mostly positive about the rating feature. Also, the mode value of 4 and the significance of the statistical tests strengthen the answer. However, the data collected later from the log-files indicated that some of the users were not sure about the scale of the rating. This is discussed in the log files analysis. The reviewing feature was less successful, with a mean value of (3.5 ± 0.97), indicating that the users were either positive, indecisive or even some negative about the feature, due the relatively low mean (still equal to 3.5) and the relatively high standard deviation. However, the mode value of 4, and the significance of the statistical tests, indicate that the results fall on the positive side more often than on the negative one. The overall results from the different questions can lead to a positive conclusion about the technological approach adopted.

Results from Log Files

In order to collect more data on the perception of the users and their opinions about the system, log files of their behaviour in the system were created, and then these log files were subsequently explored. The log files contained information about the users’ interactions with the system. When the users were asked if the advertisements shown to them were personalised for them, they all stated yes. 100% of the students agreed that the system has provided personalised advertisements.

This gives a sense that the system framework (with the simple aspects that it tried to cover) was successful in attracting the users to the system and makes this form of advertising acceptable.

Part of the system's direct feedback asked the users to rate the system on a scale of 1-5, with 1 being the lowest and 5 being the highest. Their responses are shown in Figure 5.7. The ratings of the system were collected, to examine if the approach used within this research is actually successful in triggering user acceptance, and in order to address to research question Q3.

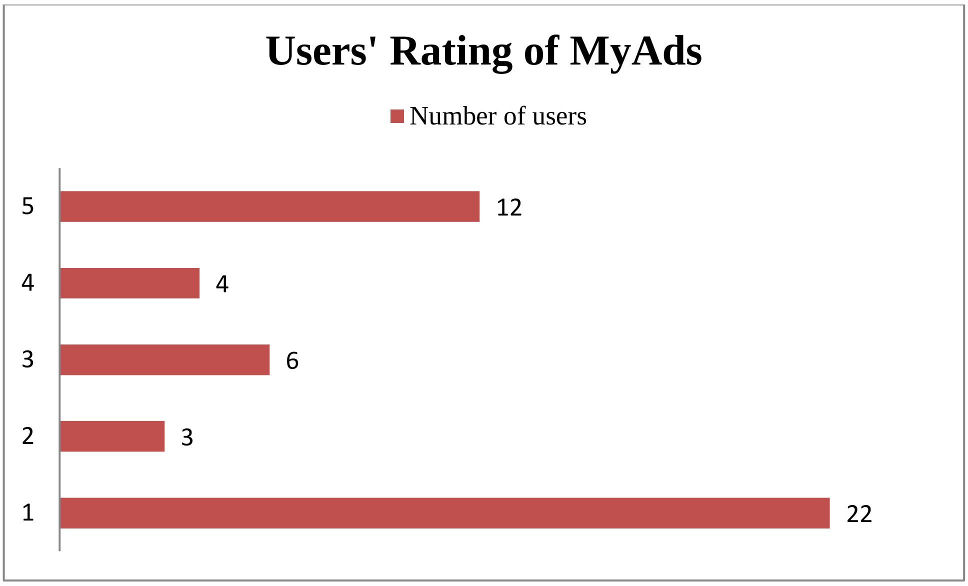

Figure 5.7: Users rating for MyAds

The figure shows that 22 out of 47 users rated the system 1 out of 5, with a percentage of 46.8%. These results raised some concerns with the overall system design and its overall features. The only slightly negative prior outcome mentioned a cumbersome registration process. Further reasons for this outcome were sought. A potential reason for this low rating of the system may have been simply due to the fact that the default value was 1. To check the correctness of this result, the researcher did some focussed interview with five students who conducted the experiment, on the following day, and asked for further explanation. The answer, from all the 5 students interviewed, was that they automatically thought that 1 is the highest value, not 5. Thus, it is possible that the outcomes were actually positive for the system. Still, this discussion showed a flaw in the system, and interviewed users pointed out that there was no explanation in the system for these values (1-5), and that perhaps a stars system, as used by other e-commerce systems, would be easier to grasp. Users interviewed were asked to discuss other weaknesses of the system. They mentioned that they had some reservations about the design of the system. Specifically, they raised concerns about the actual display of the advertisements. They additionally mentioned the fact that the system didn’t look attractive enough for them. This meant that the design of the website still needed to be revisited.

5.6. Discussions and Conclusions

This chapter suggested a new initial approach to address the problem of e-advertisements being neglected by users. The approach was derived from a set of research questions and an exploratory study conducted earlier in Chapter 4. The results of the exploratory study suggested a number of requirements that were taken into consideration in the process of system design and implementation found in Section 4.4. The main outcomes from the exploratory study recommended including the user in the experience of proposing the advertisements, by allowing them to interact with them. A theoretical framework was built, where the different stakeholders that are to use the system were addressed, based on their level of interaction with the system. The theoretical framework was divided into five main layers, to ensure the flexibility of the functionality described by each layer. Additionally, this chapter proposed the system architecture. The system architecture is divided into the client side and the server side. On the server side, all the heavy duty work is happening, where the server generates the adaptive advertisements, after mapping the user model to the related advertisements. The first iteration of the system was implemented, based on the theoretical framework and the proposed system architecture, to address to the research questions. The online system was built using Java and MySQL. The experiment was conducted at the University of Jordan, with the help of 47 senior students (in the age group of 20-22). The main outcomes of the experiment were that most of the students have agreed that the proposed system made the advertisements acceptable for them, which addresses the research questions posed.

This represented the first iteration of the system. The main issues to be addressed in the second iteration include issues such as the use of appropriate user modelling techniques, the appropriate adaptive hypermedia techniques and addressing usability issues highlighted by the users.

The next milestone to be achieved before going into iteration two of system implementation was to decide on the following:

- The appropriate user modelling technique.
- How the data collected from social networks was to be dealt with, and what appropriate techniques can be used to enhance user interest.
- The adaptation to be presented to the user. The system proposes adaptation of presentation, but could any other adaptation techniques be introduced?

The overall outcomes of the chapter do partially answer the research questions proposed, from an exploratory perspective, rather than giving concrete and final answers.

For Q1.1**:** What features from adaptive hypermedia users would want to have in adaptive advertising to reflect upon their acceptance? *This research question was answered through the experiment testing the delivery system, MyAds, including the adaptive features. The adaptive features explored were the basic adaptive navigation support and adaptive presentation support.*

For Q1.2: how can user modelling contribute to users' acceptance of the e-advertising experience? *This question was answered via the part of the MyAds experiment focusing on user modelling aspects. These aspects included the login approach and the personalisation of the recommendation based on the users' interests.*

For Q1.3: What are the main sources of user information that can be explored for adaptive advertising? *This question was answered via the MyAds experiment, by testing if the login approach is an accepted way of data collection.*

For Q2: How can online adaptive advertising be generated theoretically? *The question was answered through the updated theoretical framework and the stated motivation and reasons for the updated framework.*

Research question Q3: What technology is acceptable for online advertising? *This question was addressed by the implicit and explicit feedback gathered from the evaluation of MyAds. The evaluations indicated that the system is personalised and introduces new features, however; some reservation emerged on the design of the system, which indicated a demand for a revisited one.*

These research questions are further explored in Chapters 6 and 7. The conclusive and final answers are found in Chapter 8.

Chapter 6

6. The Extended Adaptive E-advertisement Concept

6.1. Introduction

In this chapter, the latest system design to be reflected upon the final version of MyAds is discussed. This chapter targets the refined set of user modelling and adaptation features that have been explored in the previous chapters. It also presents the final update on the theoretical framework and architecture necessarily to emulate the extended set of adaptation features to address to research questions Q1 and Q3.

The objectives to be covered are as follows below.

Objective 2: *Conduct a series of experiments that investigate the appropriate approach and features to design adaptive e-advertisements, and then test the practical development of these features in an adaptive e-advertising system, addressing the acceptance of this form of ads in the targeted evaluations.*

Outcomes of this chapter: This chapter addresses the first part of the objective “Conduct a series of experiments that investigate the appropriate approach and features to design adaptive e-advertisements” through the evaluation of the second iteration of the system design.

Objective 3: *Propose a suitable (new or extended) theoretical framework/model for the adaptive features necessary in advertising, such as a layered model.*

Outcomes of this chapter: This chapter addresses the objective that proposes the initial “new theoretical framework/model for adaptive features necessary in advertising such as a layered model”. The previous chapters tested both theoretically and technically the proposed approach; this chapter goes one step further and proposes the concluding framework and architecture.

Objective 6: *Ensure that each step of the research is conducted based on established research methodology.*

Outcomes of this chapter: In this chapter, the second and more focused design experiment takes place. The user centric design methodology is used in the experiment, as this is the common methodology applied in this thesis. Later, the qualitative results generated from the experiment are analysed, using the qualitative content analysis method, described earlier in Chapter 3.

A revisited design for the adaptive e-advertisement system MyAds has been conducted, as the results from the previous study highlighted a drawback and suggested a *more accepted interaction design* and a *richer user profiling and recommendations representation and mechanism.* The outcomes from the practical experiment can be found in Chapter 5 and these are highlighted in the results (Section 5.5.4) and the discussion Section (5.6).

Different approaches of e-advertisement have emerged. These approaches tend to make ads more targeted, for instance Groupon[4], which bases its recommendation on the geographical location of the user with discounted products marketed as ads. In this context, this thesis analyses a new form of e-advertisements, which is personalised and integrated with the users' knowledge, background and interests. The focus of personalised e-advertisements was on finding the appropriate location of advertisements within the webpage, or collecting previous browsing history via embedded cookies in web browsers [156]. More sophisticated commercial platforms, such as Amazon, have used some adaptation techniques, like collaborative filtering [34].

In this chapter, the proposed platform, which consists of both user modelling and adaptation features, is discussed in detail, to illustrate the novel design approach used to implement the final evaluation tool.

The chapter is structured as follows; the first section contains the final updated theoretical framework and system architecture. This is followed by a design experiment, which generated an updated requirement list. Next, the system design of MyAds – including all the design features –

[4] www.groupon.com

are discussed, followed by the detailed explanation of user modelling, adaptation features and algorithms. The user interfaces in relation to the whole personalisation process and experience is demonstrated through the different snapshots of the system. The chapter finally wraps up with discussions and conclusions.

6.2. Updated Theoretical Framework and Updated Architecture

MyAds is a novel software that is based on a layered theoretical framework that functions within the concept of *separation of functionalities* [50], but which, nevertheless, should be providing homogenous outcomes. Figure 6.1 illustrates the theoretical framework proposed, based on the one initially proposed in [157]. It has been updated, as this research represents a richer research platform for both adaptation and user modelling and an updated set of research questions and research objectives. The changes over the framework are not as significant as the first two versions presented in Chapter 4 and Chapter 5. The new framework addressed the problem of the stakeholders and the representation of them in the user model layer – especially the brokerage data that did not fit in here. The brokerage data should be in forms of recommendations that are presented in the later layers. Also in the data collections layer both implicit and explicit data collection approaches were presented. The final framework is divided into five main layers (as initially described in Section 4.2), with each layer serving as a model to be implemented in the system. The theoretical model in this thesis, as previously explained, is inspired by previous work in the area of e-learning, such as the layered model in [65, 158, 159]. The model here addresses the specific application area of e-commerce and e-advertisement. In the following, the layers are revisited in more details. As discussed earlier the main layers that had minor changes are the data collection layer and the user model layer. The data collection layer required containing different approaches for data harvesting which are; the implicit and explicit approaches. The user model layer needed a clarified representation of the users and stakeholders to be presented. In this case only data about the users and companies are to be processed.

The first layer contains the *data collection model*, which collects user data from different sources implicitly, via an API from social networks, and explicitly, via direct input from the users, as well as company products and data. By explicitly defining this first layer not as a data representation layer, but as a *data acquisition layer*, the emphasis is on the fact that in e-commerce, data about both products and users can be distributed, and can (and should) be collected from many different sources.

The second layer represents the *user model*, where user profiles are constructed. This layer is a standard model in adaptive hypermedia, and can be found in all models and frameworks. Differences in our approach are that the users are the buyers, and their viewing history contains ads they have seen – thus forming the data model.

The third layer is the *adaptation layer*, also a very standard adaptive hypermedia layer, where the adaptive content is built and the applicable adaptive hypermedia techniques are selected.

The fourth layer is the *presentation model*, where the personalised content is presented to users (this is based on the LAOS framework).

Finally, the fifth layer represents the *evaluation model* within the system, to track the users' behaviour and then update the second layer, the user modelling layer. The presence of this model emphasises the fact that this framework aims at continuous evaluation and a feedback loop between the users and the system. As feedback is dependent upon the interaction with multiple users, as well as their interaction amongst themselves, this model also additionally includes some social features like commenting, rating and sharing.

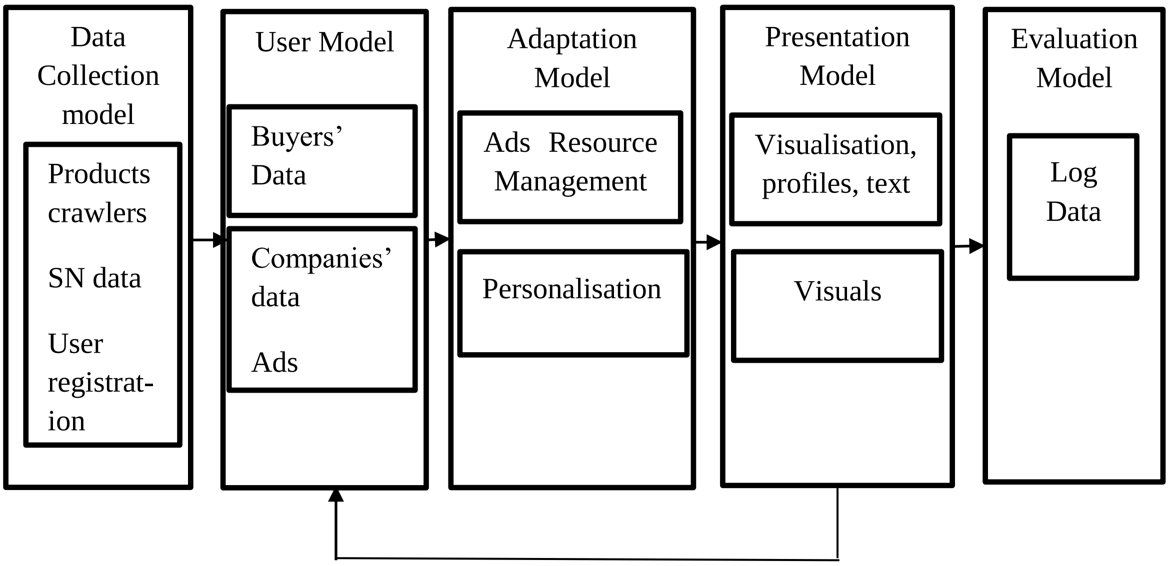

Figure 6.1: Theoretical Framework for Adaptive Advertising

The theoretical framework is further reflected in the system architecture, which is a possible technical instantiation of the theoretical framework. The theoretical framework is more generic and can be applied to a variety of systems. The MyAds system architecture, illustrated in Figure 6.2 is organising the system into a client side and a server side.

The system architecture has been changed significantly in comparison to the ones presented in Section 5.2.2. The major changes are based on the results of the implementation of the first version of MyAds. While the first version was rather simple, the new system design with the extended features needed to be accommodated in a more sophisticated manner. The new architecture is inspired from the work of AH and more precisely can be found in [52].

The new system architecture divides the work with a server side and a client side. The server side contains all the intelligence, adaptation and data collection. The client side focuses on the presentation and user interaction with the system.

The *server side* represents the first three layers of the theoretical framework. This side is formed of three main models. The *Data Collection Model*, which includes the **Product Crawler**, **Facebook API** and **User Registration forms**. The *User Modelling Model*, which includes the **Dynamic User Model** and finally it, includes the *Adaptation Model*, which is represented in the **Personalisation and Decision Making Engine** and the **Product Search Engine**.

On the server side, there are four main engines functioning are the; **Ads generator**: the product generator is connected to a crawler that brings products from e-commerce websites to display them. Each product has the following metadata: price, image, description and Amazon.com URL. The product generator arranges the products in the database.

Dynamic UM: This is one of the important engines in the system. All user data collected is then manipulated via this engine. The engine may bring the user data from two sources. One source is the direct ***user registration*** form of the system. The other source is the user data set of Facebook acquired via ***access tokens***. The engine works in two phases. The first phase is the initialisation of the user model where N is defined as the users' interaction with the system, for first time users N=1.

Personalisation and decision making engine: in this engine all the adaptation and the personalisation happens. The first step is to match the UM with the appropriate product. This is done via the navigational tree.

The *client side* represents those last two layers of the framework, including the *Presentation Model* and the *Evaluation Model*, which include the **Interactive Dashboard** and the **Social Interaction Engine**, which record users' behaviour in the system and then updates the user model, which is then reflected on the adaptation knowledge tree. Please note that N in the diagrams represents the number of login attempts by the user. If a user logs in for the first time (where N=1), this indicates an initialisation of his/her profile. If the user is a returning user, he/she will be directed via another set of operations.

The user will interact directly with the application that is going to be connected with two engines as follows;

Interactive user dashboard: the dashboard will be the interface that the user will deal with. It will show all the personalised products that are recommended for the users. This engine is particularly important, because it records all the user interaction on the system and then sends it to the UM engine to update each user's UM. It is also important, as each user log file is used for further analysis and evaluation.

Social interaction engine: in the user dashboard, the user will have the ability to comment, rate and share the recommendation. This is not used to update any UM, as the social interaction is not part of this research. The purpose of this engine is to allow for a direct evaluation of the recommendation from the user. This is imperative, as it gives a direct indication of the user's opinion, which might be forgotten by the user when they fill in the subsequent questionnaire.

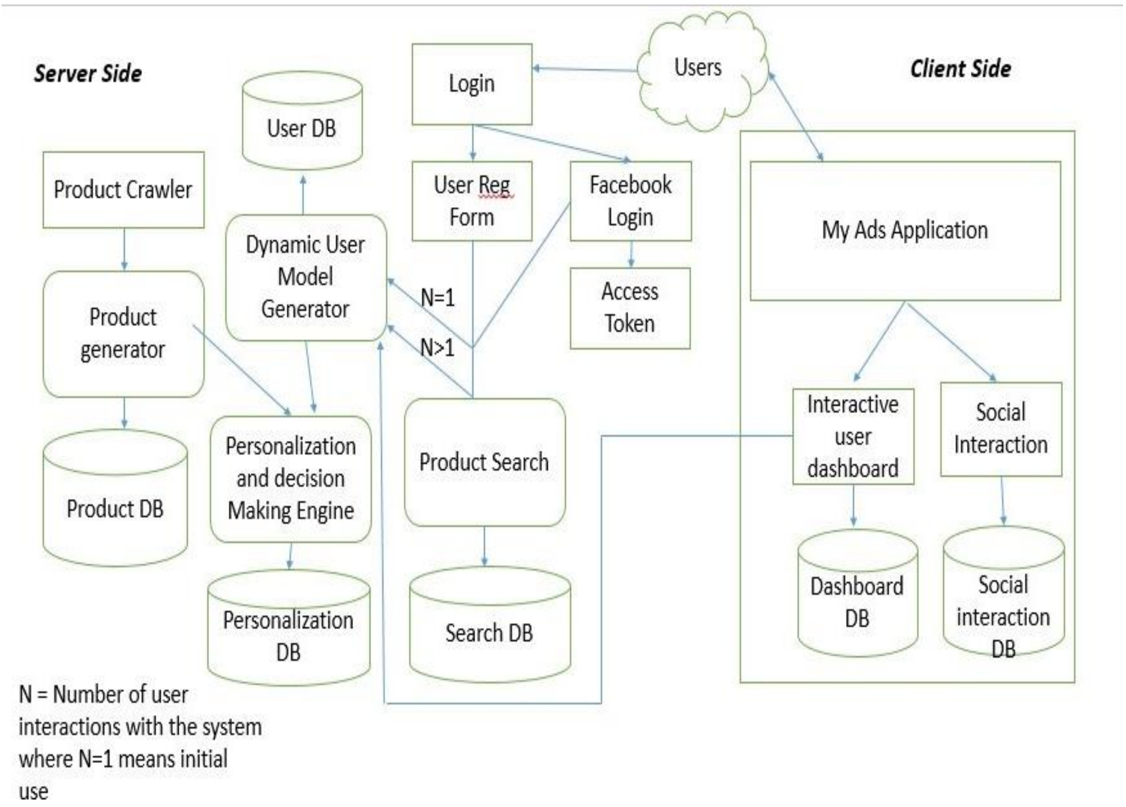

Figure 6.2: MyAds System Architecture

6.3. System Design Focus Group Study

As described in Chapters 4 and 5 MyAds system was built, as an adaptive system that provides a personalised environment for shoppers to enjoy a product and content specific shopping experience using adaptive hypermedia [157]. MyAds serves as a brokerage system, advertising products from different suppliers, and the user is recommended products based on the user model constructed, which are presented using adaptive hypermedia techniques. The initial results suggested that the system did provide a personalised experience, but the main drawback was the *system design* and *extending the user personalisation to include richer user profiling and recommendation*, as users wanted a more 'user friendly' presentation of the products [160]. Thus, a revisit of the design of MyAds was performed.

However, the focal point was not only on the system, but focusing in a more systematic way on extracting (for researchers and implementers in general) a *generic set of required features in adaptive e-advertising, which are essential for the advertising to be accepted by the user*s. The extended design aims at providing a sophisticated personalised platform that includes adaptive hypermedia properties, which can contribute to exploring the area of designing adaptive e-advertisements. Hence the research revisited applying such techniques in a more consistent way in e-advertising. Moreover, within this research, success stories so far have been discussed, towards finding a motivational platform to use, to study and analyse what features can be extracted, as well as identify what pitfalls can be addresses in the new proposed system. This research part investigates:

- what successful platforms, like Amazon, do, to make the user acceptance of their service high (in 2011, net sales grew 40%, and significant gains were obtained in 2013; Amazon ranks among the top five in customer service, speed, accuracy [161]), but also:
- What can be improved, from the point of view of adaptive hypermedia functionality?

Moreover, as users visit commercial platforms, such as Amazon, with an expectation to be offered products, and the line between advertising and product offering is a fine one, the work also researches other popular platforms that offer advertising as a business model, but whose main role is not a commercial one – such as social networks and their role in delivering targeted ads based on the information harvested about the users.

Thus, the research questions resulting and addressed within this chapter are:

Q1.1. What features from adaptive hypermedia users would want to have in adaptive advertising and how are they related to users' acceptance?

Q1.2. How can user modelling contribute to users' acceptance of the e-advertising experience?

Q1.3. What are the main sources of user information users would want to have for adaptive advertising?

Q3. What technology is accepted for e-advertising?

In this context, the design of MyAds has been revisited, by conducting an experiment, including actual users, to suggest improvements for the system design and discuss the current system, with reference to other popular platforms. This was achieved following the user centric design methodology discussed earlier in Chapter 3. Here, 17 users were included in a two-hour experiment, divided into two phases. The sample size of 17 users cannot claim any statistical significant, and no generalisability can be concluded. However, the outcomes of this experiment aligned with previous experiments, the information extracted from the state- of- the- art and the researcher own ideas all work together to address to these research questions.

More concretely, for the initial system design for the first version of MyAds, participants were asked to produce a list of system requirements. The data collected from the exploratory study was used in the first system implementation iteration, as explained in detail in Section 4.3. The main features introduced as a result of the exploratory experiment that were implemented in the first iteration of MyAds included:

- *user profiling via matching user interest and gender with products,*
- *multiple advertisements based on the stated interests,*

6.3.1. Experiment

The experiment was conducted at the University of Jordan, with the help of 17 students, studying a senior course called "e-commerce platforms". The students' age ranged from 20 to 23 years old.

They were all in the final stages of their undergraduate degree and the module chosen was an optional module. The students volunteered to participate in the experiment, which was conducted within a 2-hour session. The students were divided into three groups, with two groups containing six participants each, and one group containing five participants. The groups were of mixed gender. The moderator was the main researcher. Another moderator helped in the session organisation, but did not participate in the actual discussions. The experiment setting followed the same method as in the exploratory study, and as explained earlier in Chapter 3 Section 3.5.

The first stage was for the students to answer the questionnaire, followed by them exploring and browsing well-known platforms that offer targeted e-advertisements, such as Facebook, Amazon, Google, Google+, Groupon, Twitter and LinkedIn. This has then been followed by the discussion session, where the moderator asked open-ended questions, and the groups formed answers and generated the requirements list.

The discussion session was then more focused on the case study of Amazon.com, selected as one of the more popular e-commerce platforms, and an appropriate model of e-commerce. The moderator asked questions such as "*Have you ever used Amazon before?*", "*What are the features you like on Amazon?*", "*What are the features missing on Amazon?*". Their notes were recorded on paper and on the whiteboard, after conducting the open discussions, as before.

6.3.2. Results and Detailed Requirements list

The experiment focus was on generating qualitative data, to be then interpreted by the researcher. For the purpose of this research, some aspects have also been quantified some of the questions so the both qualitative and quantitative outcomes can be supported with each other.

Quantitative Results

The participants were asked to record their perceptions individually (via a questionnaire) as well as feedback to the moderator. When the moderator asked about the most used online system, the results showed that 42% mostly use Facebook, 35% use Google and 20% use Twitter (see Figure 6.3*: Most common websites used by the group*).

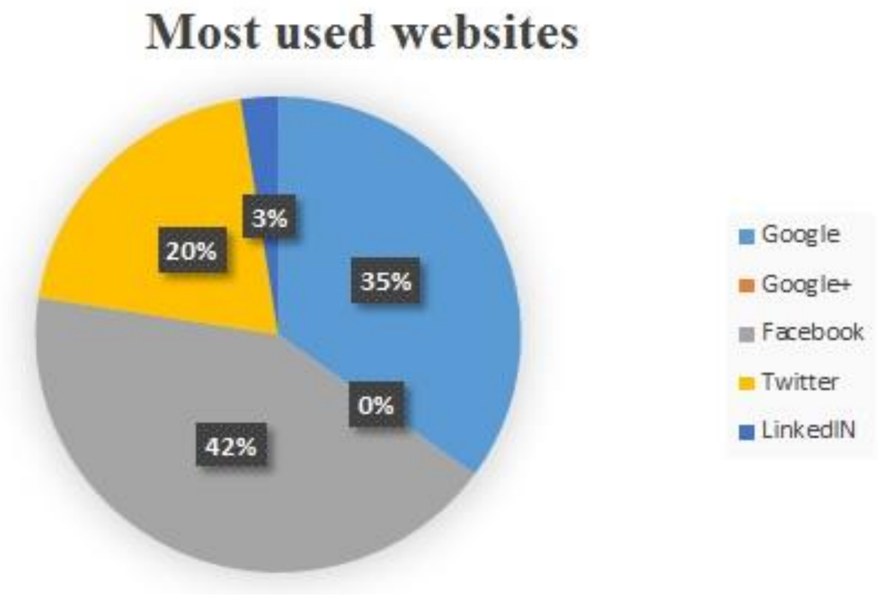

Figure 6.3: Most common websites used by the group

The participants were also asked about their opinion about the advertisements that appeared. They were encouraged to discuss as many advertisements as possible. The results showed that 35% suggested that they are annoying, 30% suggested that they are needed and the other 30% suggested that they are needed, if presented in the right way, instead of being pushed into the page randomly, or blocking the main information, so that only the ad can be viewed and 5% said it is unnecessary, (see their answers in Figure 6.4*: Group opinion of online advertisement*).

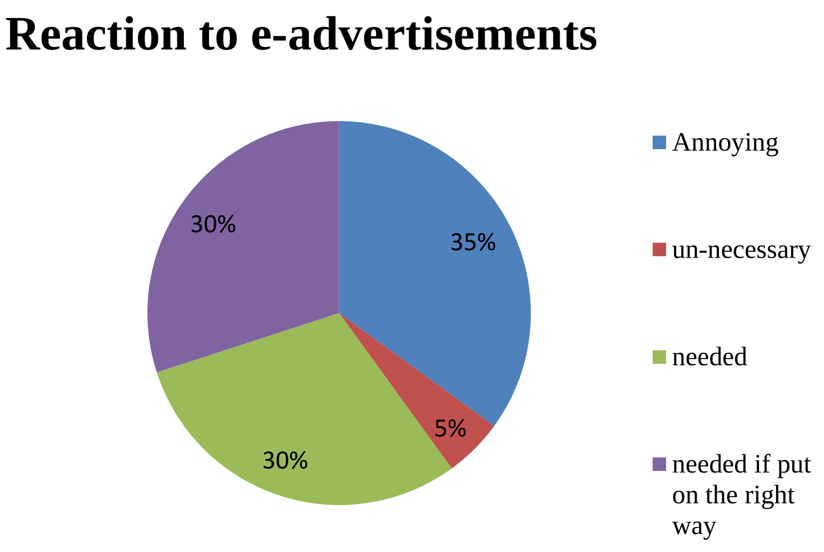

Figure 6.4: Group opinion of online advertisement

The users were also asked about their opinion on the advertisements presented in Facebook, as it is one of the successful platforms in targeted e-advertisements. The initial results showed that this is indeed a popular social network platform for the selected user group - from both their direct feedback to the moderator and from what they filled-in in the surveys. The results advocate that Facebook has introduced advertisements that are to the taste of the users (see Figure 6.5).

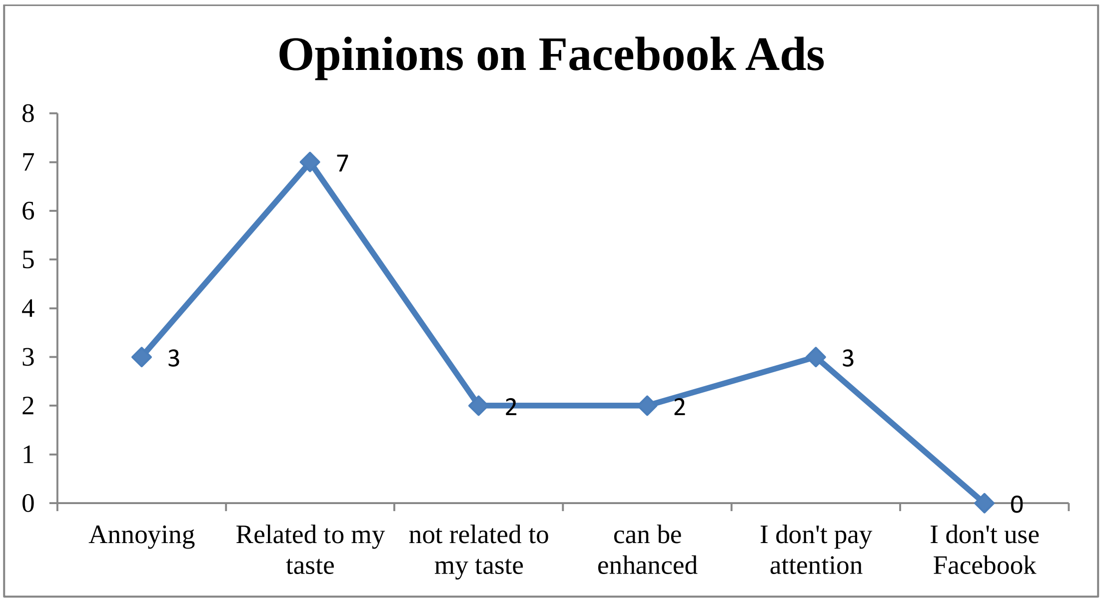

Figure 6.5: Group Opinion on Facebook Ads

As discussed above, users indicated that Facebook does play a role in their online activities. They also found that advertisements provided by online platforms are generally annoying, unless they are clearly connected to the taste and needs of the users. This provides a clear feedback that, in order to ensure users' acceptance of advertisements, the provision should be able to match their taste and needs. Moreover, when users examined the advertisements delivered by Facebook, they did agree that this platform does provide them with personalised advertisements, related to their taste. From the above it can be concluded that personalisation techniques and user modelling and profiling used by Facebook are indeed successful. They are worth exploring for further adaptation implementations of the new iteration of MyAds, by including some specific Facebook features. Some of the interesting features found in Facebook are, for example, that users can actually choose to cancel the advertisement and can then feedback on why this advertisement has been cancelled or blocked. If it was not a sponsored ad, Facebook omits thereafter this ad from the user's page.

Users were asked to also analyse Amazon.com. Since 53% of the participants had previous experience using it and the other 47% hadn't, they were given the chance to try Amazon, as it was important for this research to address its main features. Also to discuss what are the best and worse features available in such popular platform. The users indicated that they found that Amazon provides a variety of products to the users, it is easy to use, provides interactive ads, comprehensive details about products, the recommendations are sufficient and the ability to rate products is highly appreciated. These features as expressed by the users were considered the best features of Amazon (Figure 6.6).

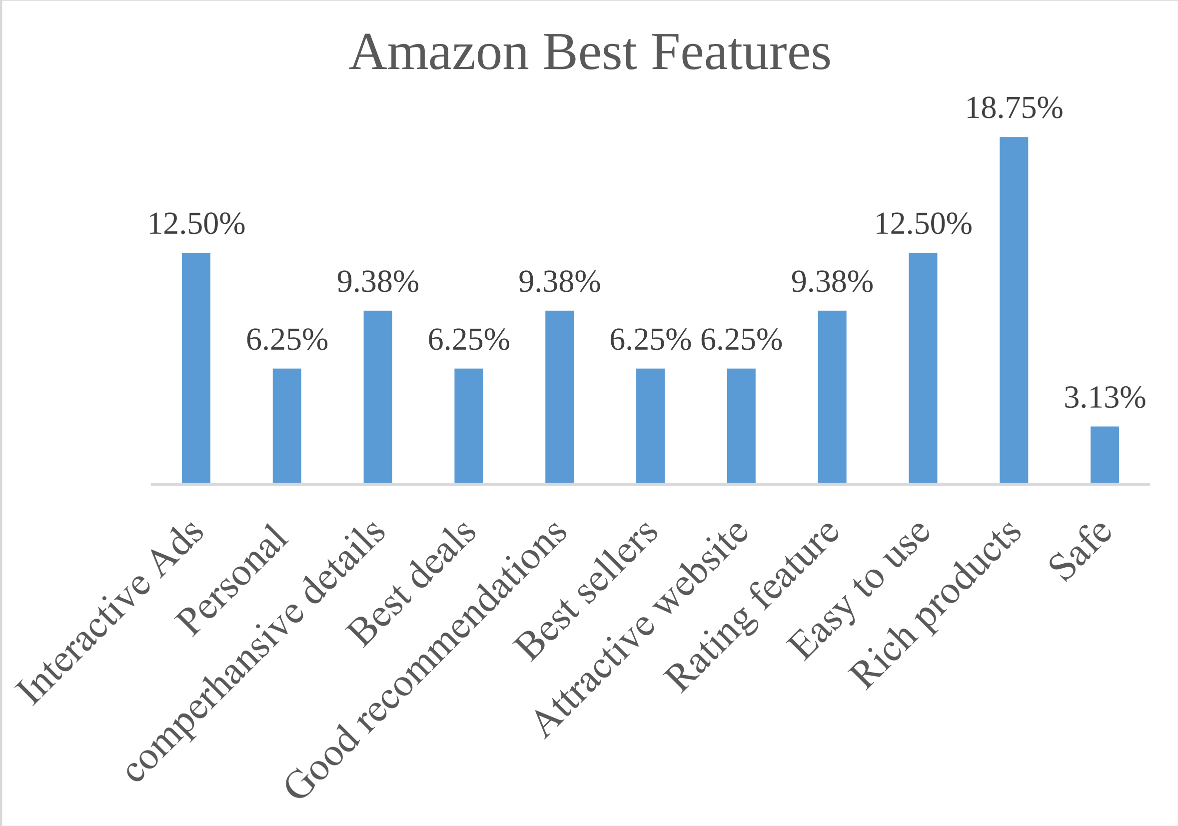

Figure 6.6: Group ideas of Amazon's best features

The least favourable features found by the users for Amazon, were that the design is overwhelming and tends to be condensed with information, as well as that it lacks the option of giving them recommendations in other languages (Figure 6.7).

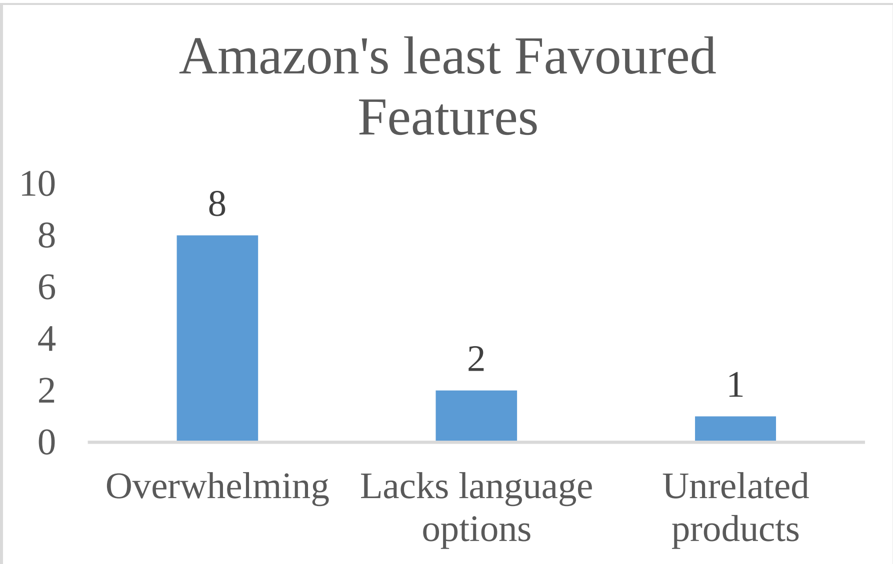

Figure 6.7: Group Ideas of Amazon's worse features

The results from the case study of Amazon pinpointed that, although Amazon is a popular platform that has many positive features, however; there are issues that need to be addressed. The outcomes of the quantitative data are used to investigate the proper features to achieve users' acceptance of e-advertisements. The outcomes include both the positive features that can be extended, as well as less favoured features that the users expressed, so they can be further investigated, while updating the second iteration of MyAds.

Qualitative Results and Revisited System Design

In order to generate the requirements list, the same approach as used earlier in Chapter 4, is applied. The qualitative content analysis approach is the basis of the analysis of the qualitative raw data collected from the users.

The users in this experiment were more aware of the system requirements, than in the previous qualitative experiment, due to their experience, firstly, and the focused discussion, secondly.

As the discussions were focused on personalisation of e-advertisements the main areas to collect information for have been established a-priori are:

- *User profiles*: this to include all the information related to the users and the richness of their profiles.
- *Related ads*: this to suggest items related to user profiles, sorted ads and explanations about ads.
- *Categories*: this to include various categories that can be added or removed based on users' own preferences.

The keywords collected for these areas are as follows:

- *User profiles*: categorised profiles; preferences; update; Facebook-like.
- *Related ads*: relevant products; contextualisation; sorting.
- *Categories*: different product categories.

The way these keywords appeared in the discussions is shown in Table 6.1 below, as the types of suggestions collected from the users. All the raw data has been independently verified by the researcher herself; however, no raw data has been stored; instead, the suggestions as in the table have been compiled during the discussions. These suggestions in Table 6.1 have been further interpreted by the researcher, in order to transform them into implementable features for the MyAds system, as shown in the second column of the table.

Table 6.1: Raw Data collected from the users and their interpretations

Types of suggestions collected from users, based on the raw data	**Interpretations of suggestions: resulting features**
The users suggested having *categorised profiles.*	The researcher proposed addressing this via '*user sub-profiles*' of the initial user profile, to make it more specific for certain needs.
Users suggested having *relevant products in terms of contextualisation.*	The researcher proposed a '*storyline'* feature, which does not recommend an individual item, but rather a set of products (which represents the context).
Users suggested ads be *sorted* based on preferences.	The researcher proposed the *sorting* of ads, *hiding and showing* of information and *explanation* of ads based on preferences.
Users suggested having *different* product *categories.*	The researcher proposed having *removable* and *addable* categories so users can add/remove the ones they want.
Users suggested *updated* recommendations.	The researcher proposed updated recommendations based on the behaviour of the user in the system.
Users suggested *"Facebook"-like* activities.	The researcher suggested using an *event* calendar to connect ads – products- with profiles and sub-profiles.

The qualitative results as presented above have been next converted into a set of new requirements about features to be included within the new system iteration of MyAds. The table below summarises these requirements, as well as categorises them into *user modelling requirements* and *adaptation requirements*. The requirement list was generated based on the focus groups information collected from the users and the interpretation of the raw data. Please refer to Table 6.2.

Table 6.2: List of System Requirements

Feature	Feature Type
User Modelling Features	
R1	Rich User Profiles that collect precise information about user.
R2	Data harvesting from social networks.
R3	Giving the user the ability to create detailed profiles via sub-profiles.
R4	Linking users' events such as birthdays and special occasions, then connecting these events with these sub-profiles and recommend items based on that.
R5	Suggesting to the user an initial set of personalised recommendations based on their profiles rather than random ones.
Adaptation Features	
R6	Providing the user with an adaptive storyline, as opposed to recommending individual and disparate items.
R7	Giving users explanations on the recommendations.
R8	Sorting the products based on the user preferences.
R9	Providing users with shortcuts, stretch text and buttons, to make it easy to navigate the system.
R10	Making the system change the recommendations based on the user behaviour on the system.
R11	Hiding unneeded information.
R12	Giving the user the ability to comment, rate and share products.

6.4. Discussions and Conclusions on the Focus Group Experiment

The work presented above aimed at revisiting the design of the adaptive e-advertisement system MyAds. A focus group experiment was conducted, and followed the user centric design methodology discussed earlier in Chapter 3. The aim of the experiment was to extract concrete outcomes, to generate an extended requirements list. Focus groups provide detailed descriptions of users' opinions and perceptions about a certain problem. The experiment was conducted with the help of 17 students in their senior undergraduate level studies. There were three focus groups that interacted, based on the questions asked by the moderator. The researcher ensured that all the data collected during the session was recorded, for the purpose of summarising the outcomes.

The main outcomes suggested that participants are familiar with popular browsing and social network platforms such as Google, Facebook and Amazon. Participants were aware of Facebook online advertisements and thought that the suggested advertisements are within their expectations and needs. Other platforms failed to trigger the same acceptance level from the participants. Amazon is another success-story for e-commerce websites. Participants believed that it provides a comprehensive, interactive and easy to use environment and they do agree that it is a proper platform to be used as a blueprint for further work to MyAds. However, shortfalls of these popular platforms were also identified.

The qualitative outcome of the experiment resulted in a detailed requirements list, to be use in the second iteration of MyAds. The requirement list was divided into *user modelling features* and *adaptation features*.

The user modelling features include *richer user profiles, using social networks to harvest personal data, including an events calendar, and detailed profiles within the system) assigning sub-profiles*. Other resulting adaptation features included *storylines, explanations of recommendations, sorting of products, hiding unneeded information* and included some features such as *rating, commenting and sharing*. All these features help to answer the research questions proposed earlier in relation to the user modelling, adaptation features and the technology to be used to generate these advertisements.

6.5. Design of MyAds

MyAds aims at providing personalised products to users, to evaluate and estimate the factors that help in leading to users’ acceptance of e-advertisements. The design of the system focuses on both producing an accurate user model and an adaptive delivery system for the users. In order to satisfy this goal, the system applied three main stages [69]:

1. *Information gathering*: different tools and approaches are used to collect information about the users’ requirements. In this research this was fulfilled in Chapter 4 in the exploratory study and in this chapter, Chapter 6 in the focus group experiment.
2. *Information representation*: this is one of the controversial stages, as there are many different approaches to be used for user modelling and data structures, to represent information about the user. This has been an on-going investigation, the previous state-of-the-art has been explained in Chapter 2 and this chapter, Chapter 6 expands the discussion.

3. I*mplementation and execution of the personalisation*: here different approaches and techniques are used to adapt to the user's directly or indirectly expressed requirements. This has been done in the first practical experiment described in Chapter 5.

Based on the previous study results, the platform is to have the look and feel of the popular website Amazon[5] and Groupon[6]. Besides the study results, there are other two compelling reasons to be inspired by Amazon and Groupon. The first reason is to unlock its personalisation and user modelling techniques, in terms of understanding the functionality of commercial websites that keep their source code and work highly confidential. The second reason is to ensure users' familiarity with these systems, since Amazon is one of the frequently used and popular e-commerce websites [27] and Groupon has gained popularity since launching.

6.6. Follow-up Analysis of Features Lacking in Commercial Websites

Through the research process, additional literature reviews and one-to-one interviews with adaptation specialists have been conducted. The aim was to reverse engineering the adaptive features of commercial systems. This aimed at investigating and collecting information about features which are not public, allowing the main issues with these existent and successful commercial websites to be explored. These form the seed of issues that need to be addressed in this new system (beside the primary issue of lacking personalisation). Below is a list of the issues identified:

1. There is the well-known problem of *cold start* [70], when the websites do not have any prior knowledge about the user, to start recommending products for him/her (this applies in general to first time users). This overlaps with the findings from the focus group discussion above, see Section 6.3 one of the ideas is:
    a. Suggesting to the user an initial set of personalised recommendations based on their profiles rather than random ones.

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[5] www.Amazon.com
[6] www.Groupon.com

2. There is no category based on the *general preferences of the user*: only static categories for the user to choose from. Most commercial websites have a set of pre-defined categories that contain the products they have. Users usually cannot omit categories that they do not wish to see.
3. There are no explanations of the categories: (for instance, by hovering over, or having an '(i)' in a circle that expands into an explanation); even sponsored ads should explain themselves, or even better, be connected to the user model. For instance, Google+ works on connecting the user with recommended items through set of questions asked in the registration process (explicit user modelling approach). This overlaps with the findings from the focus group discussion above, see Section 6.3. Some concrete ideas follow below:
    a. Giving users explanations on the recommendations to provide them with a better understanding of how the recommendation was achieved.
    b. Providing users with shortcuts, stretch text and buttons, to make it easy to navigate the system.
4. Opting out of a category does not seem to exist (and generally, a <u>scrutable</u> user model, which is changeable by the user, does not seem to exist).
5. Selecting which types of categories one wants (selecting add types from a menu), as in an adaptable system.
6. There are no clear categories for gifts (gift exists as a label, but it does not specify for whom it is – if you have many persons you are routinely buying for). As a result, distinct <u>user model sub-profiles</u> are introduced. This overlaps with the findings from the focus group discussion above, see Section 6.3. Some concrete ideas follow below:
    a. It's useful to say an item bought is not a random one but connected to a real sub-profiles;
    b. Connecting to birthdays of friends is useful.
7. There is no information harvested from Facebook accounts (the other way around – Facebook harvests information from Amazon and Google) on preferences. This overlaps

with the findings from the focus group discussion above, see Section 6.3. This implies that advertising systems should harvest data from social networks.

8. Platforms such as Amazon do not seem to use the wish list in recommendations (at least not all the time, as the recommendations depend highly on the browsing history). This overlaps with the findings from the focus group discussion above, see Section 6.3. This implies that linking users' events such as birthdays, and other special occasions to sub-profiles and recommend items based these events.
9. There is no user model based on features (such as liking books, or author X etc.) in most commercial platforms – only recently, Google+ has been known to introduce such features – there is a space to put in free text interests, but there are no suggested categories.
10. Improving the richness of the user model, to take into account (for example):
    a. Preferences: colours, types of objects (e.g., long dresses)
    b. Religion: allowing for recommendations for special celebrations, or specific items; clothing-specific items.

These are the main missing issues identified for e-commerce websites, which have been selected for the analysis because they were found to provide some kind of adaptation, although personalisation is still very primitive.

6.7. User Model

As a result of the focus group experiment and the extended research, a new design for the system evaluation tool MyAds has emerged. The modified design is focusing on user modelling and adaptation features that reflect upon the theoretical framework presented earlier. At this stage, user models are generated dynamically and are an essential part in the adaptation process. The work in UM has inspired the research presented in this thesis, towards design and implementation of a more complex UM than has been proposed in previous e-commerce and e-advertisement software. The model harvests the data from two sources.

The first source is the direct ***user registration***, using explicit user modelling, as users fill the registration form in the system. The registration form is rather rich and covers aspects that most other e-commerce systems do not, such as: traditional demographics, job, education, favourite colour, religion – to correlate with related interests – as well as celebrations and events (e.g., birthdays, anniversaries, etc.). The new design suggests the use for measurable data on a scale of 1 to 10 (this extended scale allows for fine-grained matches and results) that has not been previously proposed for e-commerce platforms. The closest to this would be Google+, which does introduce interest, without any scaling. Scaling the interests is important so that weights can be used to determine how often (or when) products should be recommended. As many have debated that users do not tend to give their private information online, some other researchers suggests that it fascinating how users tend to put a lot of personal information online, if they are ensured that the outcomes will adapt to their interests [162, 163].

The second source is via social networks, using implicit user modelling, as there is an ***access token from Facebook*** in the homepage. This access token is connected with the Facebook API to the MyAds server, which fetches the information from the social network. As a result, the initial set of recommendations is random and only considers gender, because Facebook has introduced a restricted privacy policy that only allows for first name, surname and gender to be collected. The personalisation starts to work, as soon as the user has a registered behaviour on the system.

6.7.1. User Model Update Algorithm

The user model updates via two main phases. The first phase is the initialisation of the UM represented in algorithm (1), where the user attempts to log into the system (N=1). The mechanism of including or excluding products is based on gender, age, and other factors such as favourite colour, etc. and is illustrated below. Interests are calculated via the Euclidian distance, by measuring the distance between the users' specified value and the highest value (of 10). The output is then saved in an XML file with weights. The weights determine if the user receives a recommendation related to a given interest or not. If the value is larger than 5, the user receives a recommendation related to that interest. The higher the weight, the more recommendations the user will get – with a maximum of three recommendations per interest (a total of nine recommendations). Algorithm (1) addresses the initialisation of the UM. The specific variables selected for the interests directly address the issues raised by the previous research described in this chapter.

Concretely, this phase covers the problem that most online recommending systems have, which is the cold start problem. In other systems users usually are recommended random items, until their behaviour can initialise the prediction algorithms.

Algorithm 6.1: Initialising Explicit UM

Algorithm #1. ***Initialise the Explicit User Model***

```
Input: a set of all users' information collected through the
registration process.
Output: procedure (initiate user model when n=1)
2:     if user = male [Exclude female categories] Else [Exclude
male categories]
3:        For each interest = 1 to 5 calculate Euclidian
Distance
4:          Distance = Sqr(pow(10 – [user interest value],2));
5:            if distance ≥ 5 then GENERATE kNN { Dis = 9-10 get
3 products of category, Dis = 7-8                get 2 products,
Dis = 6 or 5 get 1 product} Else {exclude category}
6:            if favourite colour = "colour value" get product
tagged "colour"
7:          if religion = "religion value" get product tagged
"religion"
8:          Array_set = SELECT * FROM products WHERE category =
category
9:          print 9 recommendations,  end for, end procedure
```

A snippet of the code for the algorithm above can be found in Annex II. The second phase is when the user starts using the system, and the behaviour of the user is recorded within the system. The system starts tracking the user behaviour by going through the clicked-through items and then calculating TF/IDF, based on term frequency of the product-related tags, in order to calculate the similarity between the products that the user clicks on [79] [62]. The highest frequency terms clicked by the user are used to calculate the Jaccard similarity between these terms, and then use this similarity, in order to recommend more products based on it [82]. All the calculations are based on the frequency of the tags and their relation to products. A refined algorithm aims at testing and evaluating the data accurately before using it and providing recommendations to the users represented in algorithm (2) and snippet of the code for the algorithm above can be found in Annex II.

Algorithm 6.2: Track user behaviour

Algorithm #2. *Track User Behaviour*

```
Input: a set of all the user's behaviour, clicked on – ads,
frequent search items
Output: procedure (update user model when n > 1)
2:    fetch "User_Session" // calculate Product Session
Array
3:      For each product =0; product <total number product;
Product++)
4:      [product_id = logSet[product][product_id];
    product_category = logSet[product][category];
    product_meta_tag =logSet[product][meta_tag]; ]
5:      Calculate TF/IDF
             {output .= (total_retrevied_documents
/value_certain_term_appearnce) * log(total / value,10);] Get
output
6:       Calculate Jaccard Similarity between output,
foreach (itemFrequency ≥ value)    Jaccard_Similarity =
((tf_idf_value ∩ total number)/ (tf_idf_value U total
number))
7:     Get products with highest out,   Recommend products
8:     End for, End Procedure
```

6.7.2. Technical Representation and Features of User Models

The structure for the return values is saved in arrays as the system needs to store mixed data from many sources, like database queries, sessions, web services and XML files. Details of the XML files and database schema can be found on Annex I.

Internal user modelling is reflected externally upon the recommendations of the users. Based on the models built for each user, the recommendations are presented in an adaptive way. The features related to user models that can be manipulated by the users are as follows:

- *Creating Events*: this is a novel approach in e-commerce websites. Social Networks do support the creation of events, but e-commerce and e-advertisements do not. Users can create events as part of their profiles (using a calendar). A reminder message will appear for the users on the day of the event.
- *Sub-Profiles creations*: users can build sub-profiles that are for a specific need or event. In the sub-profiles, they can state their interest on a scale of 1 to 10 and they will be recommended an item based on this sub-profile. Other well-known e-commerce and e-advertisements platforms allow for creating a wish list. Sub-profiles are different, as they can be dedicated to other people, and can be related to events created above.
- *Assigning products to sub-profiles*: users can assign any product they browse, or get recommended, to a sub-profile.
- Users can delete any unrelated or unwanted products or categories.
- Users can change their location, allowing only local products to be recommended.
- Users can rate, comment and/or share a product. These social interactions are for the purposes of the evaluations only. There is no direct social interaction between the users within this system – but this could be implemented in an extended version.

All the user behaviour in the system is recorded and used for further refining and updating of the user profile.

6.8. Adaptation within MyAds

The proposed adaptation method is based upon the extensive taxonomy of adaptive hypermedia systems, introduced by Brusilovsky [22]. The main advantage of this approach is that is a *de facto* standard of earlier research, especially in the domain of personalised e-learning, and has proved its success in providing a good theoretical backing to the adaptive content generation for users [22]. The main categories for adaptation techniques include *adaptive navigation support* and *adaptive presentation*, executed after the construction of a user model (UM) (as discussed in Chapter 2 in Sections 2.3).

Relevant adaptive navigation support to the work in the current thesis includes: *link ordering based on relevance* and *direct guidance via suggested shortcuts – tags, buttons, stretch text and categories, hiding and showing of links based on user behaviour, link annotation,* and *network bandwidth adaptation*.

For adaptive presentation techniques, examples are: *inserting or removing a category or product, hiding unnecessary information* and *changing of location based on the users' preference* [22].

The research in this thesis proposes an adaptive approach to deliver personalised advertisements to the users, using the method of classified advertisements. The implemented system functions as a stand-alone system that provides adaptive ads.

6.8.1. Proposed Approach: The Case Study of MyAds

MyAds is a novel software delivery tool. It aims at addressing the acceptance of e-advertisements from a user perspective. It is built as an evaluation tool to explore the various aspects of adaptation. The adaption occurs at two levels.

The first level is where the adaptive storyline is created for users, by recommending to them personalised products based on their user models and adaptive link sorting.

The next level is when a user shows interest in a product and clicks on it, and various other adaptive techniques are used. Figure 6.8 illustrates this adaptation process.

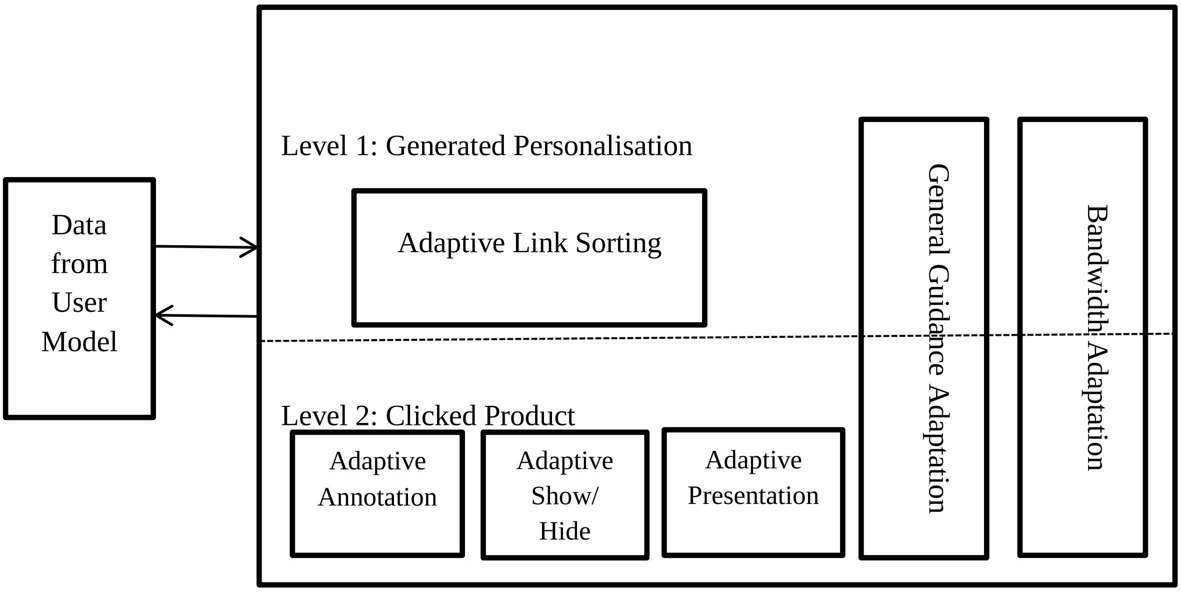

Figure 6.8: Adaptation Process

6.8.2. Algorithmic and Formal Representation

After the initialisation of the user model, the users are exposed to nine products that are sorted from the most relevant one – based on the user model – to the least relevant one. Both adaptive navigation support and adaptive presentation are used within the system, to comprehensively evaluate the adaptive experience. This is due to adaptive hypermedia using the previously mentioned theoretical techniques not being thoroughly and systematically explored in e-commerce and e-advertisements context. Most platforms focus on filtering techniques. This novel approach uses the tools of AH in a non-traditional domain. The adaptation can be described as a navigational tree and, as previously hinted at, level one of the adaptations includes:

- *Adaptive Storyline*: Throughout the user experience all the items that are recommended are not recommended as individual items but rather as a part of other set of related items. Users get a slider at the bottom of each product, suggesting a set of related items that they may like to further browse.
- *Adaptive Navigation Support:* The system explores almost exhaustively the techniques related to the adaptive navigation support. The first stage is when the user receives the set of recommendations, which implements these techniques as follows:

- *Sorting* of products is established via the k-Nearest Neighbours algorithm (*k*NN), based on relevance neighbourhoods computed from weighted user interests (stored in XML). Recommendations appear in descending order of relevance. The reason for using k-Nearest Neighbour for this particular problem is that it is one of the most efficient approaches to mining data in a scalable way. It is also simple to implement technically and understand mathematically [78]. Since the proposed feature in MyAds scores the users' interests on a scale from 1 to 10, any value they decide, this algorithm can be used to measure how far a certain user interest is from the highest value.
- *General Guidance* is provided for users in various ways to cater for different ways of processing information in human brains [19]: for instance, MyAds features stretch-text on products, a "I do not like any" button (to trigger a new set of recommendations) and another two buttons, "see different set" and "go to home page". All these buttons aim at aiding the user in their navigation experience.

Algorithm (3) below illustrates in pseudo-code the behaviour of this first stage of generating the adaptive content.

Algorithm 6.3: Adaptation within MyAds

Algorithm #3. *Create Storyline*

```
Input: a set of all users' information from the UM.
Output: procedure creates storyline for users
1:   Launch function = NavigationSupport.Guidance{  /setting
up the function.navigation support
32:     foreach item = i sort in descending order based on
output of kNN
3:                 i++;
4:                  Print product ={item['product_id']}
title={item['meta_tag']
                     Display "stretch-text" // general
guidance navigation support
5:                  if ($i % 3 == 1)  // Number of button
clicked
                        { show
6:                      "newbutton" id='like'>I Do not Like
Any< if click ==true, select new
                          products, else {keep list}
7:                       "newbutton">Go To Home Page< if
click ==true, redirect to "index.
                          Page", else  {keep list}
8:                       "newbutton">See Different Set< if
click ==true, select new products,
                          else {keep list}} end if,  End for
}
9:    Get bandwidth=value, use Lazy loader,  Get related
items ==JQuery calls }
10:  end procedure }
```

When users click on of the products that may have interested them, the following adaptation takes place during level two of the adaptation.

- *Adaptive Navigation Support*
  - *Link annotation*, where users receive an explanation why this product has been recommended to them.
  - *Link Hiding/Showing*: As soon as the users choose to consider a product, a link directing them to the original source where they can actually purchase the product appears.
  - *General Guidance*: After users click on a product, they have the options to click on "go to home page" or "start new search".
- *Adaptive Presentation:* this takes place when a user clicks on the product that he/she is interested in, as follows:

- *Text Hiding/showing*, when the users get exposed to a product, they are asked to give their direct feedback upon it. They can choose from:
    - "I will definitely consider buying this product": this will show all the product details and price.
    - "I may consider buying this product": only the product price will show.
    - "I will never consider buying this product": if selected, another subset of feedback options appears. The subset includes:
        - It was not to my taste
        - I did not have this in mind
        - I do not need this product

If the user chooses the third option, this product will be omitted from the user's recommendations and it will not be recommended again. Please refer to algorithm (4) to illustrate the behaviour of the second stage of adaptation.

- *Adaptive Bandwidth*: as users may have different devices to access the system (and from different locations) the bandwidth speed and quality can vary. To adapt to the speed and quality of the Internet, we used the *lazy loader* [164].

Algorithm 6.4: Clicked on ad

Algorithm #4. ***Clicked on Ad***

```
Input: clicked on – advertisement
Output: procedure (apply navigation support / presentation and
link)
     Get bandwidth=value, use Lazy loader
     Get function = NavigationSupport.Guidance
     Get related items ==JQuery calls
     foreach item i == true, i++ //clicked on product
        If item.click == "buy"
         Show.item == text.price
         Show.item == link.URL
         Show.item == function.link_annotation
        Else if item == "Maybe"
         Show.item == text.price
         Else item ==  "Not interested"
         Get function = feedback
        End if, End for,  End procedure
```

All the previously mentioned and used features have been derived from the past research and the three experiments conducted before. In Chapters 3 and 4 users had suggested a list of requirements. The requirement list was further refined in the focus group experiment in Section 5.3. All these experiments as well as the extensive theoretical research have developed the final set of features to highlight the novelty of the work. Some of the features have been used in other e-commerce systems; some are new and are novel part of this research. All these features have been implemented in a live system and been evaluated next in Chapter 7. A snippet of the adaptation code can be found in Annex II.

6.9. User Interfaces

The user interfaces presented to the users within MyAds have been implemented based on HTML5 and CSS3. MyAds is an adaptive web-based application, thus all the adaptation and the interfaces are generated dynamically, based on the users' behaviour on the system.

The system was designed to follow the general guidelines of usability [113]. The system was designed and implemented in way to be easy to use, functional, friendly and personalised. These features and properties were derived from different sources that influence this work, as explored in [101], [49] and [61].

In order to illustrate the process and adaptation within MyAds, the Figures below are put in sequence, to demonstrate the user experience. The actual system implementation is pretty straightforward for an online application and was outsourced; hence it is not further discussed here. The home page of MyAds contains the primarily information for users. It has two login options:

- Either via "creating an account" and initiation of the user model using explicit data collection method, or
- Through Facebook login, as the system automatically fetches the data of the users from Facebook to initiate the user model using implicit data collection.

The page also has information about MyAds and states that it is a research based evaluation tool.

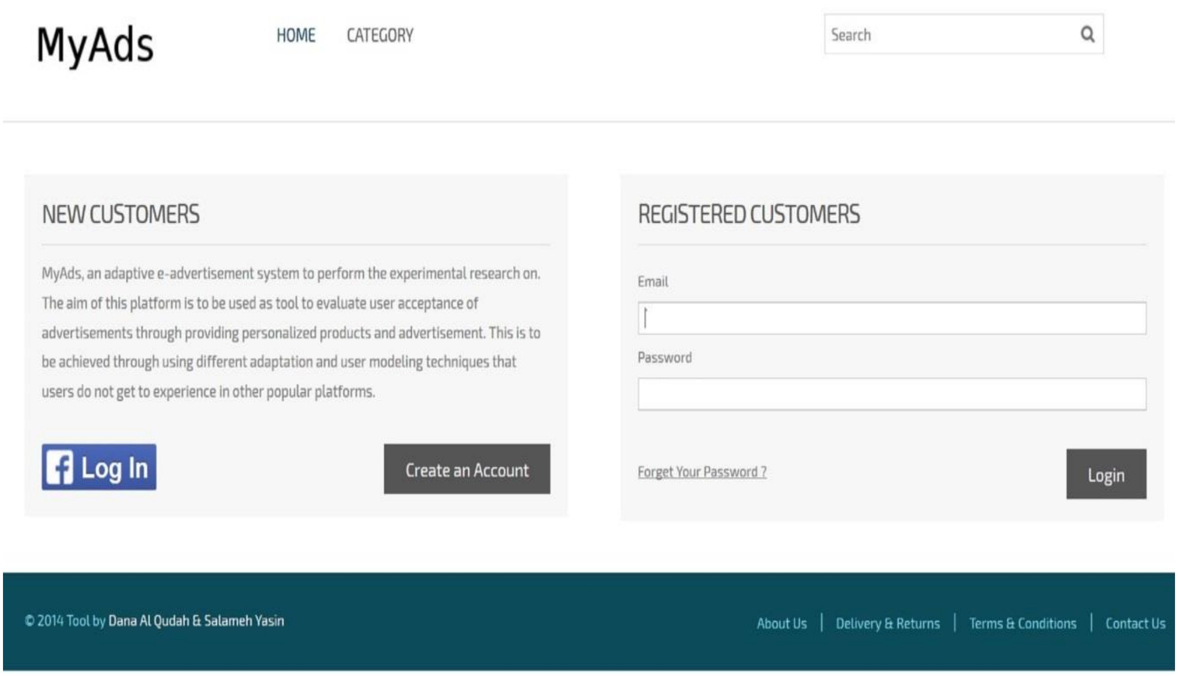

Figure 6.9: MyAds Home Page

The user's registration form consists of slots for various data to be collected. Not all the data are mandatory. Only the interest-related scales (vital for the adaptation process) are the ones that the user needs to inform the system about, so that the appropriate recommendations can be generated. And Figure 6.11 illustrate the registration form in detail.

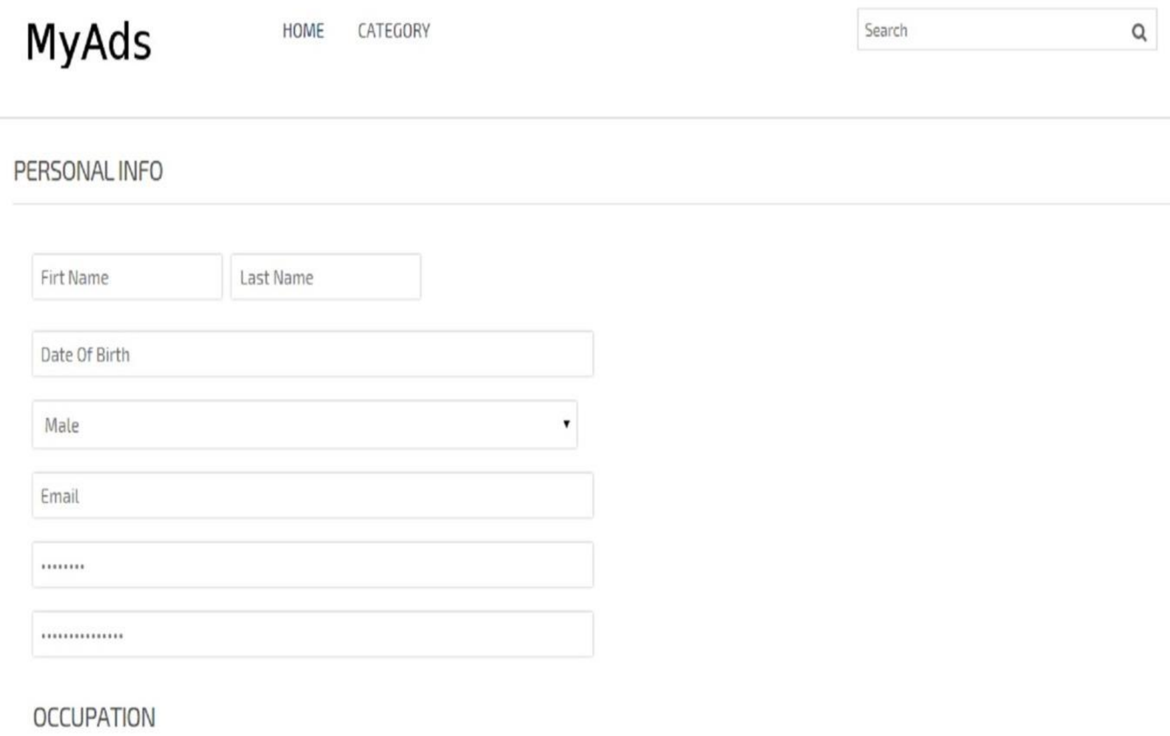

Figure 6.10: Part one of the registration form

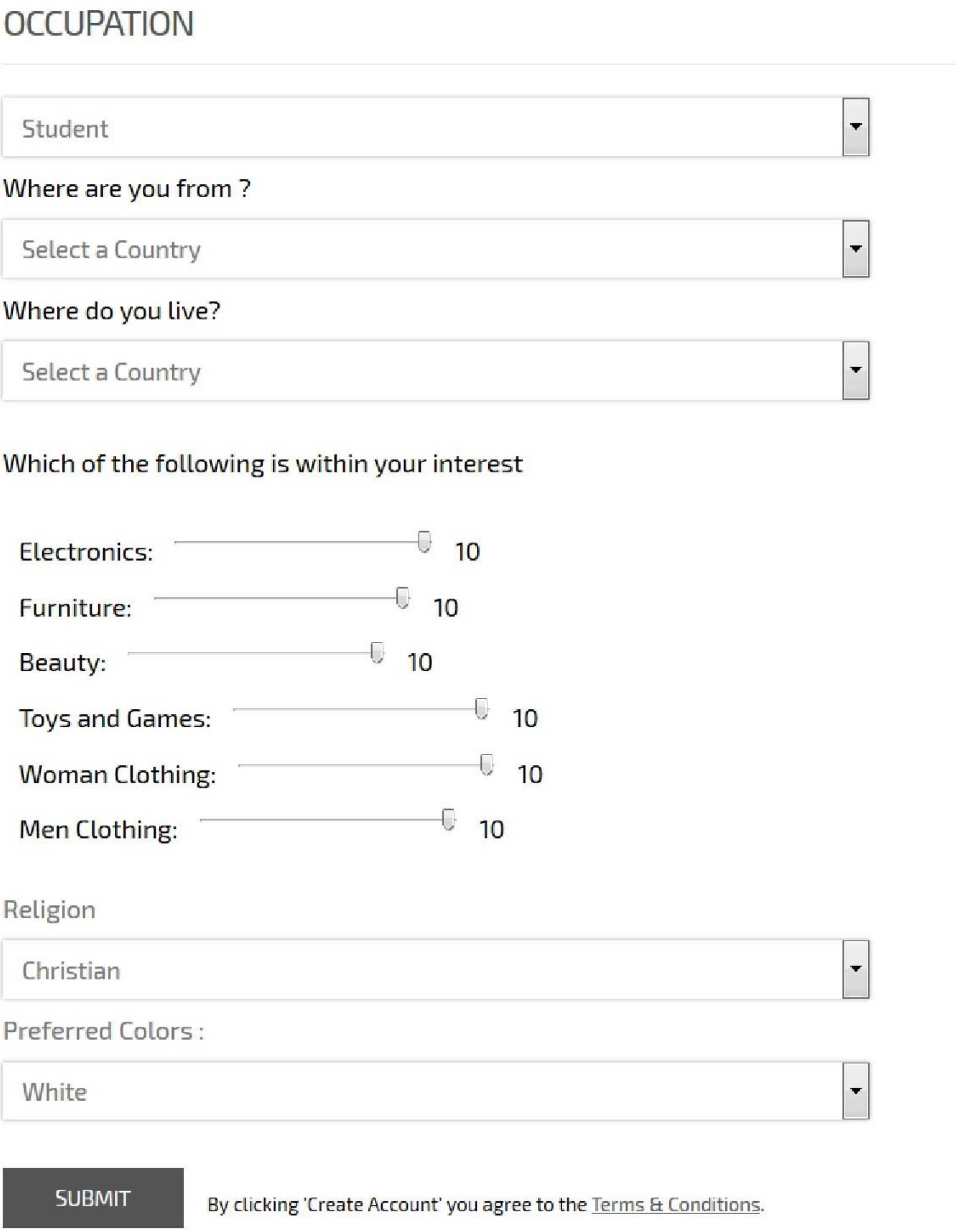

Figure 6.11: part two of the registration form

The forms are quite rich in the amount of data required. The users can choose which parameters to include for their personalisation. As soon as they submit the registration form, they will be directed to the index page, which will contain the initial set of recommendations, based on the data provided before, as shown in Figure 6.12.

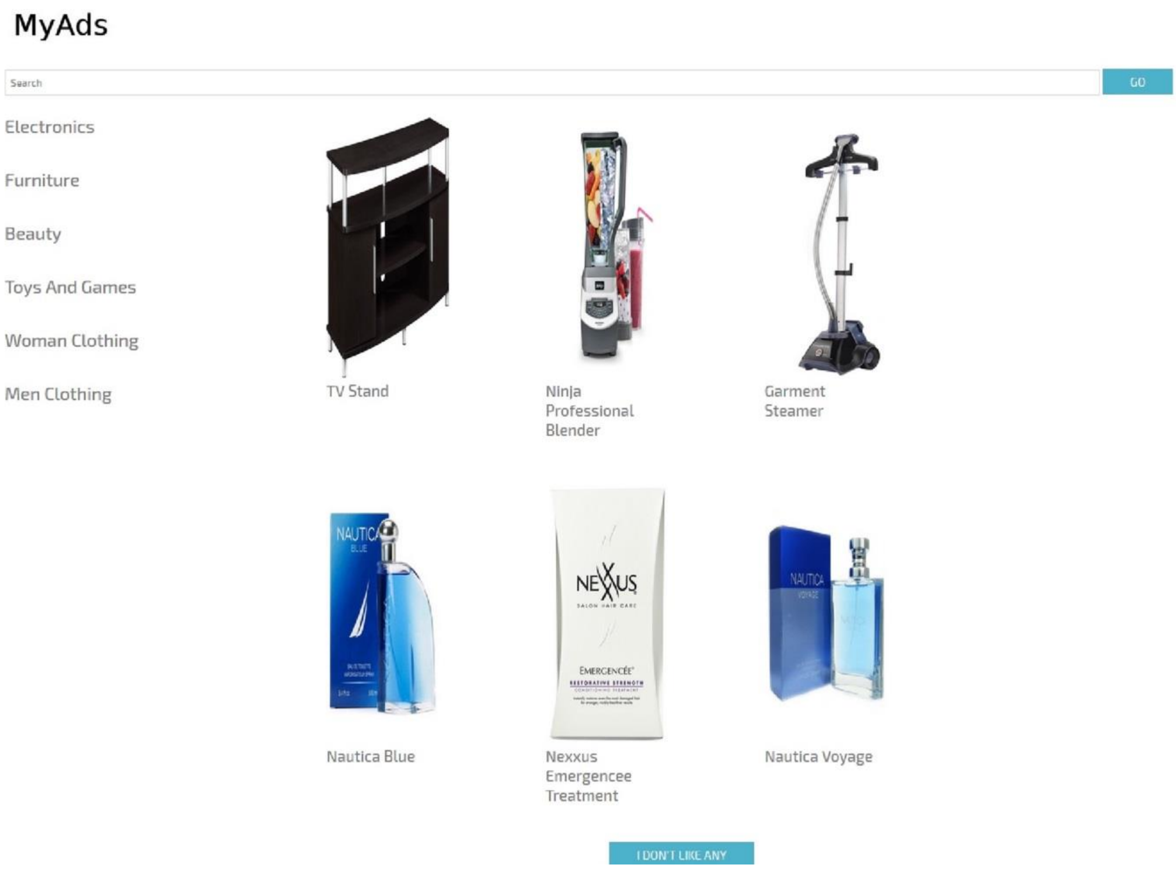

Figure 6.12: Initial Recommendation based on directly stated Interests

The dataset includes 5 different categories, based on the interests, which are: *clothing*, *toys and games, beauty, furniture* and *electronics*[7]. A user can change the location of the product, delete a category, etc. Such actions are recorded as the user's behaviour within the system. This is then used to update the user model.

For example, from the initial set, an initial assumption could be that the user is a male, interested in furniture and beauty products equally.

Please note the initial sorting of the products is based on the stated preferences (via the registration form). If the user presses on the "I do not like any" button, the following two buttons will appear, as in Figure 6.13.

[7] These relatively limited five categories were chosen because of a lack of data, due to the crawlers being blocked by the commercial website.

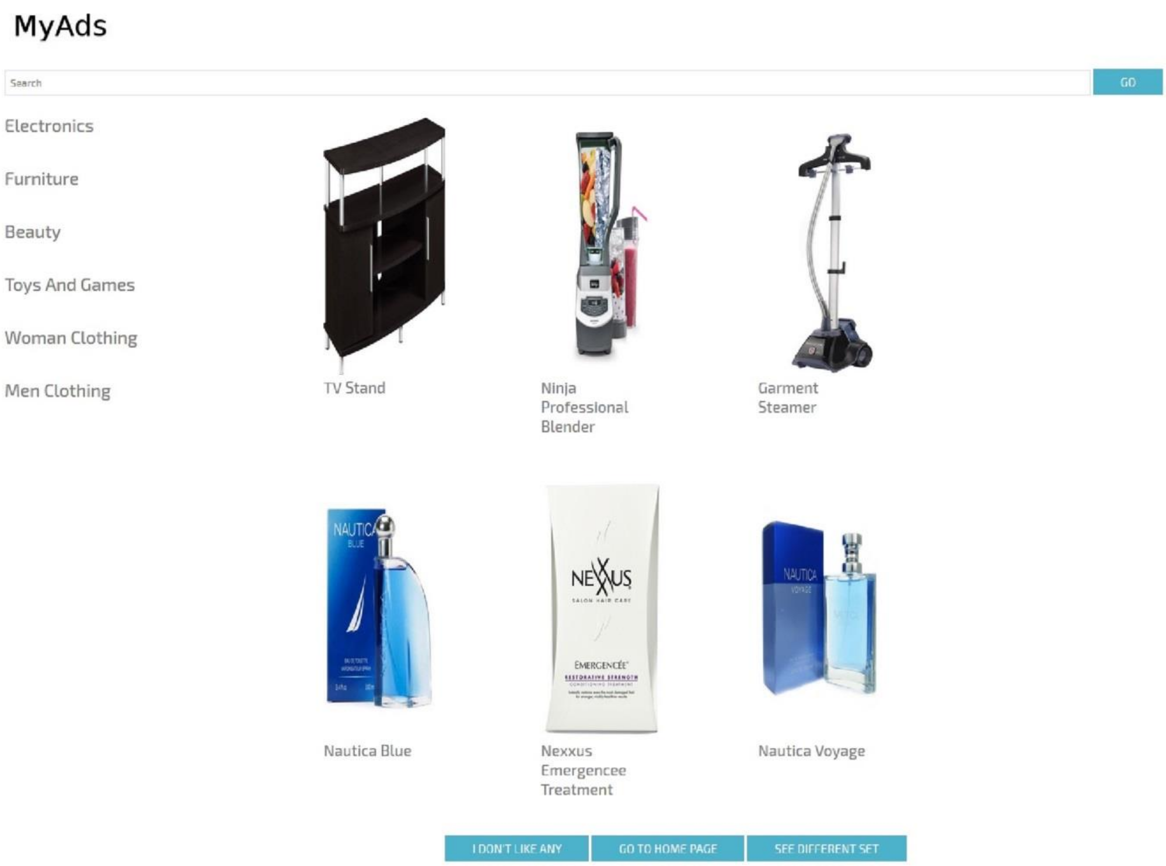

Figure 6.13: Options for lack of interest

The user has the option of going to the home page, where a random set of products will be shown, or to see a different set of products, based on the same interests as indicated earlier. Figure suggests a new set of products within the same interest category; Figure 6.14 suggests new random products. The user can also search for any products at any time by using the search box.

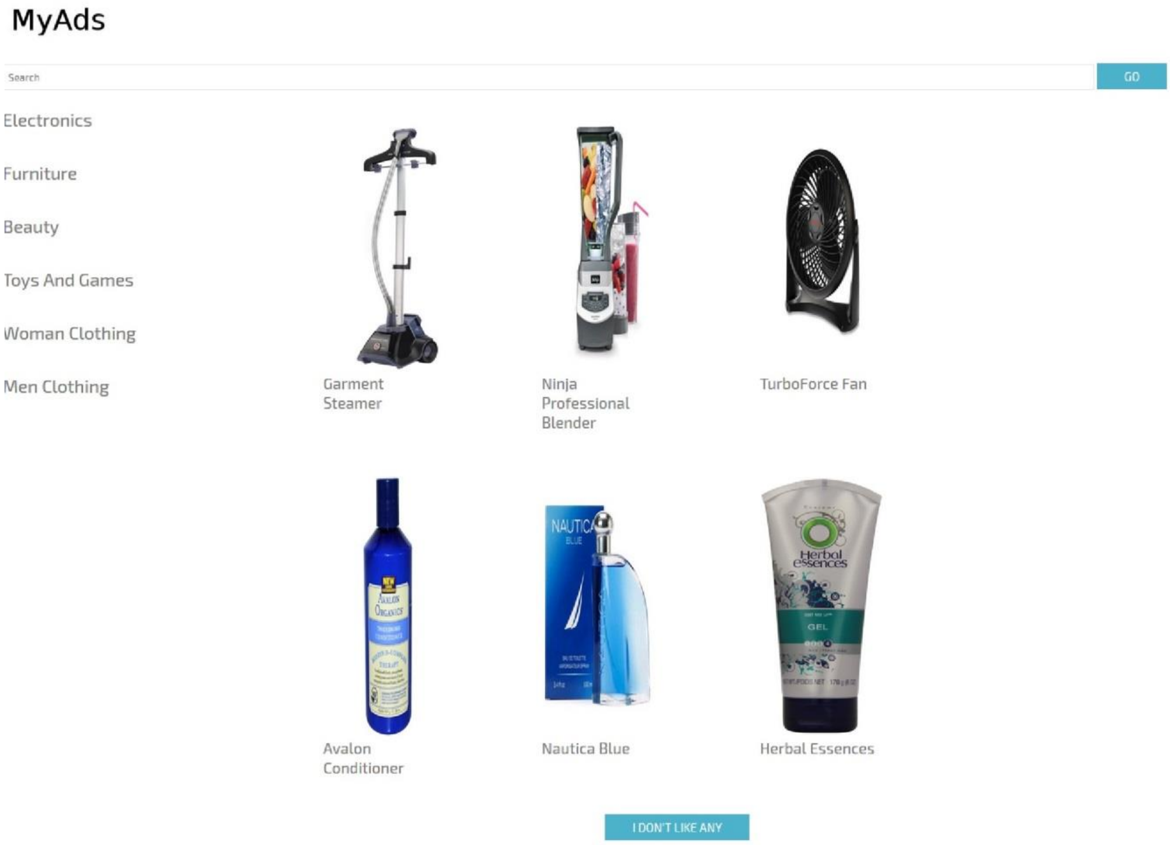

Figure 6.14: A new set of products is recommended based on interests

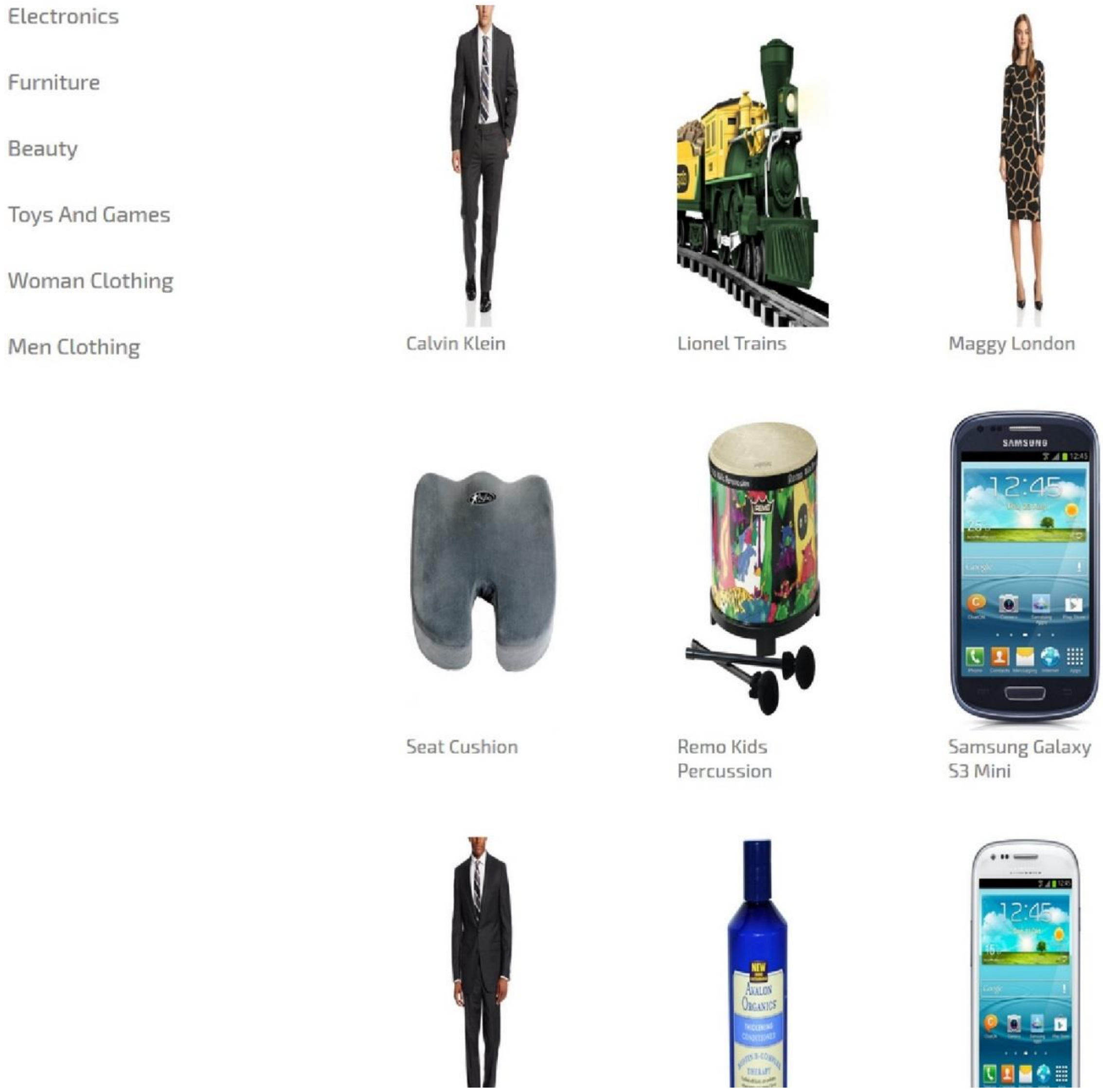

Figure 6.15: A new random set of recommendation

If the user actually clicks on a product that he/she want to explore more, the following page will appear, as in Figure 6.16.

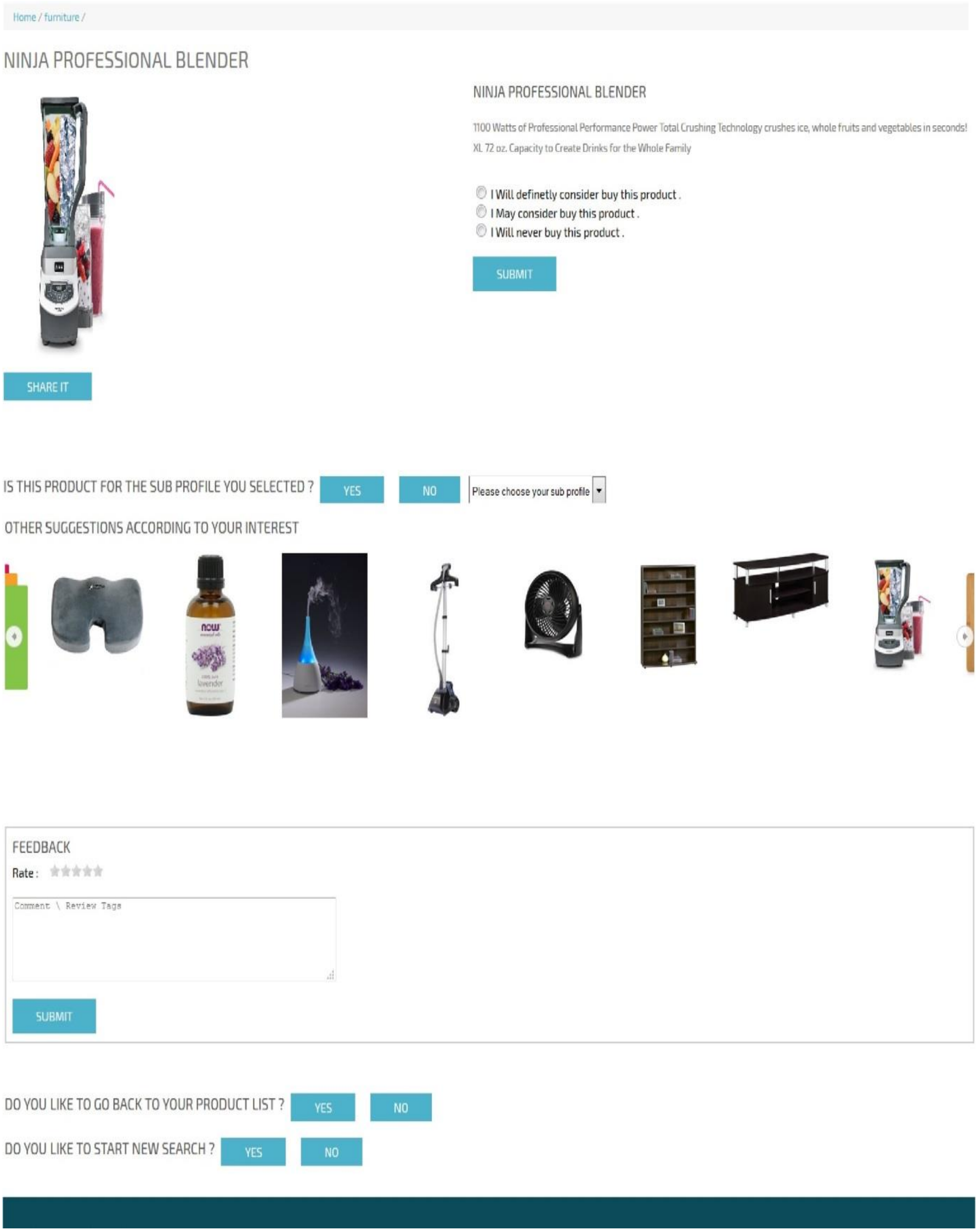

Figure 6.16: User has clicked on an Ad

The user is not recommended a separate item, but will see also a set of recommendations as part of an *adaptive story line*. The user also has the option to return to the product list, or start a new search, as part of the direct guidance adaptation. Moreover, for evaluation purposes, the user can comment, share or rate the product, to show to what extent the user is interested in the product.

There is, furthermore, the option of creating a sub-profile, as the user can assign any product to a sub-profile (shown in Figure 6.22, Figure 6.23 and Figure 6.24). However, the important parts are the three options above, as the user has to choose one of the options and, based on the chosen option, the details of the product will be displayed. Figure 6.17 illustrates the user choosing "I will definitely buy this product". *Adaptive presentation* is explored, because text that gives information about the price and additional information about the product is displayed. *Adaptation annotation* is explored, as the user is given information on why this product has been recommended. *Adaptive link hiding/showing* is also introduced, as the link to the product website will appear, based on the user preferences; in this case, this is the Amazon product link, as illustrated in Figure 6.18.

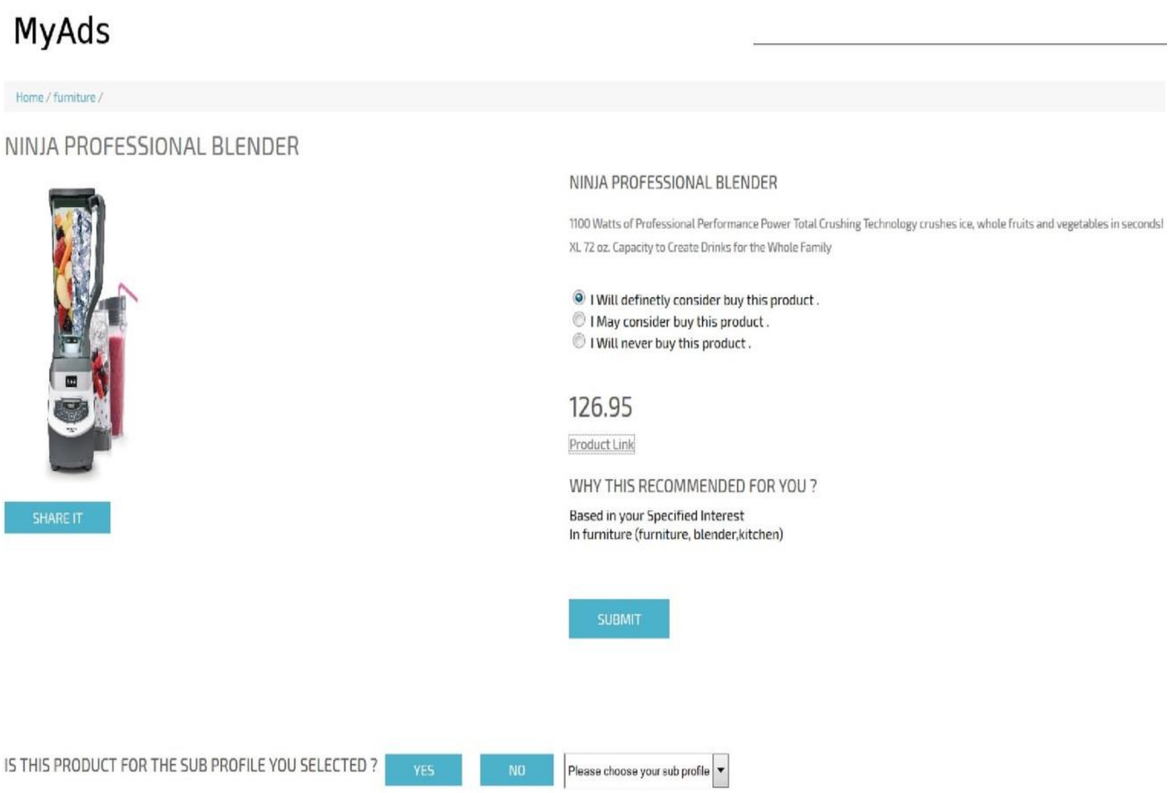

Figure 6.17: User chooses to buy the product

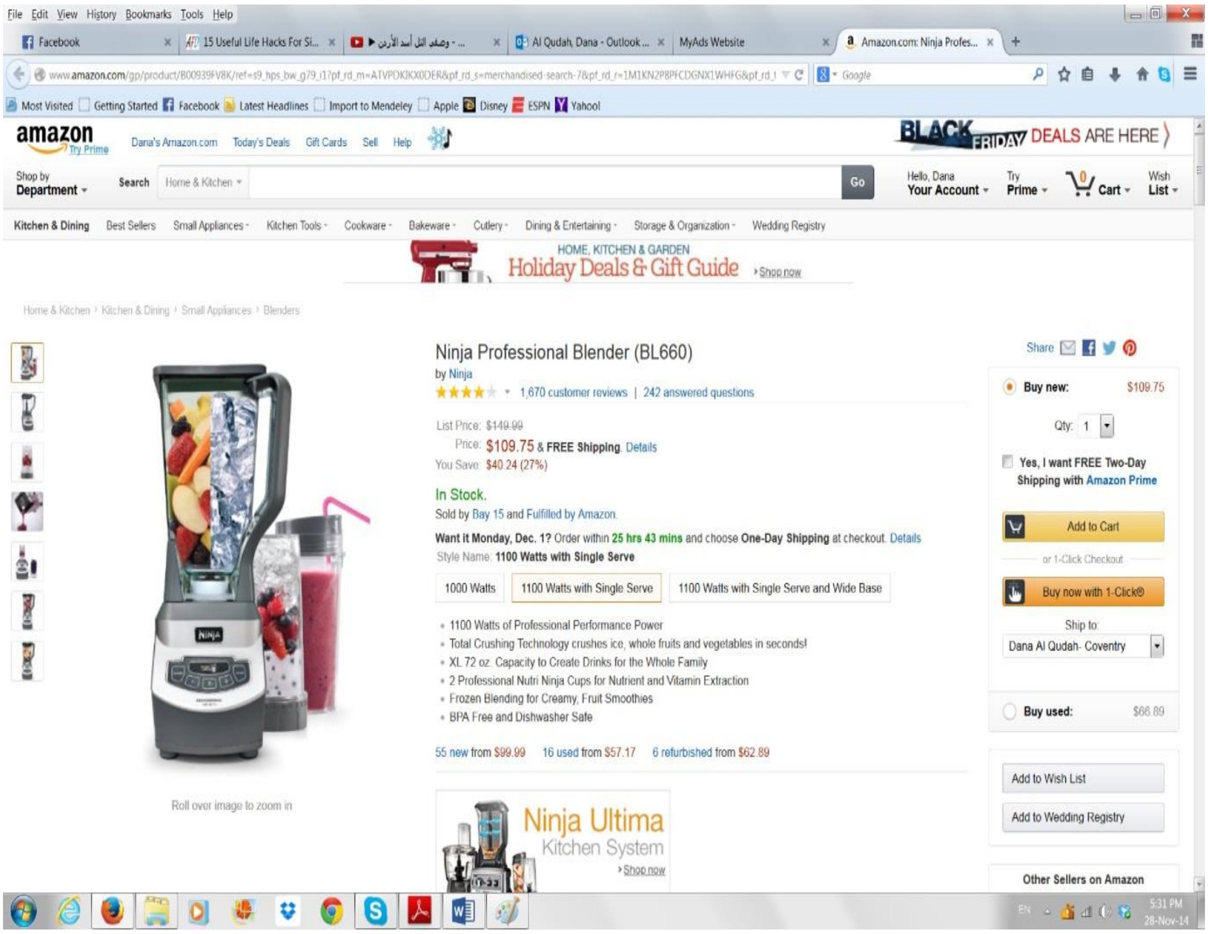

Figure 6.18: Amazon re-directed product

As soon as the user returns to the product list, after submitting the definite interest in a product, a new set of recommendations will be shown, within the same category, but without the product already bought, as in Figure 6.19. The latter is normally not implemented in commercial websites, resulting in annoying recommendations of products one has already purchased.

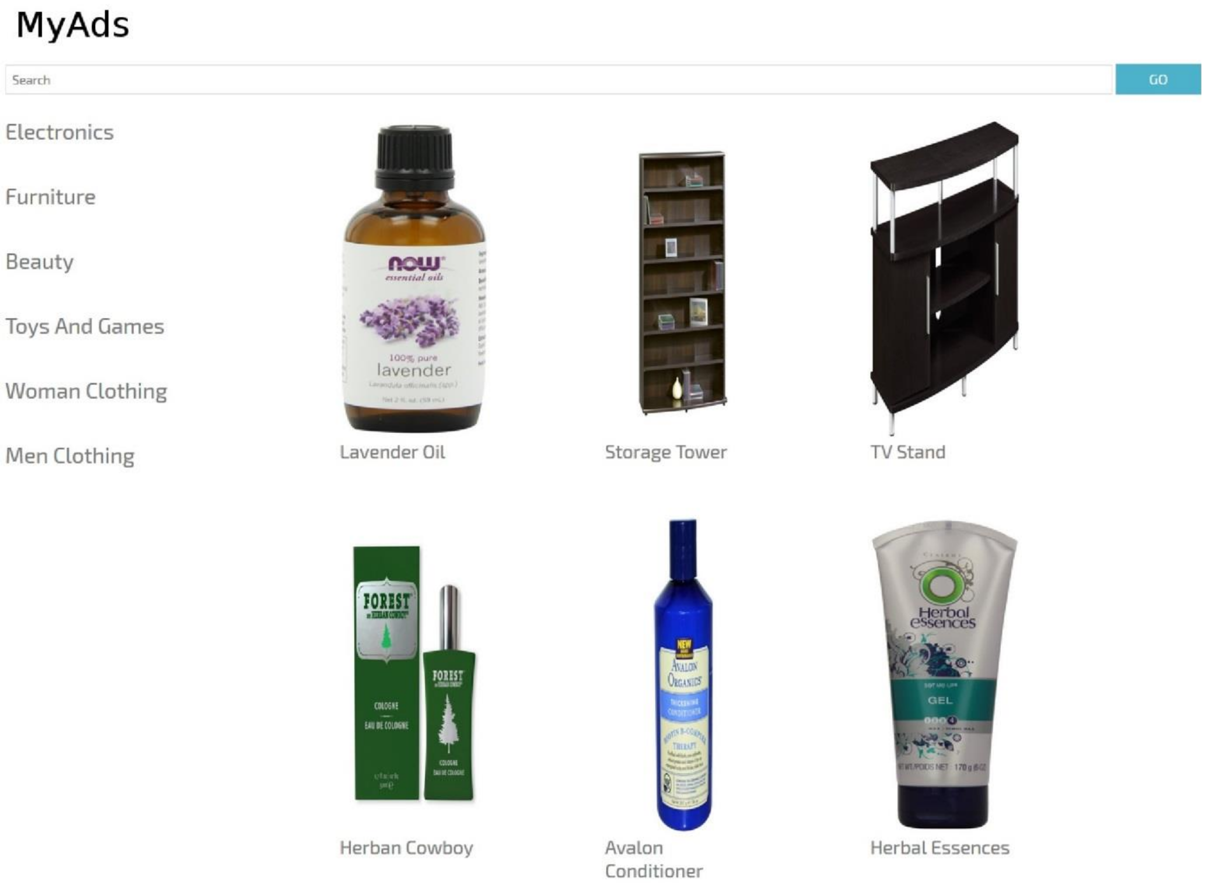

Figure 6.19: The new set of recommendation after the initial behaviour on the system

The new set recommends the products based on the calculation of TF-IDF and Jaccard similarity, to match it with new products within the same set of interests.

If the user clicks on the second option, which is “I may consider buying the product”, a set of adaptation features, like *link hiding/showing* and *adaptive presentation* will be applied. This is achieved without link annotation, in order not to overwhelm the user with the amount of information available. Figure 6.20 illustrates the process.

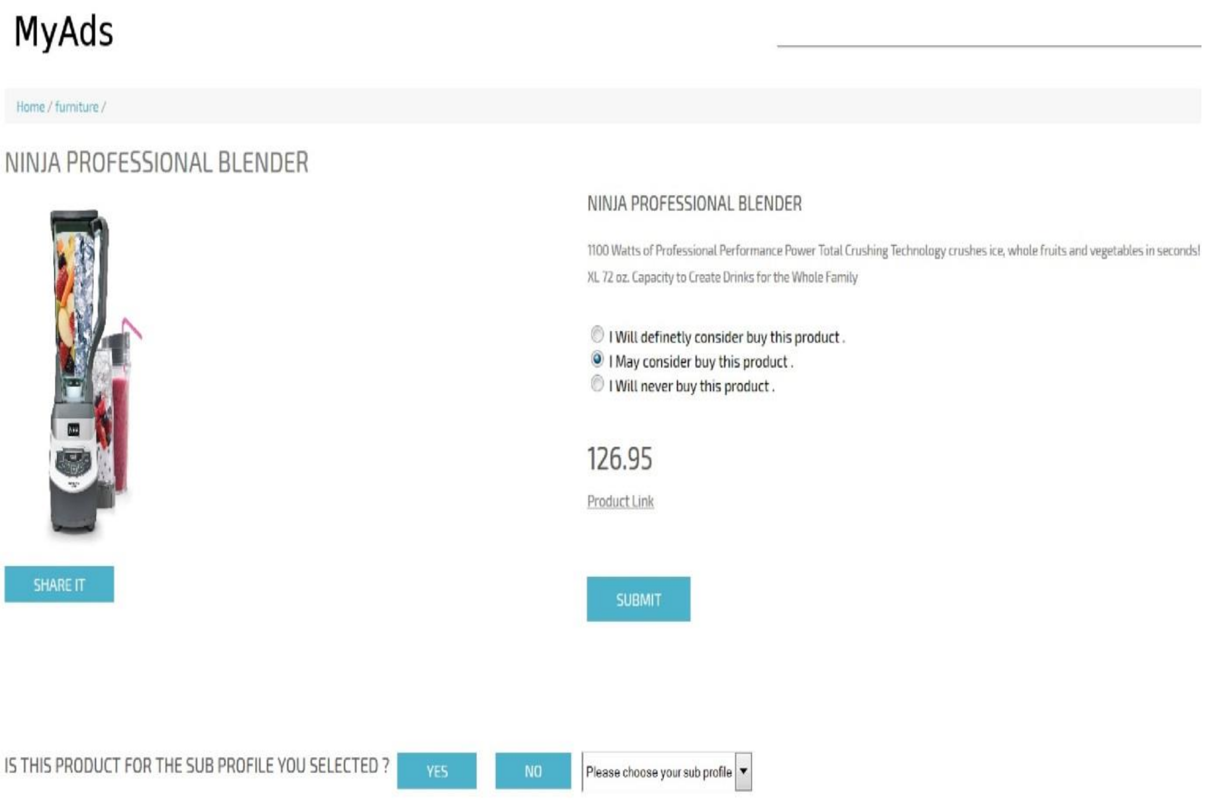

Figure 6.20: User show less interest in the product

The final option is where the user will “never consider buying” the product. In this case, the system automatically asks for the reason and omits the product from the user’s product list, meaning it will never be recommended again. Figure 6.21 illustrates the process.

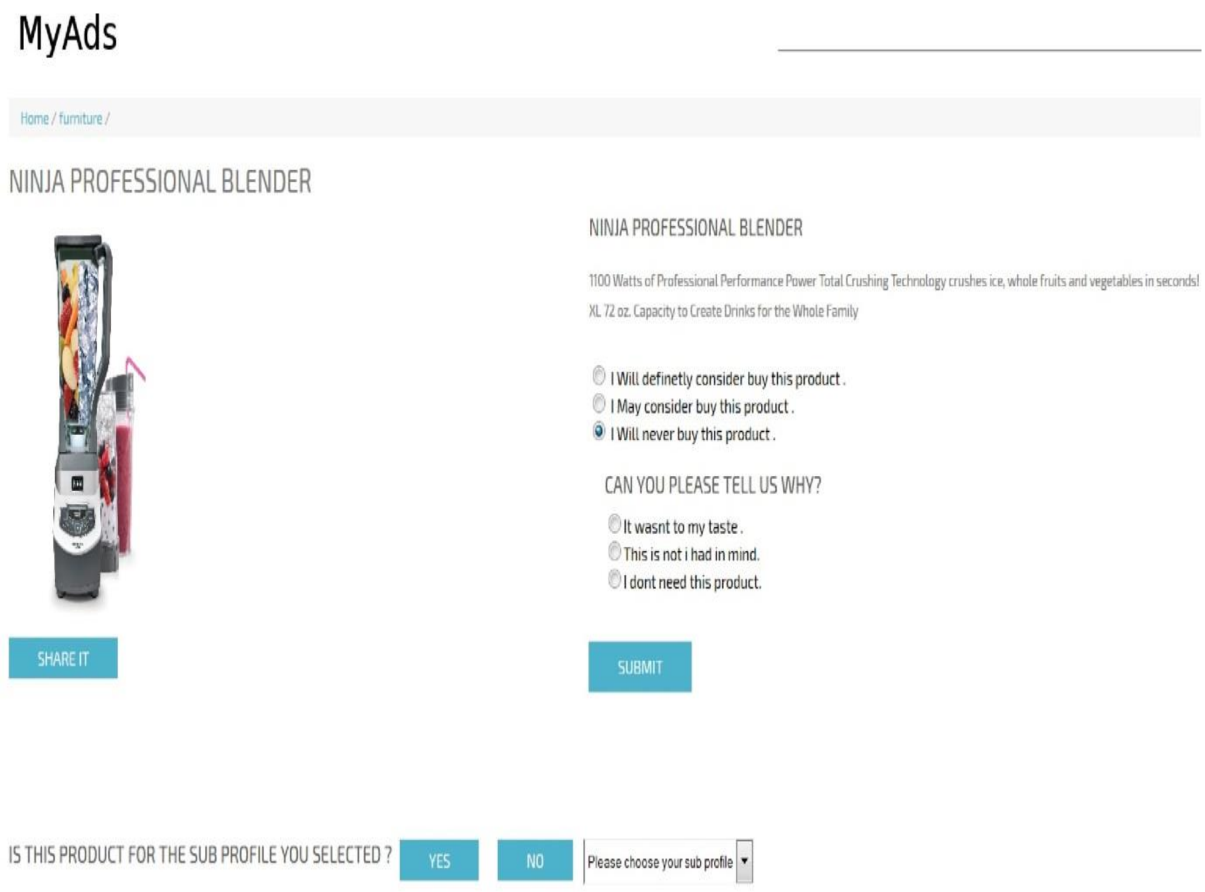

Figure 6.21: User does not have any interest in the product

Sub-profiles and *events* can be created as soon as the user starts interacting with the system. The sub-profile form is much simpler than the registration form and one recommendation will be generated on the recommendation list, based on the interests from the sub-profile. Figure 6.22 contains the details of the sub-profile form.

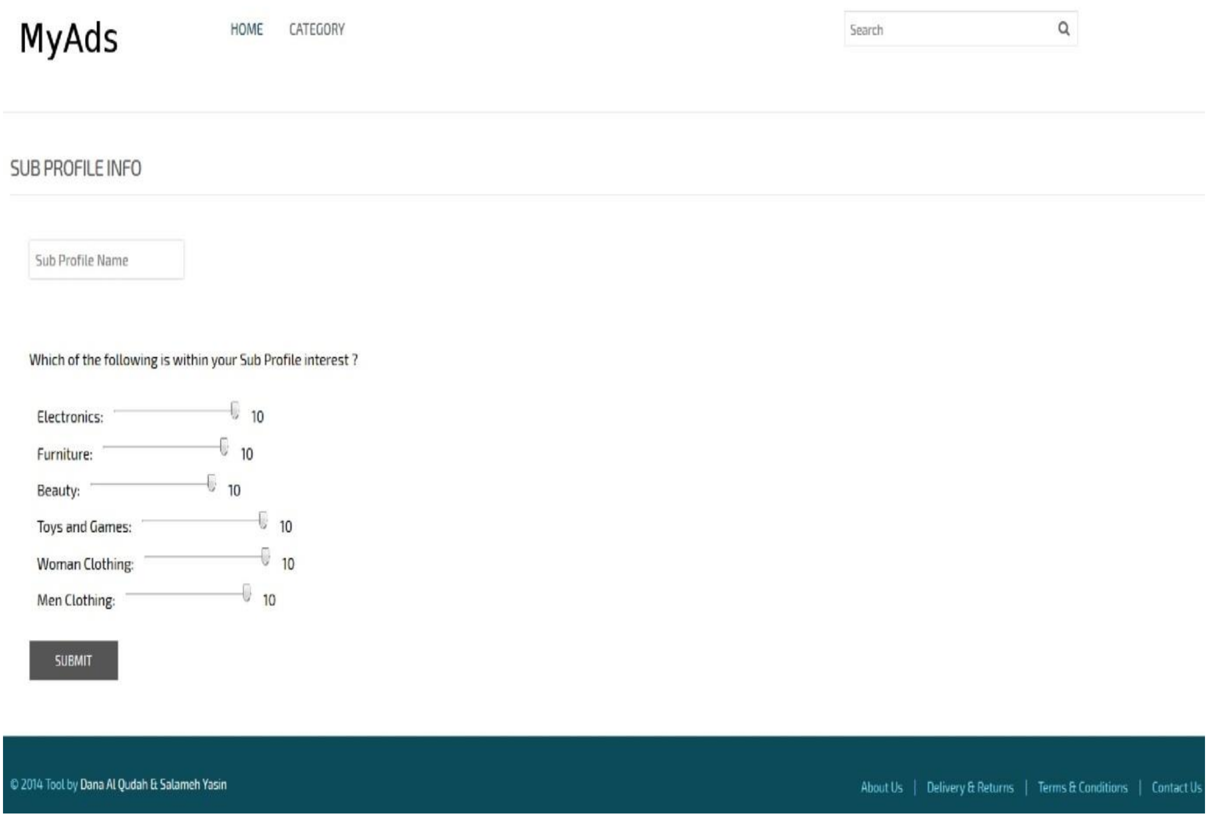

Figure 6.22: Sub-profile form

In the recommendation list, a new product appears, related to a sub-profile, created for a young boy, as shown in Figure 6.23. This would be the case, for instance, where a mother would be recommended products for herself, as well as for her young son.

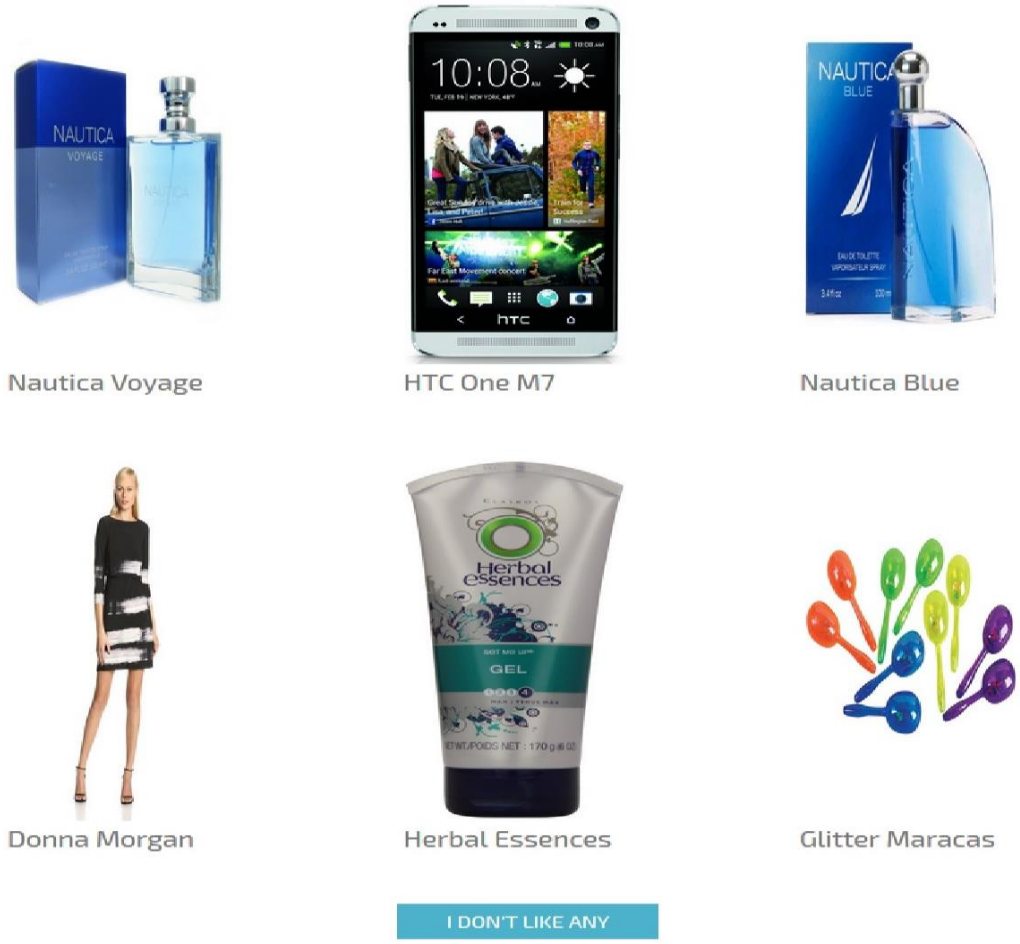

Figure 6.23: Recommendation list updated to include products related to sub profile

When clicking on the product that is related to the sub profile, the user can see a detailed list, as above, and can assign this to one specific sub-profile, as the user can create as many as s/he wishes, as shown in Figure 6.24.

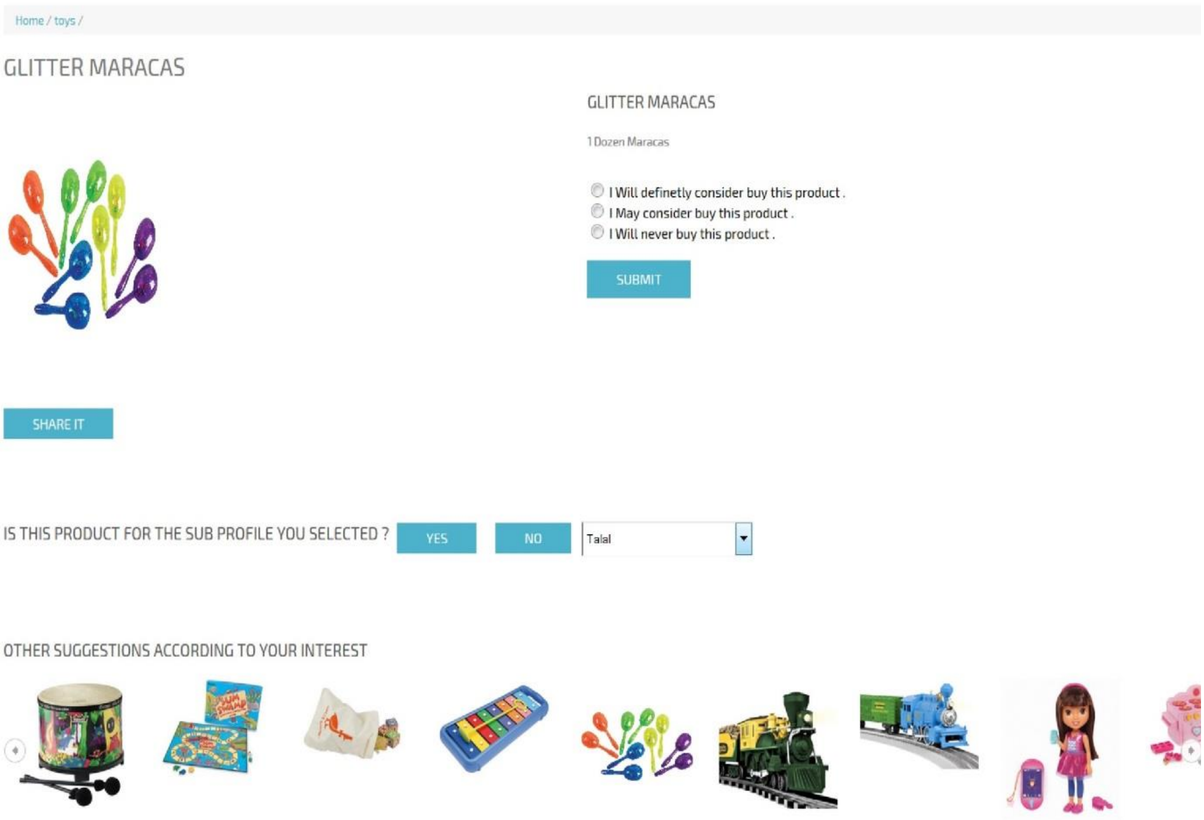

Figure 6.24: Product assigned to sub profile called “Talal”

Events can be created from the user’s home page. Figure 6.25 contains the event creating form and the reminder on the day of the event for the user.

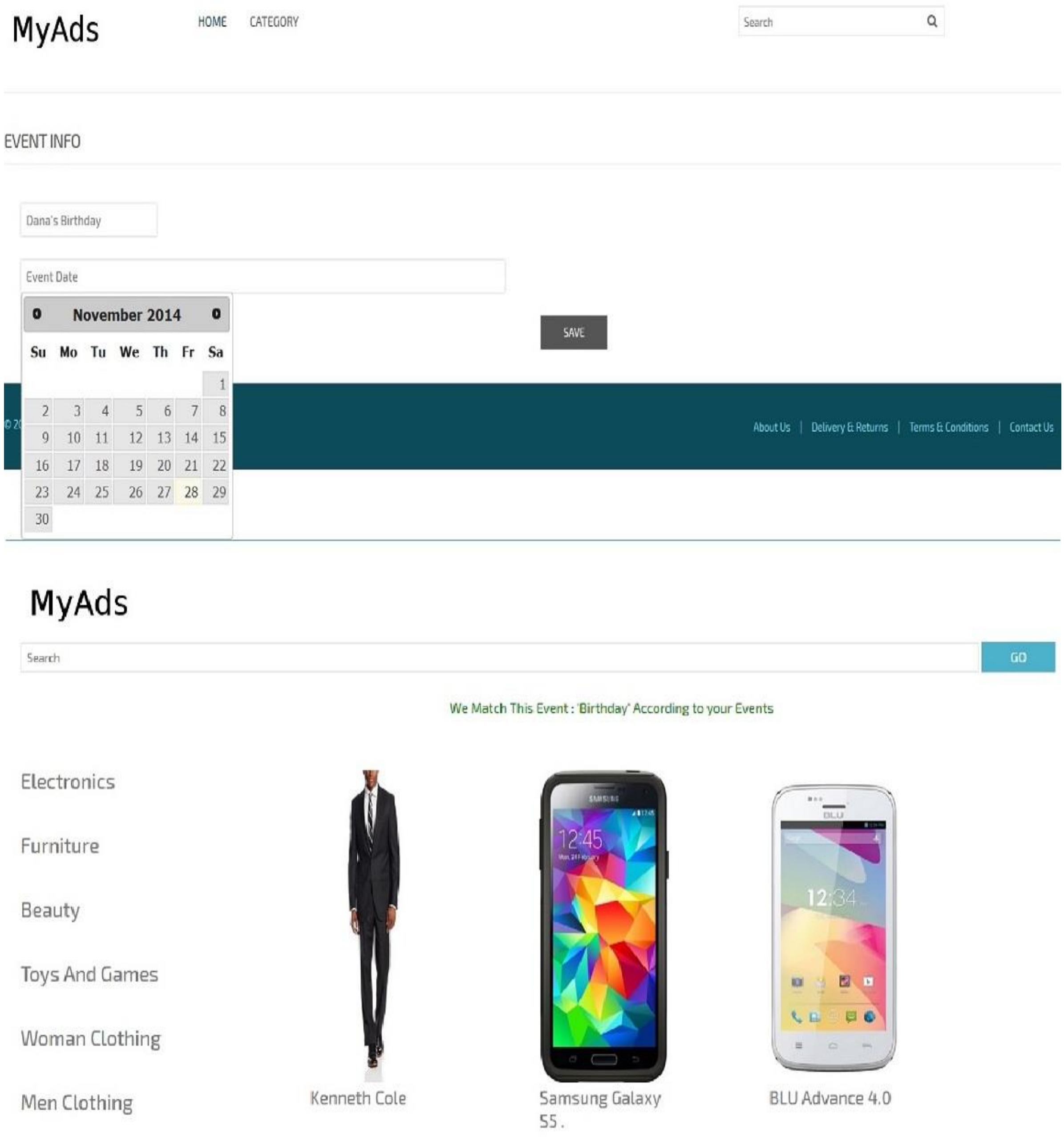

Figure 6.25: Event creation and reminder on home page

6.10. Discussions and Conclusions

The research goal of this chapter is to finalise the system design in relation to the research requirements and theoretical basis created earlier. In order to decide on the appropriate adaptive hypermedia user modelling features, as well as the algorithms that contribute towards positive user acceptance of e-advertisements. The research was conducted both theoretically and practically, by focusing on a new technological approach of a standalone system, to generate adaptive advertisements. The research theoretical backbone was based on the extensive research conducted in adaptive hypermedia, in the domain of e-learning and other applications. The final MyAds design and implementation is inspired by two popular commercial applications, Amazon and Groupon. The reason for using these well-known and famous platforms was derived from the results of the focus group experiment. Additionally, however, the experiment results suggested that user modelling features should be richer, more dynamic, novel and attractive. The presentation of the ads should contain a storyline, be understandable and usable.

All this feedback served as the blueprint for the new design of MyAds. Both the implicit and explicit user modelling algorithms were created to address these issues. Adaptive hypermedia included *link navigation support* and *adaptive presentation* as well as *bandwidth adaptation*.

The overall outcomes of the chapter do suggest a design and implementation approach for answering the research questions Q1.1 **What features from adaptive hypermedia users would want to have in adaptive advertising and how are they related to users' acceptance?,** the answer for this question is divided between user modelling and adaptation features. The user modelling features include rich user models, sub profiles and an event calendar connected to their events. From adaptation features, adaptive story line, explanation of recommendations, shortcuts, sorted recommendation are to be included. **Q1.2 How can user modelling contribute to users' acceptance of the e-advertising experience?** The answer to this question is by giving users both rich user profiles and control over the system in on end, on the other hand, allow for recommendations to be updated based on the users' behaviour. **And Q1.3 What are the main sources of user information that can be explored for adaptive e-advertising?** The main sources included data from Social Networks and data from registration forms. This has been answered by the extended feature list generated earlier in the Section 6.6.

Moreover, this chapter also further extends the answer to research question Q2**: How can online adaptive advertising be generated theoretically?** This has been discussed via the final updated version of the theoretical framework found in Section 6.2.

Finally, the chapter also partially answers research question **Q3: What technology is acceptable for online advertising?** This question has been discussed thoroughly, to understand the best way to generate the adaptive features, the standalone system design and features. The answers have been detailed in Sections 6.5, 6.6, 6.7, 6.8 and 6.9.

Chapter 7

7. Evaluation of Personalised Adaptive E-advertisements Delivery

7.1. Introduction

This chapter is the final chapter in the cycle of evaluations. It addresses the research questions and objectives in a more detailed manner. It also proposes a set of hypotheses in relation to the research questions. A large scale evaluation has been conducted, to acquire further evidence on the indicated results obtained from earlier chapters. Concretely, in this chapter, the following objectives are addressed:

Objective 2: *Conduct a series of experiments that investigate the appropriate approach and features to design adaptive e-advertisements, and then test the practical development of these features in an adaptive e-advertising system, addressing the acceptance of this form of ads in the targeted evaluations.*

In this chapter, this objective is addressed in a systematic, research-oriented way, analysing the steps and features needed to introduce adaptation in e-commerce. Based on existent taxonomies, such as Brusilovsky's and Knutov's taxonomies [23], [22], which are the most popular, this chapter, which are the most popular, this chapter explores the different adaptive hypermedia features defined by these taxonomies and their actual contribution to users' acceptance of e-advertisements.

Outcomes of this chapter: results from the evaluations are focused on the adaptation features and their role in the user acceptance of e-advertisements. The acceptance is measured using the evaluation measures of *usability*, *usefulness* and, in specific cases, their *needs* and *desires*.

Objective 3: *Propose a suitable (new or extended) theoretical framework/model for the adaptive features necessary in advertising, such as a layered model.*

Outcomes of this chapter: this chapter presents the final version of MyAds. It reflects the features of the latest version of the theoretical framework. There is no direct evaluation of the framework as a whole. However, features corresponding to the theoretical framework are evaluated, to understand how the framework has addressed the research requirements.

Objective 4: *Design, implement and update a dedicated system for testing the adaptive advertisements and measure the level of acceptance from the end users through the evaluation of their subjective and objective feedback.*

Outcomes of this chapter: the evaluations conducted in this chapter are based on the usage of the delivery system MyAds. The version used for the purposes of this chapter's evaluations is the second and more refined version of the system, which includes all the adaptation and user modelling features described in Chapter 6.

Objective 5: *Ensure that each research question is represented in the framework and in the delivery system.*

Outcomes of this chapter: this chapter includes the final evaluations of the research questions. Moreover, this chapter introduces a set of hypotheses to help examining the research questions.

Objective 6: *Ensure that each step of the research is conducted based on established research methodology.*

Outcomes of this chapter: this chapter contains the final set of evaluations. As the user centric methodology has been adopted throughout the thesis, this chapter follows the same approach used earlier in Chapter 5 for the evaluation purposes.

Due to the fact that the nature of this research is HCI-related and targeted towards users' acceptance, the engagement of users has been obtained throughout the process, as recommended by the literature [165]. The evaluations have been conducted to provide quantitative feedback via questionnaires. Moreover, qualitative feedback is collected via comments and mini-interviews applied within the experiment. For an abstract and objective feedback, the log files were analysed, by directly tracking user behaviour within the system.

The main evaluation parameter is users' *acceptance*. It is targeted by the research question Q1 stating "can adaptive e-advertising lead to users' acceptance in terms of being usable and useful from a user perspective?" Acceptance in this research is measured via *usability*, *usefulness* and in some cases, the *desires* and *needs* of users, as already explained in Chapter 3. The reason for selecting these specific measures, other than the research requirements, is that they have been described as a good representation of the users' acceptance of web-based systems [10]. The detailed evaluations applying these different measures are found in Section 7.3 and Section 7.4. The traditional approach that has been explored extensively throughout the research, advocates that user acceptance of a new web-based system is to be examined carefully, based on several key aspects. These aspects include exploiting the user intuition, establishing an unobtrusive technology to capture the user attention, support throughout the process of discovering the application and dynamic control of the application variables [119].

Controlled experiments are considered one of the powerful experimental design processes. In them, two groups of users are traditionally used: one of them is the *experimental group*, while the other one is the *control group* [140]. The experimental group is the one that actually experiences the application to be evaluated, while the control group is exposed to the same goal oriented application, but without the precise features to be evaluated in the experimental application. In the experiments, the control group and the experimental are the same sample of users. The reason was to ensure that all users could compare between traditional methods and the ones proposed here, as well as to keep the number of users exposed to both methods as high as possible. Thus, users were firstly exposed to non-adaptive systems, to be aware of what is missing in them. The same users had, at a later stage, their actual hands-on experience with MyAds, the adaptive e-advertisements system. The evaluations described in this chapter were conducted via two experiments, as follows: one large scale experiment, with 221 participants, and another follow-up experiment, which is more focused and which covers some aspects missing evaluations from the first experiment, with 46 participants. Details of the experiments are discussed further on in the chapter (in Section 7.3 and Section 7.4). Thus this chapter gathers data from 267 participants.

The remainder of this chapter is structured as follows. Section 7.2 elaborates on the set of hypotheses that have been evaluated within the experiments presented in this chapter. Section 7.3 is a large scale evaluation section, with the first experiments and their related details. Section 7.4 is the follow-up experiment, also with all its related details. To summarise the findings, the chapter ends with concluding remarks and recommendations.

7.2. Hypotheses

The previous research and experiments up to this point was were mainly of exploratory nature, so, whilst they partially addressed the main research questions, the presentation of the results did steer away from listing specific hypotheses. Instead, the research was oriented into exploring the different aspects and directions in which to approach the answers to the research questions posed. Specifically, the outcomes from both the design experiments were more of a qualitative nature than a quantitative one. In the first practical experiment presented in Chapter 5, the work was also exploratory, and specific evaluation measures and features were only briefly explored.

A hypothesis is defined as "a tentative statement predicting a particular relationship between two or more variables". In these two experiments, hypotheses are used, because the experiments are highly quantitatively oriented, the approach to answer the research questions is experimental and the outcome of the research is measurable [140].

In the following, the main hypotheses to be validated by the experiments in this chapter are formulated, as a response to their associated main research question.

Q1: Can adaptive e-advertising lead to users' acceptance in terms of being usable and useful from a user perspective?

Hypothesis 1: Adaptive hypermedia leads to users' acceptance, in terms of being *usable* (A) and *useful* (B) from a user perspective.

Q1.1: What features from adaptive hypermedia users would want to have in adaptive advertising and how are they related to users' acceptance?

Hypothesis 1.1: It is necessary, from a user perspective, to allow for different adaptation approaches, such as:

i. adaptation (system driven) using adaptive storylines,
ii. adaptive navigation support,
iii. adaptive presentation support;
iv. general guidance, in terms of: shortcuts, buttons, stretch-text combined with recommendations,
v. Bandwidth adaptation.

The user perspective and acceptance is measured in terms of *usability* (A) and *usefulness* (B).

Q1.2: How can user modelling contribute to users' acceptance of the e-advertising experience?

Hypothesis 1.2: By having a rich personalised e-commerce platform, based on a *rich user model* and *extended user control* over the system, the users' acceptance can be achieved in terms of *usability* (A), *usefulness* (B), *needs* (C) and *desires* (D).

i. Specifically, the following features should be present in the Populating the UM with initial preferences, to allow suggestion of a set of items based on these initial values.
ii. Populating the updated UM based on the user behaviour over the system.
iii. Providing sub-profiles for users, to reflect the fact that a user may have sets of (possibly disjunctive) interests, depending on the circumstances they are in.
iv. Creating rich user models, by adding uncommon features, such as religion, favourite colour.
v. Creating user-related calendar events with reminders and relations between events and personalised products (e.g., birthday reminders, with family/friends' preferences connected to them).
vi. Adding social network features to the user model.

In terms of extended User Control, this should be over:

vii. manipulating *advertisement location*,

viii. *appearance* and

ix. *selection*: providing categories for advertising products for users to select from.

Q1.3 What are the main sources of user information that can be explored for adaptive advertising?

Hypothesis 1.3: The study of *implicit* versus *explicit* user models will illustrate and allow for comparison of the different sources of user model data for adaptive advertising.

Q3: What technology is acceptable to users for online advertising?

Hypothesis 3: Adaptive advertising supported by a standalone system can lead to users' acceptance in terms of *usability* (A) and *usefulness* (B).

7.3. Experiment I

The first experiment was conducted over 3 days. Every day was divided into two sessions, where each session took around two hours, with an average of 32 participants per session, who volunteered for the experiment.

The total number of participants was 221 (this is considered a relatively large sample, in comparison with other studies [131], [132], [133] and [134]; however, it still remains under the ideal sample size of 384, please refer to Chapter 3 for more details on the sample size considerations). The experiment was conducted in the University of Jordan. The users were students and belonged to the age group of early twenties. Whilst this can be seen as a potential limitation, as this is a business-oriented application, it was appropriate to involve students as users, as, firstly, students are frequent Internet users and knowledgeable of e-commerce websites, and secondly, they have high expectations from Internet applications [166]. Moreover, students were selected from different faculties, so that the experiment could be as objective as possible in terms of covering many different perspectives from e-commerce websites users. Please refer to Chapter 3 for further details of the sample size, generalisability and limitations of the proposed approach for evaluation.

Each session was divided into three phases, using the methodological approach discussed in details in Chapter 3, as follows:

The first phase of the experiment was a preliminary phase, which started before the allocated time, with the presence of the main researcher, who ensured that only users with previous experience with e-commerce and e-advertisements systems should participate in this experiment. The reason for this was to achieve a fair comparison between MyAds and other e-commerce systems, and to be able to conduct a controlled experiment that can reflect objectively on the results. The initial number approached was around 300 participants, but this process filtered some out, and the remaining number was 221 participants.

After the researcher ensured that all the participants are familiar with other e-commerce systems, she introduced the research and guided the participants through the process of the experiment. The users had around one and half hours to conduct the experiment that started by firstly exploring other e-commerce and e-advertisement systems, to update their knowledge of them. They were asked to explore these systems (especially Amazon and Groupon), before they started using MyAds.

The second phase was after the first half of an hour, when they were asked to log in via MyAds, and to start using and manipulating the system, and to try using the features within the system and interact with it.

The third and final phase was when they were asked to fill-in a questionnaire, to evaluate their experience.

Please note that the results gathered via the questionnaire method represent the perceived user experience, which may potentially deviate somewhat from the actual user experience. Nevertheless, the user perception is more interesting in commercial applications than their actual experience [167].

Moreover, the MyAds system is quite rich with many features, functions and layers. In order to ensure users' understanding of the system and allow for an objective reflection in the answers of the questionnaire, the users were granted a reasonably long amount of time, to allow for the exploration of all the features. Concretely, throughout the experiment, the users' were asked every 30 minutes if they needed more time, or if they were satisfied with this amount of time. The users' were hesitant in the beginning to give a direct answer. Because the experiment participation was voluntary, most of the users wanted to be granted more time, so that they could thoroughly explore the system. After an hour and a half, most users were satisfied with their experience and started requesting the questionnaires. Please note that the time allocated from the administration was up to three hours. So there was no pressure to finish faster than that, and the users confirmed this was plenty of time.

All the participants in this first experiment were in the age group of 20-23, studying a senior course of "Social Networks" that is taught in their final year of studies. The students were a mix of males and females, with a dominate percentages of female participants (63% compared with 37% males). The participants had different academic backgrounds, being enrolled in courses such as Computer Science, Computer Engineering, Information System, Business Information Systems and Management Information Systems. All of the participants were performing their undergraduate studies in their final year (senior students), and declared to have prior knowledge of e-commerce systems. The latter was important for this study both in terms of expectation management, as well as in terms of being able to have a good basis for comparison. Issues with the selection of the group and its implications have been already considered in more details in Chapter 3.

The implemented MyAds system aims at addressing the research goal of achieving users' acceptance of e-advertisements, in terms of (perceived) *usefulness* and *usability*. This has been explored through the use of the evaluation tool, looking at the various aspects of adaptation and user modelling. MyAds refers here to the second version of the novel software that has been used to conduct the evaluations. It is based, as explained in previous chapters, on a layered theoretical framework that functions within the concept of separation of functionalities, but which, nevertheless, should be providing homogenous outcomes. The detailed design and implementation has been discussed in details in Chapter 6.

In the first experiment of this chapter, described in this section, only explicit user modelling was explored, as the implicit user modelling API (the Facebook login) was not enabled at the time of this experiment. The second experiment addressed the issue of explicit user modelling, further detailed in Section 7.4. The results of the first experiment are described below.

The experiment generated results that evaluate users' acceptance of the proposed research approach via evaluating their perceived usability and usefulness. The results were a combination of quantitative, qualitative and log files data. However, the results are highly quantitatively oriented, because of the analysis of the questionnaires' responses. The results from the questionnaires are discussed in relation to the hypotheses. This first experiment did not address all the different features in the hypotheses. Moreover, as not all features were evaluated in this first experiment from both a usability and usefulness perspective, as the questionnaire was kept relatively short and only the main aspects were covered in this first experiment. However, the follow up experiment did then cover the missing aspects of the hypotheses and the questionnaire's questions addressed each feature from both the usability as well as usefulness perspective. Furthermore, where the hypothesis demanded it, needs and desires were also evaluated, next to usability and usefulness.

7.3.1. Quantitative Results

The questionnaire aimed at addressing the issues of (perceived) *usability* and *usefulness* of the system and was structured around 28 questions, which used answers on a Likert scale, from 1 to 5 (1= strongly disagree, 2= disagree, 3= null value of neither, 4 = agree and 5= strongly agree). The questions were divided as follows:

- *System Usability Questions*: these questions followed the guidelines for designing usability questions and their related concepts, such as: usage in context, interface and interaction, development process - as the user is in the centre of the design process.

- *System Usefulness Questions*: these questions aim at assessing the features of the system in terms of adaptation and user modelling functionality.

For **Hypothesis 1** indicating that "Adaptive hypermedia leads to users' acceptance, in terms of being *usable* (A) and *useful* (B) from a user perspective."

This hypothesis addresses the general perceptions of users' perceived usefulness and usability of adaptive hypermedia. It investigates if the overall adaptation will lead to users' acceptance. To address this hypothesis, two tables are generated. Table 7.1 addresses the features related to the usability aspects and Table 7.2 addresses the features related to the usefulness aspects.

Table 7.1**:** Results for usability questions for H1

Related Questions		**Mean**	**Mode**	**Std.**	**t-test**	**Mann – Whitney**	**Wilcoxon test**
No.	***Hypothesis 1, N= 221***						
1.	I think that I would like to use this system again.	3.61	4	1.02	0.00	0.00	0.00
2.	I think that the system increased my acceptance level of personalised e-commerce websites.	3.65	4	1.05	0.00	0.00	0.00
3.	I found the system not very cumbersome to use.	3.48	4	0.98	0.00	0.00	0.00
4.	I thought the system was easy to use.	3.66	4	0.90	0.00	0.00	0.00
5.	I would imagine that most people would learn to use this system very quickly.	3.80	4	0.82	0.00	0.00	0.00
6.	I found the system provided understandable recommendations.	3.54	4	0.85	0.00	0.00	0.00
Overall Usability		**3.62**	**4**	**0.93**	**0.00**	**0.00**	**0.00**

The results from the table above indicate that for the overall aspects related to **usability**, the users expressed positive feedback. The mean values are dealt with as discussed earlier in Chapter 3. Any mean value equal or larger than (3<) 3.5 is considered convincingly positive, of course, after taking into consideration the standard deviation.

Users expressed their willingness to use the system again, with a mean value of (3.61 ± 1.02) and a mode of 4, the latter indicating the most frequent answer of agreeing. The rest of the results align with the results generated from the first statement. A. Acceptance of this form of e-advertisements is found positive (Question 2) with the mean of 3.65 ± 1.05. The aspect regarding the ease of use is also positive, as reflected in Questions 3, 4, 5, and 6 with mean values of (3.48 ± 0.98), (3.66 ± 0.90), (3.80 ± 0.82) and (3.54 ± 0.85), respectively, and a mode value of 4. The largest mean value is generated for the question asking if learning to use the system can happen quickly. Overall, the results indicate an ease to use system. The overall usability mean value is (3.62 ± 0.93). To strengthen the validation of the proposed hypothesis, significance statistical tests were conducted. Please refer to Chapter 3 for general details on the performed tests. One parametric test, which is the t-test, is conducted, as well as two non-parametric tests, the Mann Whitney and Wilcoxon significance tests, to strengthen the results.

The results from all the questions showed statistical significance, as all the probability values for all tests have a value starting with 0.00, even for the usability average value. This value is less than 0.05, the accepted threshold which is used to measure if the results are statistically significant or not. This is an indication that the answers to all questions were statistically significant, for both parametric and non-parametric tests.

Additionally, the results regarding the questions related to **usefulness** are listed in Table 7.2.

Table 7.2 Results for usefulness questions for H1

Related Questions		**Mean**	**Mode**	**Std.**	**t-test**	**Mann – Whitney**	**Wilcox on test**
No.	***Hypothesis 1, N= 221***						
1.	I found the various functions in this system were well integrated.	3.91	4	0.81	0.00	0.00	0.00
2.	I found the system provided enough recommendations.	2.71	2	1.17	0.00	0.00	0.00
	Overall Usefulness	**3.31**	**3**	**0.99**	**0.00**	**0.00**	**0.00**

Two questions addressed to the overall approach of the usefulness of adaptive hypermedia in MyAds. From the users' perspective on the system's functions integration, users found the various features well integrated, with a mean value of (3.91 ± 0.81) mode value of 4. This indicates that the various functions provided were useful for the user. However, there has been an issue with the amount of products available in the system. The statement 'I found the system provided enough recommendations' seems to contradict the overall results, as for the majority of the participants, this was the only statement they were obviously not agreeing with, with mean value of (2.7 ± 1.17) and a mode value of 2. This is potentially due to the fact that this is a prototype system, and there were not enough products available in the system, to recommend to participants. This is further discussed in Section 7.5. The lack of products did affect highly the overall users' feedback on usefulness, with an overall mean value of (3.31 ± 0.99) and a mode value of 3. Again, to strengthen the validation of the proposed hypothesis, the statistical significance tests are conducted. All the values from the statistical tests generate the value starting with 0.00, which is less than the threshold of 0.05, meaning that they are statically significant within the sample used in this experiment.

Describing the results based on individual features and their respective questions may not be enough to indicate the actual measures of evaluation being discussed. User's acceptance in this research is measured, as said, by the (perceived) *usability* and *usefulness* of the different adaptation features. In order to address this directly, the overall mean and standard deviation are computed, to indicate the overall acceptance. Additionally, the correlation between these evaluation measures is calculated, to find out how the evaluation of one influenced the other, from a user perspective. Table 7.3 summarises the results.

Table 7.3: Combined H1 correlation between usability and usefulness

Hypothesis	**Measures of Acceptance**	**Mean**	**Std**	**Overall Mean**	**Overall Std**	**Pearson's Correlation Usability via Usefulness for H1 at 0.01 level**
H1	Usability	3.62	0.93	3.47	0.96	0.33
	Usefulness	3.31	0.99			

Usability is slightly higher, with a mean (3.62 ± 0.93), implying that the majority of participants mostly accepted that adaptive hypermedia is usable for online advertising. The value for usefulness is above 3, the neutral threshold, but below 3.5, the self-imposed higher threshold for a more convincing positive outcome. The main reason for this lower outcome is that the system did not provide enough recommendations and products for the users. As explained before, this is due to the fact that this is a prototype system, and harvesting large and various amounts of products goes beyond the scope of this research. However, in a real-life application, the size of the pool needs to be taken into account, as it clearly reflects upon the perceptions of the users. This is further discussed in Chapter 8, Section 8.5 and Section 8.6.

Acceptance is measured by both usability and usefulness, so the overall average for the two scores affects hypothesis H1. With a mean of 3.47 and a standard deviation of 0.96, the 'acceptance' value is just below the self-imposed 3.5 threshold for a more convincing positive outcome. It is clearly positive (>3) and statistically significant, so it can be concluded that *the results show that adaptive hypermedia leads to user acceptance, mostly in terms of being usable, and somewhat in terms of being useful, from a user perspective*. This represents the answer to research question Q1. These results, it has to be reiterated, are statistically significant for the given number of users participating in this relatively large-scale evaluation. More discussions on the actual and desired scale of the evaluation can be found in Chapter 3.

Additionally, the correlation between these two measures should be considered, in order to explore if one of them does affect the other or not. To understand the strength of the correlation between variables, it is described that if the output is between (0.00-0.19) the correlation is considered "very weak”; if it is between (0.20-0.39) it is considered “weak”; if it is between (0.40-0.59) it is “moderate”; if it is between (0.60-0.79) it is “strong”; and, finally, the values between (0.80-1.0) are considered with a “very strong” correlation [168]. The correlation found between usability and usefulness is (0.328), indicating that there is only a weak correlation between the users’ perceptions of usability and usefulness. This actually can be interpreted as a positive outcome, as the users showed themselves able to clearly differentiate between usability and usefulness questions. It also shows that the lack of products did not actually affect users’ perception about the ease of use and the usability of the system.

For the **Hypothesis 1.1** indicating that ""*It is necessary to allow for different adaptation approaches, in particular:*

i. adaptation (system driven) using adaptive storylines,

ii. adaptive navigation support,

iii. adaptive presentation support;

iv. general guidance, in terms of: shortcuts, buttons, stretch-text combined with recommendations,

v. Bandwidth adaptation."

This hypothesis investigates the adaptation features found in MyAds more in-depth. These features are discussed mainly from the usefulness point of view, as usability has been dealt with in a more generic way in Hypothesis 1. The other reason for doing this was to keep the number of question as low as possible, because there are many aspects to evaluate. However, some questions about a certain feature can touch both the issues of usability and usefulness, although they are mainly focused on the usefulness and the functionality of the adaptive features, as this was one of the main concerns. The results are grouped based on the functionality of the adaptive features as in Hypothesis 1.1 so easier connection between the features and the items within the hypothesis can be established. The results relating to this hypothesis are grouped in Table 7.4. Please note that this hypothesis was one of the hypotheses that were not fully covered in the large scale evaluation. Not all the features stipulated by the hypothesis were evaluated by the questionnaire, although they were present in the system. For this reason, a further evaluation was conducted, as a follow up experiment, to address the missing features, covering both usability and usefulness measures, as follows: "adaptation (system driven) using adaptive storylines", adaptive presentation and general guidance. Further discussions are in Section 7.4

Table 7.4: Results for usefulness questions for H1.1

Related Questions		Mean	Mode	Std	t-test	Mann – Whitney	Wilcoxon test
No.	***Hypothesis 1.1, N= 221***						
iv	***General Guidance Usefulness***						
1.	I found the shortcut, buttons, and stretch text provided with recommendations useful.	3.84	4	0.84	0.00	0.00	0.00
ii	***Adaptive Navigation Support Usefulness***						
2.	I found the system provided logical grading of information.	3.88	4	0.85	0.00	0.00	0.00
3.	I found the recommendations were ordered based on my preferences.	3.68	4	0.88	0.00	0.00	0.00
4.	I found the system hiding unnecessary links useful.	3.83	4	0.86	0.00	0.00	0.00
5.	I found the explanation of recommendation useful.	3.62	4	0.76	0.00	0.00	0.00
	Overall Usefulness for Navigation Support	*3.75*	*4*	*0.83*	*0.00*	*0.00*	*0.00*
v	***Bandwidth Adaptation Usefulness***						
6.	I found the recommendations loading changed when the internet bandwidth changed.	3.60	4	0.92	0.00	0.00	0.00
iii	***Adaptive Presentation Support Usefulness***						
7.	I found the system showing the needed information useful.	4.04	4	0.74	0.00	0.00	0.00
Overall Usefulness		**3.78**	**4**	**0.83**	**0.00**	**0.00**	**0.00**

The results are grouped based on the functionality of the features (measured by their usefulness), as one of the evaluation measures to reflect on acceptance, as explained in details in Chapter 3. The general guidance given to the user is addressed by one question and is found positive. The mean value of the feature is (3.84 ± 0.84) and a mode value of 4. The mean value remains above 3.5 and the standard deviation is not too high. The adaptive navigation support features are also positive, as all the mean values are above 3.5. The adaptive link sorting are features evaluated with Questions 2 and 3. The mean values for the link sorting are (3.68 ± 0.88) and (3.88 ± 0.85) respectively, and a mode value of 4. Both values are positive and fall within the agreement part of the discussion. Link hiding, is also evaluated as positive with a mean value of (3.83 ± 0.86) and a mode of 4. Link annotation is also positive with a mean value of (3.62 ± 0.76) and a mode value of 4. All the adaptive navigation support features are useful from the user perceptive.

The bandwidth adaption is also positively evaluated, positive with a mean value of (3.60 ± 0.92) and a mode of 4. However, the standard deviation is larger than the previous values, indicating that some users' answers varied within this statement. This is maybe due to the reason that students did not have the opportunity to test this adaptation feature, as they had accessed the system throughout the experiment with a constant bandwidth. Although, some of the students preferred to use their mobile phones to navigate the system and noticed that it changes the appearance to fit to the mobile screen.

The adaptive presentation support is one of the useful features from the user perceptive with the largest mean value of (4.04 ± 0.74) and a mode of 4 indicating that users did find this feature useful.

The overall usefulness of the adaptive features is also evaluated as positive, with a mean value of (3.78 ± 0.83) and a mode value of 4. The results are an indicating that the adaptive features all together are indeed useful, from the user perceptive. To strengthen the validation of the hypothesis, statistical tests are conducted, as also illustrated in Table 7.4. All the features are statistically significant, with a probability value smaller than 0.00, which is less than the accepted threshold of 0.05, indicating the significance of the results.

For some of the features, the usability has been further explored, as shown in Table 7.5.

Table 7.5: Results for usability questions for H1.1

Related Questions		Mean	Mode	Std	t-test	Mann – Whitney	Wilcoxon test
No.	***Hypothesis 1.1, N= 221***						
ii	***Adaptive Navigation Support Usefulness***						
1.	I found the system provided logical grading of information.	3.88	4	0.85	0.00	0.00	0.00
2.	I found the recommendations were ordered based on my preferences.	3.68	4	0.88	0.00	0.00	0.00
	Overall usability of adaptive navigation support	*3.75*	*4*	*0.83*	*0.00*	*0.00*	*0.00*
v	***Bandwidth Adaptation Usefulness***						
3.	I found the recommendations loading changed when the internet bandwidth changed.	3.60	4	0.92	0.00	0.00	0.00
Overall Usability		**3.72**	**4**	**0.88**	**0.00**	**0.00**	**0.00**

As discussed before, this experiment is highly focused on the functionality of the system. The questionnaire nevertheless contained some questions that can be used to reflect on both usability and usefulness. The questions and results in Table 7.5 are such questions which also reflect usability. Again, the results are grouped based on the functionality of the feature, to investigate if these features are usable from the user perspective or not. For the adaptive navigation support, the mean values for the links sorting (ordering of recommendations) are (3.68 ± 0.88) and (3.88 ± 0.85) respectively, and a mode value of 4. The features are positive from the user perspective, as both values are above 3.5. This is an indication that the users find these features usable, as well as useful. The bandwidth adaption evaluation is also positive, with the mean value of 3.60 ± 0.92 as this feature is connected directly to the users' perception of the system ability to adapt to the different network capabilities and devices.

The current overall usability of the features covered within the system is evaluated at (3.72 ± 0.88); this remains positive, as an indication that these features are usable from the user perspective. Moreover, all the results are statistically significant, with the probability value under 0.00, which lead to the conclusion that the confirmation of this part of the hypothesis is statistical significant.

This hypothesis looks at the distinct features of adaptive hypermedia, whilst the evaluation measures include both usability and usefulness. The correlation between these two measures is investigated, addressed as was done for in Hypothesis 1. The results are in Table 7.6.

Table 7.6: Combined H1.1 correlation between usability and usefulness

Hypothesis	**Measures of Acceptance**	**Mean**	**Std**	**Overall Mean**	**Overall Std**	**Pearson's Correlation Usability via Usefulness for H1 at 0.01 level**
H1.1	Usability	3.72	0.83	3.71	0.85	0.40
	Usefulness	3.83	0.88			

For Hypothesis 1.1, the usefulness of the adaptive features has a slightly higher mean than the usability, indicating that the distinct features were considered relevant by the intended users. The usability remains also positive, but lower than the usefulness, as these features may need an improved representation. The correlation between usability and usefulness is moderate, indicating that they have not really affected each other. This shows that users considered the features useful, and were able to analyse the functionality separately, even if they might have wished for easier to use representations of the features.

The mean values fall within the accepted positive values and the distinct features are statistically significant. However, Hypothesis 1.1 cannot be confirmed or rejected yet, due to the fact that there are missing features that have not been evaluated as well as a shortage of the usability coverage within the questions. The hypothesis is thus further examined in the follow-up experiment.

Hypothesis 1.2: By having a rich personalised e-commerce platform, based on a rich user model and extended user control over the system, the users' acceptance can be achieved in terms of *usability* (A), *usefulness* (B), *needs* (C) and *desires* (D). Specifically, the following features should Specifically, the following features should be present in the Rich User Models:

i. Populating the UM with initial preferences, to suggest a set of items based on the initial values.
ii. Populating the updated UM based on the user behaviour over the system.

iii. Providing sub-profiles for users, to reflect the fact that a user may have sets of (possibly disjunctive) interests, depending on the circumstances they are in.

iv. Creating rich user models, by adding uncommon features, such as religion, favourite colour.

v. Creating user-related calendar events with reminders and relations between events and personalised products (e.g., birthday reminders, with family/friends' preferences connected to them).

vi. Adding social network features to the user model.

In terms of extended User Control, this should be over:

vii. manipulating *advertisement location*,

viii. *appearance* and

ix. *Selection*: providing categories for advertising products for users to select from.

This is one of the most extended hypotheses. First of all, it divides user modelling features between *rich user models* or *user control*. Then, each part has its distinct features, as grouped above. This large scale evaluation focused mainly on the usefulness of the proposed features for both the rich user model and user control. Usability, desires and needs were not covered extensively in this evaluation and have been discussed in the follow up discussed later in Section 7.4. The features that have not been addressed from of the hypothesis are: “Populating the updated UM based on the user behaviour over the system”, “Creating user-related calendar events with reminders and relations between events and personalised products” and “*Selection*: providing categories for advertising products for users to select from.” The following results were obtained from the first experiment, as in Table 7.7.

Table 7.7 Usefulness answers for Hypothesis 1.2

Related Questions		Mean	Mode	Std	t-test	Mann – Whitney	Wilcox-on test
No.	***Hypothesis 1.2, N= 221***						
i	***Rich User Model - Populate UM Based Recommendations***						
1.	The system provided better user profiling compared to other e-commerce websites.	3.59	4	0.89	0.00	0.00	0.00
2.	I found the system provided the recommendations I want.	4.15	4	0.77	0.00	0.00	0.00
	Mean value for rich UM	*3.87*	*4*	*0.83*	*0.00*	*0.0*	*0.00*
iii	***Rich User Model - Sub Profiles***						
3.	I found the sub-profiles very useful.	3.58	4	0.83	0.00	0.00	0.00
v	***Rich User Model – Data Collected***						
4.	I found the information collected very rich.	3.40	4	1.02	0.00	0.00	0.00
vi	***Rich User Model – Social Features***						
5.	I found the system rating feature useful.	3.93	4	0.78	0.00	0.00	0.00
6.	I found the commenting feature useful.	3.94	4	0.80	0.00	0.00	0.00
7.	I found the sharing feature useful.	3.92	4	0.86	0.00	0.00	0.00
	Mean value for social features	*3.93*	*4*	*0.81*	*0.00*	*0.00*	*0.00*
vii	***User Control – Change Location***						
8.	I found the ability to change recommendation location useful.	3.74	4	0.76	0.00	0.00	0.00
viii	***User Control – Change Appearance***						
9.	I found the ability to opt for categories useful.	3.75	4	0.84	0.00	0.00	0.00
Overall Usefulness		**3.77**	**4**	**0.86**	**0.00**	**0.00**	**0.00**

The results for this hypothesis are divided between features related to rich user model and features related to the user control. With regards of the rich user model, the first feature to be examined is the accuracy of the recommendations given based on the composed user model. The values for this feature are positive, as in comparison to other e-commerce websites, the user profiling in MyAds has a mean value of (3.59 ± 0.89) and a mode value of 4. The values can be accepted as positive, as the mean value is larger than 3.5 and the standard deviation is relatively small. When examining if the system provided the actual recommendations the users' wanted, the results are positive, with a mean value of (4.15 ± 0.77) and a mode value of 4. This is one of the highest means achieved throughout the evaluation, indicating that the user model was accurate enough to produce actual recommendations that meet users' profiles. To enrich the user profile, the users were given the ability to create sub-profiles, to be used as part of their profiles and get recommendation based on these sub-profiles described earlier in Chapter 6. The mean value with regards to this feature is (3.58 ± 0.83) and a mode value of 4. Although the mean value is only slightly above 3.5, it is still as a positive result. Moreover, when the users were asked about the amount of data collected and whether they believed these data amounted to a rich user model, the users had a neutral and un-decisive response, respond with a mean value of (3.40 ± 1.02) with a mode value of 4. Although, the mode value is 4, the responses for this question were quite distributed and the mean value was less than 3.5, so no positive outcomes can be concluded. Users' social features are among the successful ones from a user perspective with rating, commenting and sharing features. The features achieved the following mean values of (3.93 ± 0.78), (3.94 ± 0.80) and (3.92 ± 0.86),) respectively, and a mode value of 4. All the values fall on the positive side of the argument and suggest that they were found useful from the users. User Control covered two aspects with regards to the location of the recommendation and the appearance of the recommendation. When the users were asked whether the ability to change the recommendation location was useful, users found it was, with a positive mean value of (3.74 ± 0.76) and a mode value of 4. The user ability to control the appearance of the categories and recommendations, by allowing them to opt out of unwanted ones, was also considered positive; with the mean value of (3.75 ± 0.84) and a mode value of 4.

The overall usefulness mean value is (3.77 ± 0.86) and a mode of 4, which also indicates that the overall user model features evaluated within the experiment were found useful, from the users' perspective.

The usability of user modelling features has not been investigated thoroughly, with the exception of .the features related to the initial recommendations. The results can be found in Table 7.8.

Table 7.8: Usability results for Hypothesis 1.2

Related Questions		Mean	Mode	Std	t-test	Mann – Whitney	Wilcox-on test
No.	***Hypothesis 1.2, N= 221***						
1.	The system provided better user profiling compared to other e-commerce websites.	3.59	4	0.89	0.00	0.00	0.00
2.	I found the information collected very rich.	3.40	4	1.02	0.00	0.00	0.00
Overall Usefulness		**3.50**	**4**	**0.95**	**0.00**	**0.00**	**0.00**

The usability overall mean value is (3.50 ± 0.95) and a mode of 4. These values are just on the threshold of being considered positive. However, the standard deviation is quite high, which indicates a variety of opinions with regards to the usability issues.

On the positive side, all the user modelling related features are statistically significant for the statistical test. This strengthens the validation of the hypotheses and the results generated from the descriptive statistics.

Once more, the correlation between usability and usefulness is calculated, to examine if these two aspects affected each other or not, for user modelling features. The results are in Table 7.9.

Table 7.9: Combined H1.2 correlation between usability and usefulness

Hypothesis	Measures of Acceptance	Mean	STD	Overall Mean	Overall Std	Pearson's Correlation Usability via Usefulness for H1.2 at 0.01 level
H1.2	Usability	3.50	0.86	3.63	0.90	0.43
	Usefulness	3.77	0.95			

The results show a moderate correlation, which is a not well connected relationship falling in the middle [168] between usability and usefulness, indicating that the users do not necessarily see that a useful feature is also usable and vice versa. This is not necessarily a negative outcome, as it potentially shows that users do distinguish between how usable the feature is for them and how useful it is.

The hypothesis H1.2 cannot be confirmed just yet, due to the fact that some features are missing from the evaluation and further investigation was conducted to examine the missing features.

For Hypothesis 3 indicating that, "Adaptive advertising supported by a standalone system can lead to users' acceptance in terms of *usability* (A) and *usefulness* (B).", this hypothesis investigates the new technological approach of a standalone system. The results are collected in Table 7.10.

Table 7.10: Usefulness results for Hypothesis 3

Related Questions		**Mean**	**Mode**	**Std.**	**t-test**	**Mann – Whitney**	**Wilcoxon test**
	Hypothesis 3, N= 221						
1.	I found the system more useful than other e-commerce websites I use.	3.21	3	0.9	0.00	0.00	0.00
2.	The system provided more related recommendation than I usually get.	3.30	3	1.0	0.00	0.00	0.00
3.	The system was more flexible and allowed for more control *compared* to other e-commerce websites.	3.92	4	0.98	0.00	0.00	0.00
Overall Usefulness		**3.47**	**3.3**	**0.96**	**0.00**	**0.00**	**0.00**

This hypothesis investigates the usefulness and usability of the proposed standalone technology to generate adaptive e- advertisements. The results with regards to this hypothesis cannot be accepted as clearly positive, as the mean values fall under 3.5 and have a large standard deviation. When the users were asked about whether the adopted approach is more useful than other e-commerce systems, the mean values were (3.21 ± 0.90) and a mode of 3. The results indicated that the users were somewhat indecisive about the approach. Although the results are indecisive, the comparison between a prototype system and well developed commercial websites can only be inequitable. There are many differences and limitations of the comparision that can only be objective, if it is made against same style of systems. This outcome also shows again when investigating the amount of personalised features, with a mean of (3.30 ± 1.00) and a mode of 3. The mean value is below 3.5, the standard deviationdeviaton is quite large and the mode value is 3, leaving the users fall within the indecisive part of the argument. However, an advantage of the system over other approaches was stated by the users when investigating the flexibility of the system. The mean value was (3.92 ± 0.98), with) a mode value of 4. The overall usefulness of the proposed approach has the mean value of (3.47 ± 0.96),) which is just under the accepted value of 3.5. This is not an evaluation for the overall approach, however, as some features were more successful than others.

The usability of the proposed approach is also examined and the results are illustrated in Table 7.11.

Table 7.11: Usability results for Hypothesis 3

Related Questions		Mean	Mode	Std.	t-test	Mann – Whitney	Wilcoxon test
	Hypothesis 3, N= 221						
1.	The system was not overwhelming/ complex compared to other e-commerce websites.	3.50	4	1.0	0.00	0.00	0.00
2.	The system was more flexible and allowed for more control *compared* to other e-commerce websites.	3.92	4	0.98	0.00	0.00	0.00
Overall Usability		**3.71**	**4**	**0.99**	**0.00**	**0.00**	**0.00**

A standalone system for personalised e-advertisements is quite an uncommon approach among both the state of art and the commercial systems. Comparing the usefulness of the proposed approach against the “big players” can be tricky. However, usability aspects are found to be positive, with users agreeing that the system is not complex or overwhelming with a mean value of (3.50 ± 1.00) and a mode of 4 indicating an easy to use approach, which is one of the important outcomes. Flexibility is also positive, as users found the system more flexible, with a mean value of (3.92 ± 0.98) and a mode of 4 indicating a flexible approach. The overall usability is thus also positive, with a mean value of (3.71 ± 0.99) and a mode value of 4 indicating that the system is both easy to use and flexible.

All the previous statements are statistically significant, indicating that the results generated are valid and are a good representation to the actual perceptions of the users in our experiment. The correlation between usability and usefulness is summarised in Table 7.12.

Table 7.12: Combined H3 correlation between usability and usefulness

Hypothesis	**Measures of Acceptance**	**Mean**	**Std**	**Overall Mean**	**Overall Std**	**Pearson's Correlation Usability via Usefulness for H3 at 0.01 level**
H3	Usability	3.71	0.96	3.59	0.97	0.71
	Usefulness	3.48	0.99			

This hypothesis is the first hypothesis to produce a strong correlation between the two measures. For the overall system performance and use, users found that systems' performance is connected to the ease of use and vice versa, which was not the case in previous hypotheses.

The research also explores the reliability and the internal consistency of the questions asked, so the need to test the inter-rater reliability with the questionnaire using the Likert scale was addressed. *Cronbach's alpha* was used to test the reliability of the results [141]. The Cronbach's alpha value for the used questions is 0.7*2*, indicating a good inter-rater reliability within the questions. This supports the previously implied assumption that the set of questions used are reliable to be used within the evaluation.

7.3.2. Qualitative Results

The last part of the questionnaire was left to the users to provide qualitative feedback on their experience. The main objective of the qualitative feedback is to cover any aspects that the questionnaire did not address and the users thought were worth further exploring. They were given enough space to put as many comments as they want. The questions that were asked are as follows:

- What are the *best* features in MyAds, please state as many as you like.
- What are the *worse* features in MyAds, please state as many as you like.
- Do you have any *suggestions* to improve MyAds, please state as many as you like.

Out of 221 questionnaires given, 436 comments were collected. These comments were divided as follows; 279 comments about the best features of MyAds, 121 comments about the worse features and 36 comments about further suggestions. Details of the features and the frequency are found in Table 7.13 below.

The average comments were about 2 comments per user. Some users provided more feedback than others, depending on their interest in the work and willingness to help.

The analysis of the qualitative feedback was through firstly grouping the comments into best, worst and suggestions. Then, all the comments were grouped into a table and the frequency of the comments was recorded; please refer to Table 7.13 for more details.

Table 7.13: Analysis of users' qualitative feedback

Best Qualities	Frequency	Worst Qualities	Frequency	Suggestions	Frequency
Easy to use	87	Not enough products	58	More products and expand it	18
Personalised	65	Not enough details	9	Ads	1
Social Interaction Options	16	Themes are not colourful enough	8	Add more languages and currencies	4
Adaptation knowledge tree	12	Design	8	Make the website more attractive	7
Categories	12	No sub-categories	5	Add social interaction	2
Fast	12	Slow	5	Add a help tutorial	2
Simple	10	Not integrated	4	Search	1
Comfortable	10	Improve the recommendation system	4	People add their products	1
Has many options	8	Not enjoyable	4		
Create events	7	Search	3		
Different login options	7	Many language support	2		
Gives many options	6	More buttons	2		
Useful	6	Complicated	2		
logical arrangement of products	6	Not secure	1		
Can opt the product didn't like	6	Social interaction	1		
Use of Facebook	4	Search not functioning	1		
Varity of products	2	No directions	1		
Secure	2	Sub profiles not important	1		
Sub-profiles	1	Mobile browsing	1		
		Can't save products on laptop	1		
Total	279		121		36

The information from the table has been further visually analysed in Figure 7.1*:* Users' perceptions on MyAds least preferred features and Figure 7.2, by exploring the most frequent positive and negative features, as follows.

Figure 7.1 presents the worst features the users experienced in MyAds. The main issue was the lack of products, as they stated, there are not enough products: 58 of the 121 negative feedback, with a percentage of 48% of the negative feedback, was around this issue. This also emphasises the issue raised by the quantitative feedback and the results collected earlier, as the users had the lowest mean of 2.3 for the availability of the products, as described in Section 7.3.1.

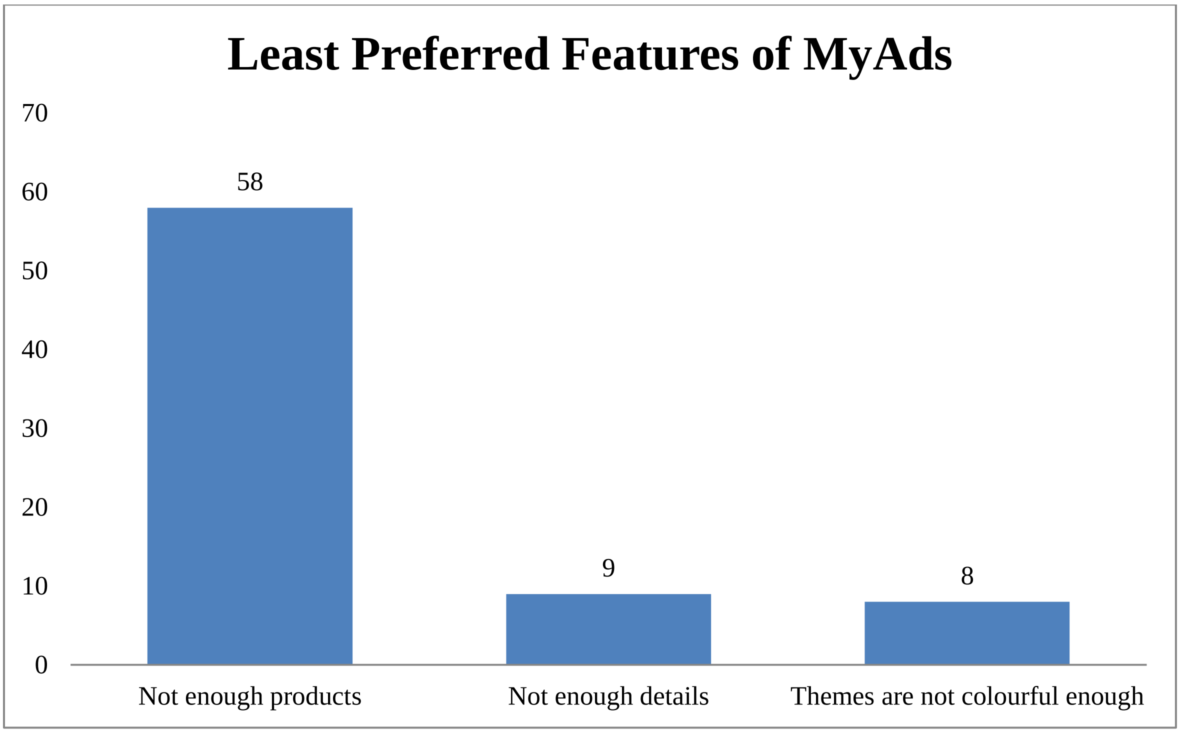

Figure 7.1: Users' perceptions on MyAds least preferred features

The positive feedback collected was 279 comments out of the 436. An overall of positive comments, with a percentage of 64% of the feedback was positive, as in Figure 7.1: Users' perceptions on MyAds least preferred features. The users listed 19 positive features in the system, with various frequencies. The most frequent positive feature was the *ease of use* and *personalisation*. This matches the information collected from the quantitative feedback, as the mean value for the ease of use was 3.66 and the personalisation mean of 3.65 as discussed in Section 7.3.1.

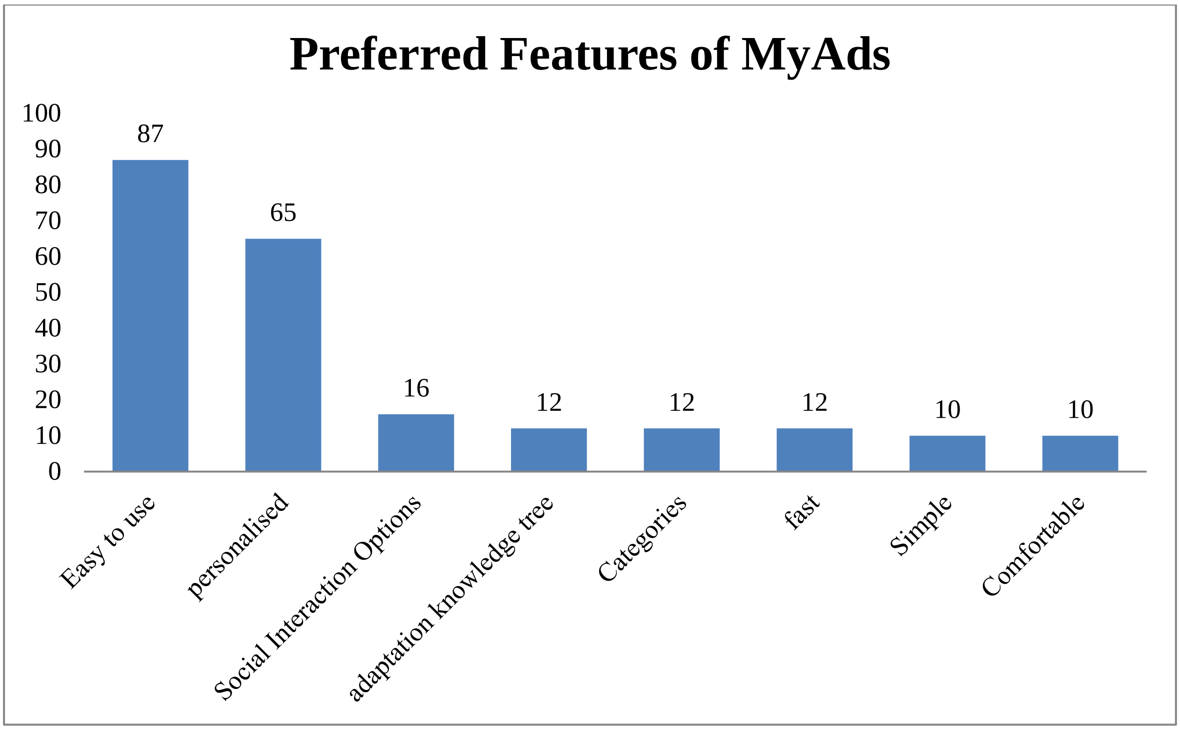

Figure 7.2: Users' perception of MyAds' preferred features

The results collected from the qualitative feedback match the results collected from the quantitative feedback in the areas where quantitative feedback was given.

7.3.3. Log-files Results

Log-files were used to trace the behaviour of the users, to record their interaction with the system. On the system, the features that were traced are the creation of sub-profiles, the direct feedback on the clicked products and the commenting on the product presented to them. The total number of clicks on the advertisements was 739 clicks from the 221 users who used the system. This is a percentage of 3.3 clicks per user.

The number of users who created a sub-profile was 87 out of 221, a percentage of 39.3% of the users.

In terms of the users' feedback on the system, 96 out 221 students left comments on the system. The comments included "nice"," good idea", "interesting"," I wish we can have it live" and "I do not like the products recommended". The feedback was, generally speaking, positive.

The last type of behaviour recorded by the log files was the users' interest in buying products, as they were given the options to "I definitely consider buying this product" "I may consider buying this product", and "I will never buy this product". Out of the 739 clicks on the advertisements, 265 stated that they will definitely consider buying the recommended product, which represents a percentage of 36%. Also, 240 stated that they may consider buying this product – a percentage of 31%. This sums up the total percentage of acceptances of the products of 67%. However, 137 users stated that they will never consider buying the product suggested to them, with a percentage of 18.5%. When they were asked about why they would not buy the suggested product, 27 users indicated that the recommendation "was not to their taste", 45 users indicated that "it was not what they had in mind" and 43 users suggested that they "Do not need the product".

7.3.4. Limitations of experiment I

The large scale evaluation conducted in experiment I generated the results discussed in the previous Section 7.3.1. Whilst the experiment covered many aspects of the research and addressed most parts of the hypotheses, it still had the following limitations:

- For Hypotheses 1.1 and 1.2, some parts were not fully covered in the questionnaire. This is due to the extended time of the experiment, so the questionnaire was designed to be as short and direct as possible. This has caused the focus on the functionality of the adaptive features.
- Also, from the previous limitation, another one was generated, which is the lack of coverage of the usability aspects for evaluations. For Hypothesis 1, which is a more generic hypothesis, both usability and usefulness were covered. For the detailed Hypotheses 1.1 and 1.2 that has distinct adaptive user modelling and adaptive features to evaluate, the questionnaire was more focused on the usefulness, rather than usability. Hypothesis 3, which also focuses on the stand-alone approach, was also more focused on the usefulness rather than usability of this approach.
- Hypothesis 1.3 was not covered at all in experiment I, as the Facebook login token was not activated.

The previously mentioned limitations could not be ignored and should be addressed as the hypotheses were not fully evaluated. To overcome these limitations, another follow-up experiment was conducted and explained in details in Section 7.4.

7.4. Experiment II

The analysis of experiment I has addressed some of the hypotheses. However, not all the different aspects have been covered within the evaluation. For example, in hypothesis 1.1 on adaptive presentations, *adaptive navigation support*, *general guidance* and *adaptive story lines* were not covered thoroughly within the evaluations. Moreover, usability and usefulness were not separated enough in the questions. For hypothesis 1.2 on rich user models, the *event* feature and *updated user model based on behaviour* as well as *uncommon features* were not fully evaluated. Moreover, *user control appearance* was not targeted. Another issue with hypothesis 1.2 was that the evaluation measures focused mainly on usefulness and slightly on usability, though the hypothesis also mentions *needs* and *desires*.

Hypothesis 1.3 was not targeted at all, as the Facebook access token did not connect with the server in the initial experiment. As a result, no implicit user data was collected, as the users only had the option of using the registration form.

To address the previously mentioned missing points that are important for the evaluations, a follow-up experiment was conducted.

The follow-up experiment was conducted with the same setting as the first experiment, with differences in the length, evaluation sample and demographics of the participants.

7.4.1. Experimental setting

The experiment was conducted in one day, over two sessions, each session of around 2 hours length. It was conducted at the University of Jordan, department of *Business Information Technology* (BIT), with the help of students studying a course entitled “advanced web applications”. The participation was voluntary and the students had the choice to participate or not.

The total number of participants was 46; 24 students participated in the first session and another 22 in the second session. All the students approached took part in the experiment, giving a 100% participation rate.

The sample in this experiment was well knowledgeable of web-based applications, as they were studying the course entitled “Advanced Web Applications” and had already studied the pre-requisites for it. All of the students had excellent knowledge about web-based applications and especially about the e-commerce ones, as they specialised in the department of Business Information Technology, and most of their courses were e-commerce oriented.

The demographics of the experiment were again female dominant, with 43% males and 57% female. The age group of the students was between 21 and 22, as they were senior students in their last year on their undergraduate course. Please note that the sample size in this experiment is relatively low. However, as this experiment aimed at complementing the missing evaluations from the previous one, this, in combination with the previous experiment with the sample size of 221, achieve a total of 267 participants questioned in relation to the same hypotheses. Please refer to Chapter 3 for more discussions in relation to sample size.

The experiment was again conducted over three phases. *The first phase* was with the researcher introducing the research and explaining the setting of the experiment. In *the second phase*, the users had around one and a half hours to take part in the experiment. It started by firstly exploring other e-commerce and e-advertisement systems, to update and refresh the students' knowledge. They were asked to explore especially Amazon and Groupon, before they started using MyAds. After the first half hour, they were asked to log in via MyAds and start using and manipulating the system, to use the features within the system and to interact with it. *The third and final phase* was when they were asked to fill-in a questionnaire, to evaluate their experience.

7.4.2. Results and analysis

The survey questions within this evaluation were focused on covering the missing aspects from the prior experiment. A clear distinction between usability, usefulness, needs and desires -related questions was ensured. This was especially stressed because in the previous experiment, some hypotheses were highly focused on either usability or usefulness; thus, the updated approach resolved this issue, by addressing each aspect separately. Again, the questions allowed for answers on a Likert scale (1 is the lowest value = strongly disagree and 5 is the highest value = strongly agree).

The analysis in the following studies each hypothesis separately. Then, the reflection upon explicit via implicit user modelling is studied to evaluate Hypothesis 1.3.

7.4.3. Hypotheses Analysis

The hypotheses in this section only cover the missing features that were not covered fully in the previous experiment. Please refer to Section 7.2 for the full and extended version of the hypotheses.

For hypothesis 1.1: It was necessary to address the acceptance of users' based on perceived usefulness and usability of the following:

I. *Adaptive presentation support*;

II. *general guidance, in terms of shortcuts, buttons, stretch-text, combined with recommendations* and

III. *Adaptation (system driven) using adaptive storylines (logical grading).*

The following results in Table 7.14 have been obtained.

Table 7.14: Hypothesis 1.1 - follow up experiment descriptive statistics

Hypothesis 1.1, Follow up Experiment , N=46		**Mean**		**Mode**		**Std**	
No.		***Usable***	***Useful***	***Usable***	***Useful***	***Usable***	***Useful***
I	***Adaptive Presentation Support Features***						
1.	I found the system providing more text and details about products based on my selection.	3.78	3.54	5	3	1.19	1.12
2.	I found the system hiding some text and product details about products.	3.63	3.41	4	3	1.14	1.18
	Overall mean for adaptive presentation support	*3.70*	*3.64*	*4.5*	*3*	*1.16*	*1.15*
	General Guidance Features						
3.	I found the system providing the “Select different set of items” button.	4.06	3.89	5	5	1.10	1.23
4.	I found the system providing the “Go Back to original product list” button.	4.34	4.10	5	5	0.97	1.15
5.	I found the system providing the “I Do not like any” button.	4.26	4.10	5	5	1.16	1.25
6.	I found the system providing the “Start a new search” button.	3.82	3.69	5	5	1.20	1.39
	Overall mean value for general guidance	*4.1*	*3.94*	*5*	*5*	*1.10*	*1.24*
	Adaptive Story Line Feature						
7.	I found the system providing a storyline based on my preferences.	3.84	4.00	4	4	1.21	1.07
	Overall Mean	**3.96**	**3.81**	**4.71**	**4.28**	**1.13**	**1.19**

Analysing these results, for hypothesis 1.1, the missing feature of adaptive navigation and presentation support is addressed by questions 1 and 2. The analysis of *usability* resulted in means of (3.78 ± 1.19) and (3.63 ± 1.14), and modes of 5 and 4 respectively. This is an indication that it is an easy to use system. However, the results for *usefulness* were not really decisive, with lower means of (3.54 ± 1.12) and (3.41 ± 1.18) for questions 1 and 2, respectively, and a mode value of 3 for both questions, respectively. The users didn't have a decisive answer with regards to how useful these features are. The mode, which is usually a good indication of the most frequent answer, also suggests that the users have not had a decisive answer.

Questions about the general guidance features found in questions 3-6, received better scores from the users, as all the means of the usability were relatively high with mean values of (4.06 ± 1.10), (4.34 ± 0.97), (4.26 ± 1.16) (3.82 ± 1.20) and the mode for the answers of 5. The features were also found useful, with fairly high means (3.89 ± 1.23), (4.10 ± 0.97), (4.10 ± 1.16), (3.69 ± 1.20), with a mode of 5 for all the questions. Moreover, all the mean values are above 3.5, indicating a positive agreement on the statement. Thus, the overall usefulness is perceived as positive, with a mean value of (3.81 ± 1.13) falling within the agreement (3.81>3.5) that the features are overall useful form the users' perspective.

The final feature examined here was the adaptive storyline. Users found it both useable and useful, generating a mean value of (3.84 ± 1.21) and a mode of 4.The usefulness of this feature had a higher mean and less distributed answers, with a mean of (4 ± 1.07) and again a mode of 4. The overall usability has a mean value of (3.96 ± 1.13), indicating a positive total reflection upon the features, higher than the accepted value of 3.5.

Another set of tests were conducted to examine the results from the questionnaires, which are: a statistical tests for parametric data, the t-test, and a non-parametric test, the Mann- Whitey, both being explained in more details in Chapter 3. The following results are generated, as seen in Table 7.15.

Table 7.15: Hypothesis 1.1 - follow up experiment statistical significance tests

Hypothesis 1.1, Follow up Experiment , N=46		**t-test**		**Mann-Whitney**		**Wilcoxon test**	
No.		***Usable***	***Useful***	***Usable***	***Useful***	***Usable***	***Useful***
I	***Adaptive Presentation Support Features***						
1.	I found the system providing more text and details about products based on my selection.	0.00	0.00	0.00	0.00	0.00	0.00
2.	I found the system hiding some text and product details about products.	0.02	0.00	0.00	0.00	0.00	0.00
	Overall mean for adaptive presentation support	0.00	0.00	0.00	0.00	0.00	0.00
	General Guidance Features						
3.	I found the system providing the “Select different set of items” button.	0.00	0.00	0.00	0.00	0.00	0.00
4.	I found the system providing the “Go Back to original product list” button.	0.00	0.00	0.00	0.00	0.00	0.00
5.	I found the system providing the “I Do not like any” button.	0.00	0.00	0.00	0.00	0.00	0.00
6.	I found the system providing the “Start a new search” button.	0.00	0.00	0.00	0.00	0.00	0.00
	Overall mean value for general guidance	0.00	0.00	0.00	0.00	0.00	0.00
	Adaptive Story Line Feature						
7.	I found the system providing a storyline based on my preferences.	0.00	0.00	0.00	0.00	0.00	0.00
	Overall Mean	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

All the features are statistically significant within the sample used, for both evaluation measures of usability and usefulness. This is to strengthen the results already generated from the descriptive statistics.

For hypothesis 1.2, on having a rich personalised e-commerce platform, based on a rich user model, the users' acceptance can be achieved in terms of usability (A), usefulness (B), needs (C) and desires (D). The following features should be present:

Creating richer user models by:

I. *Populating the updated UM based on the user behaviour over the system.*
II. *Adding uncommon features, such as religion, favourite colour;*
III. *Creating user-related calendar events with reminders and relationships between events and personalised products (e.g., birthday reminders, with family/friends' preferences connected to them);*
IV. *Giving the user control*
V. Manipulating *advertisement appearance* providing categories for advertising products for users to select from.

The results are summarised in Table 7.16 and Table 7.17. The analysis is first done to measure *usability* and *usefulness*. The same question is then used to evaluate *needs* and *desires*, except for Questions 6 and 7, which were not included in the latter analysis. They were not included because they do not need to measure needs and desires. These questions are instead oriented to establish the usability and usefulness of the system.

Table 7.16: Hypothesis 1.2 part I - follow-up experiment

Hypothesis 1.2 **Follow up Experiment , N=46**		*Useful. (***Usefulness***)*			*Usable. (***Ease of Use***)*		
No.		Mean	Mode	*Std*	Mean	Mode	*Std*
I.	***Rich User Model : Updated UM based on the user behaviour over the system***						
1.	I found the system updating my recommendations based on my behaviour on the system.	3.69	5	1.24	3.47	3	1.31
2.	I found the system updating my recommendations based on my direct feedback on the system.	3.78	5	1.26	3.73	4	1.16
	Overall mean of rich UM – User behaviour	*3.73*	*5*	*1.25*	*3.60*	*3.5*	*1.23*
II	***Rich User Model by Adding Uncommon Features***						
3.	I found the system's rich user profile.	3.56	3	1.12	3.76	3	1.01
4.	I found the system harvesting religion and favourite colour.	3.47	5	1.47	3.47	4	1.29
	Overall mean for rich UM – Uncommon features	*3.51*	*4*	*1.29*	*3.61*	*3.5*	*1.15*
III	***Rich User Model by Adding Event Calendar***						
5.	I found the system providing the calendar “event feature”.	3.87	5	1.18	3.84	5	1.26
IV	***User Control: Appearance of e-advertisements***						
6.	I found the system providing the user with many options and data to input made the system appearance.	4.00	5	1.09	3.78	5	1.22
	Overall values	**3.75**	**4.71**	**1.22**	**3.69**	**4.41**	**1.21**

The results are grouped based on the features specified in the hypothesis. For the first feature that examines users' opinions with regards to implicit updating of the recommendations, the results for the *usability* questions are mainly positive. The mean values are (3.47 ± 1.31) and (3.73 ± 1.26), with a mode of 3 and 4 respectively. However, the usability aspect related to the implicit updating of recommendation within the system is just under the accepted value for positive means of 3.5. Moreover, the standard deviation is quote large in relation to the mean, indicating that the responses are quite varied and the mode value of 3, suggests that no conclusive result can be obtained. The usability of the feature giving users more control by allowing them to give direct feedback is more positive, with an accepted mean value of 3.73. Again, the standard deviation is quite large but it is still acceptable within the range of the positive argument. The usability of the uncommon features of religion and favourite colour is examined. Users found the user profiles rich and useable, with a mean value of (3.76 ± 1.01) and a mode value of 3. Although, the mode value is 3, the mean is still above the accepted value of 3.5, indicating that the results do fall within the positive part of the argument. Additionally, harvesting uncommon features of religion and favourite colour is not as usable from the users' perspective, with a mean value of (3.47 ± 1.29) and a mode of 4. Although, the mode value is 4, the mean value is just under 3.5 and the standard deviation is relatively large with respect to the mean. On the other hand, the event feature is declared positively usable by the users with a mean value of (3.84 ± 1.26) and a mode value of 5. User control over the appearance of the advertisement is also found positively usable, with a mean value of (3.78 ± 1.22) and a mode value of 5 indicating that most of the users "strongly agreed" with the statement. The overall perceived usability mean is (3.69 ± 1.21) and an average mode of 4.4. It can be argued that the overall usability is positive and that the users found that these features can help them achieve their goals of using the system; however, some features remain more positive than others, due to many factors. Some of these factors include the fact that some features are uncommon, and since the users were not familiar with them, this may have caused some confusion.

The perceived *usefulness* of the proposed features is also analysed. The implicit updating of the advertisement is useful from the user perceptive, with a mean value of (3.69 ± 1.24) and a mode value of 5. However, the explicit updating of features is found even more useful, with a mean value of (3.78 ± 1.26) and a mode value of 5 indicating an agreement with the statement. Uncommon features within rich user models are found not that useful, with a mean value of (3.47 ± 1.47) and a mode value of 5. Although the mode value is high and the mean is slightly under the accepted value of 3.5, the standard deviation is quite large, indicating a large distribution of users' perceptions, which can go as low as 2 or as high as almost 5. However, users found that rich profiles are relatively useful, with a mean value of (3.56 ± 1.12) and a mode value of 3. The event feature is also one of the positively useful features, with a mean value of (3.87 ± 1.18) and a mode of 5, indicating users' agreement with this statement. Users found that having control over the system appearance is useful, with the mean value of (4.00 ± 1.09) and a mode value of 5. The overall usefulness is positive, with the mean value of (3.75 ± 1.22) and an average mode of 4.7. The results indicate that the users found the overall features useful. Some of the novel features, such as the event feature and manipulating the appearance of the advertisement have the highest mean values, and strengthen the hypothesis. However, the uncommon data harvesting feature, which is also quite novel, was not as successful as the other features.

As both usability and usefulness have been evaluated using the same measures and covering the same aspects, for this hypothesis' features, the users found that these features are more useful than usable, although the mean values are relatively close.

Statistical tests have also been undertaken for the usefulness and usability of these features and the results generated were as follows in Table 7.17.

Table 7.17: Hypothesis 1.2 - follow up experiment statistical significance tests

Hypothesis 1.2, Follow up Experiment , N=46		**t-test**		**Mann-Whitney**		**Wilcoxon test**	
No.		***Usable***	***Usable***	***Useful***	***Useful***	***Usable***	***Useful***
1.	I found the system's rich user profile.	0.00	0.00	0.00	0.00	0.00	0.00
2.	I found the system providing the user with many options and data to input made the system appearance.	0.02	0.0	0.02	0.00	0.00	0.00
3.	I found the system providing the calendar “event feature”.	0.00	0.00	0.00	0.00	0.00	0.00
4.	I found the system updating my recommendations based on my behaviour on the system.	0.00	0.00	0.00	0.00	0.01	0.00
5.	I found the system updating my recommendations based on my direct feedback on the system.	0.00	0.00	0.00	0.00	0.00	0.00
6.	I found the system harvesting religion and favourite colour.	0.00	0.00	0.00	0.00	0.02	0.05
	Overall Usability	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
	Overall Usefulness	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

All the features for both measures are statistically significant, except the usability issue in "I found the system updating my recommendations based on my behaviour on the system", which has probability of 0.06, which is higher than the value of 0.05 for the non-parametric test of Mann-Whitney.

As stated earlier, not all the features in this hypothesis are further investigated, to include needs and desires: only the features directly connected to them. The following results are the descriptive statistics tests for the measures of need and desires that are further used to measure acceptance.

Table 7.18: Hypothesis 1.2 part II - follow-up experiment

Hypothesis 1.2 **Follow up Experiment N=46**		*Satisfactory*.**(Needs)**			*Desirable* **(Desire)**		
No.		Mean	Mode	*Std*	Mean	Mode	*Std*
I	***Rich User Model : Updated UM based on the user behaviour over the system.***						
1.	I found the system updating my recommendations based on my behaviour on the system.	3.58	5	1.27	3.47	3	1.18
2.	I found the system updating my recommendations based on my direct feedback on the system.	4.02	5	1.18	3.86	5	1.10
	Overall mean Feature I	*3.8*	*5*	*1.22*	*3.66*	*4*	*1.14*
II	***Rich User Model by Adding Uncommon Features***						
4.	I found the system's rich user profile.	3.67	4	1.15	3.67	5	1.26
III	***Rich User Model by Adding Event Calendar***						
6.	I found the system providing the calendar “event feature”.	3.69	5	1.17	3.69	5	1.26
IV	***User Control: Appearance of e-advertisements***						
7.	I found the system providing the user with many options and data to input made the system appearance.	3.67	4	1.13	3.76	5	1.15
	Overall Mean	**3.72**	**4.6**	**1.18**	**3.69**	**4.6**	**1.19**

The users' satisfaction was the highest for the recommendations provided for the users via their explicit feedback on the system behaviour, with the value of the mean (4.02 ±1.18) and a mode value of 5. All the other features mean ranged between (3.58) and (3.67), and mode values of both 4 and 5, showing the users' satisfaction with the proposed features. The values are all above the value of 3.5, indicating a positive perception. However, the feature of the implicit updating presented in Question 1 is not very conclusive, as the mean value is (3.58 ± 1.27) and a mode of 5. Although, the mode is high, the standard deviation is also large, indicating that the results fall between 2 to 5, with a large variance between the answers, although the majority are on the agreement side.

For the users' desires, they indicated that almost all of the features met their desires, and that they were happy with them, with values of the mean ranging from (3.67 to 3.86). The novel features remain desired by the users, as the mean values are above 3.5, which is the accepted threshold. The exception is the implicit updating of the recommendation, with a mean of (3.47 ± 1.18), as they preferred the recommendations provided via their explicit feedback. The mode of 3 also indicates a clear neutral opinion about implicit updating of recommendations. The overall mean for the desired features is (3.69 ± 1.19) and an average mode of 4.6, as an indication that the overall perspective on the features is positive.

Comparing the overall mean values of the questions related to satisfaction against the ones on the desirability of the features, the overall mean value of satisfaction is slightly over the desirability; however, the difference remains small as they almost generated the same results.

Furthermore, the set of significance tests (t-test and Mann-Whitney) for the satisfaction and desires are found in Table 7.19.

Table 7.19: Hypothesis 1.2 - follow up extended measures statistical significance tests

Hypothesis 1.2, Follow up Experiment N=46		**t-test**		**Mann-Whitney**		**Wilcoxon test**	
	Question	***Satisfaction***	***Desires***	***Satisfaction***	***Desires***	***Satisfaction***	***Desires***
1.	I found the system's rich user profile.	0.00	0.00	0.00	0.01	0.00	0.00
2.	I found the system providing the user with many options and data to input made the system appearance.	0.00	0.00	0.00	0.00	0.00	0.00
3.	I found the system providing the calendar “event feature”.	0.00	0.00	0.00	0.00	0.00	0.01
4.	I found the system updating my recommendations based on my behaviour on the system.	0.01	0.00	0.09	0.01	0.04	0.01
5.	I found the system updating my recommendations based on my direct feedback on the system.	0.00	0.00	0.00	0.00	0.00	0.00

All the results are statistically significant, except for the satisfaction value probability of 0.09, which is larger than 0.05, for the statement "I found the system updating my recommendations based on my behaviour on the system".

For hypothesis 1.3, *"The study of implicit versus explicit user models will illustrate and allow for comparison of the different sources of user model data for adaptive advertising."*. This hypothesis has not been explored before and aims at discussing the different data harvesting approaches and their implications. The results are listed in Table 7.20

Frequency analysis of the 46 responses indicates that the study's participants had a slightly higher preference for the explicit – registration – (56.5%) compared to the implicit – Facebook – (43.5%) form of registering/logging into the system, as shown in Table 7.21.

Table 7.20: Percentage of explicit via implicit UM

Type of Login	**Frequency**	**Percentage**
Registration	26	56.5%
Facebook	20	43.5%
Total	**46**	**100.0**

Descriptive analysis was performed to investigate user perception about the implicit versus the explicit approach to data collection for user models. Three questions were used to measure user perception on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The findings presented are for the 46 collected responses, separated between the implicit and explicit approach.

Table 7.21: User reflection of explicit via implicit UM

		Implicit user modelling *Facebook*			Explicit user modelling *Registration*		
No.	Question	Mean	Mode	*Std*	Mean	Mode	*Std*
1.	I found the system collected enough information about me.	4.05	4	0.82	4.11	4	0.65
2.	I found the system built a rich user profile that reflected upon my recommendations.	3.60	4	0.82	3.11	3	0.95
3.	I find the logging approach useful for the system to know about me and thus how to recommend me appropriate articles from the start.	4.15	5	0.93	3.53	4	1.13
	Overall values	**3.93**	**4.3**	**0.85**	**3.58**	**3.67**	**0.91**

The implicit data collection method was more successful in addressing the user expectations with respect to the amount of information collected. Users found that the implicit approach produced a richer UM, as reflected in their responses, with a mean of (3.6 ± 0.82) and a mode of 4. The explicit approach, however, had a mean of (3.11 ± 1.13) and a mode of 3, clearly showing they were indecisive about explicit UM.

The logging approach via the implicit method is noticeably different, with a mean of (4.15 ± 0.93) and a mode of 5, while the mean value of the explicit approach is (3.53 ± 1.13) and a mode of 4. The only aspect for which users found that the explicit UM data collection approach was more successful was about the amount of information collected. This is due to the fact that the registration form is quite thorough. However, the mean value of (4.11 ± 0.65) did not differ too much from the implicit approach of (4.05 ± 0.82).

Nevertheless, these results are not enough to argue that there is any difference between the different approaches, so the need for a significance test has emerged. For each question, separately, an independent sample t-test has been conducted, as can be found in Table 7.22.

Table 7.22: Independent Samples Test for H1.3

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Login approach	Equal variances assumed	1.99	0.16	0.30	44	0.76	0.06	0.21	0.37	0.50
Enough Information	Equal variances assumed	0.49	0.48	-1.81	44	.076	-0.48	0.26	-1.02	0.05
Recommendations Presented	Equal variances assumed	1.27	0.26	-1.94	44	.058	-0.61	0.31	-1.24	.021

The variances for the two groups are approximately equal, meaning that the distribution of explicit versus implicit user modelling is similar in shape. Due to the fact that the significance value for the t- test is higher than 0.05, it can be assumed that both explicit and implicit user modelling have equal variances.

Moreover, if the standard deviation is examined – which is the square root of the variance – the values are similar. It is not possible to assume that there is a significance difference between the implicit and explicit approach, because the significance value of the (2-tailed) test is larger than 0.05. Consequently for Hypothesis 1.3, no assumption can be made that there is any difference between the two approaches, and thus no preferred approach can be determined and thus both can be used equally.

The research aims at investigating the effect of implicit versus explicit UM, not only on these questions related to Hypothesis 1.3, but to also examine the reflection upon the previous Hypothesis of 1.1 and 1.2, found on Table 7.23 and Table 7.24.

For Hypothesis 1.1, the analysis was performed via the comparison of usability and usefulness measures, and the role of the different UM approaches. The results are shown in Table 7.23.

Table 7.23: Independent Samples Test for H1.1

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Usefulness	Equal variances assumed	0.62	0.43	-1.18	44	0.24	-0.24	0.20	-0.65	0.17
Usability	Equal variances assumed	1.31	0.26	-0.74	44	0.46	-0.13	0.17	-0.49	0.22

The results in Hypothesis 1.1 match the results generated in 1.3, as the t-test indicated that the equal variances can be assumed, because of the larger than 0.05 significance value of (0.43) and 0.26 for usefulness and usability, respectively. The significance value for the independent sample test also is larger than 0.05; both measures indicate that there is no significant difference between the two approaches.

Similarly, the implicit versus explicit user model for each measure has been examined for Hypothesis 1.2, and the results are shown in Table 7.24.

Table 7.24: t-test Independent Samples Test for H1.2

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Desire	Equal variances assumed	0.03	0.85	-0.23	44	0.81	-0.059	0.25	-0.56	0.44
Needs	Equal variances assumed	0.00	0.97	0.70	44	0.48	0.177	0.25	-0.32	0.68
Usability	Equal variances assumed	0.57	0.45	-0.27	44	0.78	-0.067	0.24	-0.56	0.43
Usefulness	Equal variances assumed	1.80	0.18	-0.33	44	0.74	-0.083	0.25	-0.59	0.42

The results in Hypothesis 1.2 match the results generated in 1.3 and 1.1, as the t-test presumed that the equal variances can be assumed, because of the larger than (0.05) significance value of (0.85, 0.97, 0.45 and 0.18) for desire, needs, usefulness and usability, respectively. The significance value for the independent sample test is also larger than 0.05 in all measures, assuming that there is no significant difference between the two approaches.

7.5. Discussions and Hypotheses Validation

The experiments discussed within this chapter aimed at addressing at the research questions and related hypotheses. Some of the main concerns of both experiments were the sample size and generalisability of the results achieved.

The sample size has added up to a total of 267, from both experiments. The number is still less than the accepted sample size to claim world-wide significance, which is 384. However, taking into consideration that these experiments are research-oriented, and given the limitations that have been discussed in Chapter 3, this number can be accepted for the context of this research. Please note that all references to significance within this chapter when discussing the results represent significance with respect to the sample, which is computed with standard statistical methods, as detailed in Chapter 3.

Another issue that can be raised here is the demographics of the sample size. Most of the participants are of a young age, between 20 and 22. This, as previously discussed, can be positive, as these participants are both knowledgeable of Internet businesses and thus the main commercial competitors of this research, as well as highly demanding in their expectations of Internet-based delivery. However, this is still posing a limitation, as it raises the question of how representative this age group is of the whole world population accessing the Internet. Another limitation within the demographics of this sample size is the fact that all the participants were from Jordan, due to the limitations of numbers in the UK and the inaccessibility of participants from other countries. Within this overall research, it has been attempted to alleviate this, involving also participants from

Romania in previous experimental studies, as well as having plenty of discussions with English colleagues and peers. However, the research has to be viewed as potentially limited by these factors as described above, to obtain a higher level of objectivity of the research and be able to reach a proper interpretation of the results.

As said, all the results achieved within the experiments are considered as within the above described context, with limitations of research sample size and demographics. However, please note that, especially in the area of the adaptive web, sample sizes and demographics are even more restricted, usually due to similar considerations such as in [128], [133], [131] and [132].

All the results presented in the Section 7.3.1 and Section 7.4.2 aimed at testing the proposed hypotheses, presented in Section 7.2. All the results have been generated from the quantitative results that have been the main focus of the experiment as different statistical tests have been used. The results generated from this analysis are the main source for hypothesis validation.

Hypothesis 1: Adaptive hypermedia leads to users' acceptance, in terms of being *usable* (A) and *useful* (B) from a user perspective.

Confirmation: Hypothesis 1 is supported based on the statistically significance findings and statistical tests (Section 7.3.3), which indicate that adaptive hypermedia leads to users' acceptance, in terms of being *usable* (A) and *useful* (B) from a user perspective. This implies that using adaptive hypermedia as a way for personalisation will eventually lead to users' acceptance of the proposed adaptive advertisements. This is achieved because users found the system both usable and useful. It is usable in terms of being personalised, easy to use, can learn to use it quickly, provided understandable recommendations and would be used again. It was found useful in terms of the various functions were well integrated. However, the system lacked large amount of products, due to the fact that it is a prototype system and not a lot of product could be crawled. Based on the above, Hypothesis one can be confirmed.

Hypothesis 1.1: It is necessary, from a user perspective, to allow for different adaptation approaches, such as:

i. adaptation (system driven) using adaptive storylines,
ii. adaptive navigation support,
iii. adaptive presentation support;
iv. general guidance, in terms of: shortcuts, buttons, stretch-text combined with recommendations,
v. Bandwidth adaptation.

The user perspective and acceptance is measured in terms of *usability* (A) and *usefulness* (B).

Confirmation: Hypothesis 1.1 is one of the extended hypotheses that aim at exploring the different adaption features. The hypothesis is supported by the results generated in Section (7.3.2) that have statistical significant findings. Moreover, as the first experiment missed some aspects out of the evaluation the second experiment emphases and extend the results achieved earlier as in Section (7.4.2). Within this hypothesis, the distinct adaptation features are explored; as in the adaptive general guidance feature that helped the users through their navigation experience, making it easy to manipulate the system and use the different functionalities. Adaptive navigation support and adaptive presentation support features that have been found both usable and useful, as they helped the user to look at the products, sort or hide unnecessary links or texts, show the relevant ones and give explanations about the recommendations they received. Moreover, the system could adapt to the change on the device type and connection, making it both useful and usable. The system provided the users with a comprehensive experience, as they were presented a set of products to complement the product recommended, and they had access to many other features which led to users' acceptance. Therefore, this hypothesis can be confirmed.

Hypothesis 1.2: By having a rich personalised e-commerce platform, based on a rich user model and extended user control over the system, the users' acceptance can be achieved in terms of *usability* (A), *usefulness* (B), *needs* (C) and *desires* (D). Specifically, the following features should be present:

Rich User Models to include:

i. Populating the UM with initial preferences, to suggest a set of sponsored items based on the initial values.
ii. Populating the updated UM based on the user behaviour over the system.
iii. Providing sub-profiles for users, to reflect the fact that a user may have sets of (possibly disjunctive) interests, depending on the circumstances they are in.
iv. Creating rich user models, by adding uncommon features, such as religion, favourite colour.
v. Creating user-related calendar events with reminders and relations between events and personalised products (e.g., birthday reminders, with family/friends' preferences connected to them).
vi. Adding social network features to the user model.

User Control over:

vii. manipulating *advertisement location*,
viii. *appearance* and
ix. *Selection*: providing categories for advertising products for users to select from.

Confirmation: This is again one of the extended hypotheses that have number of detailed features. Thus, this hypothesis, similar to Hypothesis 1.1, has been tested over two experiments. It also extends the evaluation to include the needs and desires of users for certain features. The hypothesis is supported based on the statistically significant findings and statistical tests (7.3.1) and section (7.4.2). The user model richness and giving user control do eventually lead to users' acceptance, as these features have been found useful, usable and in some cases desired and needed. The novel features, such as the "event creating", sub-profiles, social interaction and scrutable user models, all generated positive results. However, users were not decisive about harvesting uncommon features such as religion and favourite colour, as they suggested that it may lead to different interpretations. Nevertheless, overall, this hypothesis can be confirmed.

Hypothesis 1.3: The study of implicit versus explicit user models will illustrate and allow for comparison of the different sources of user model data for adaptive advertising.

Confirmation: the hypothesis examined different data harvesting approaches that will eventually be used in populating the user model. The two sources that were examined are the ones from direct users' registration over the system, related to the explicit user modelling, and the data collected via Facebook login, that does not give any data about the user. Throughout the investigation, no statistical significance could be claimed, and the results indicated there is no difference between the two approaches. Users who used either of the approaches responded similarly to each other. Achieving a fair comparison between both approaches have been conducted and, therefore, this hypothesis can be confirmed.

Hypothesis 3: Adaptive advertising supported by a standalone system can lead to users' acceptance in terms of *usability* (A) and *usefulness* (B).

Confirmation: the hypothesis is supported based on the statistically significant findings and statistical tests (Section 7.3.3). Although descriptive statistics indicated results closer to the neutral point, the different features examined achieved statistical significance, indicating that adaptive advertising supported by a standalone system can lead to users' acceptance in terms of *usability* and *usefulness*, and therefore, the hypothesis can be confirmed.

7.6. Conclusions

All the hypotheses proposed throughout the chapter have been investigated extensively. This chapter has introduced a highly refined set of hypotheses, which addresses all the aspects of adaptation and user modelling for e-advertisements related to this research. The evaluations were executed over two experiments, a large scale experiment, with 221 users and a smaller more focused follow-up one, with 46 users. Both experiments were conducted in the University of Jordan in Jordan. The large evaluation generated results that are close to the representative sample size. Both experiments though had statistical significance for most of the questions, showing that results were conclusive within the users questioned. The issues related to the first experiment were that some adaptation and user modelling features were not examined properly (or not at all) via the initial questionnaire answered by the users. Thus, the need for follow-up experiment (described in Section 7.4) emerged. The follow-up experiment followed the same setting as that of the large scale one, but the questionnaires were more detailed, and a clear distinction between the evaluation measures has been achieved.

Hypothesis 1 and Hypotheses 1.1, 1.2 and 1.3 reflected upon the adaptation and the adaption features. Hypothesis 1examined the general perceptions of the users with regards to adaptation. Hypothesis 1.1 examined adaptive navigation support features, adaptive presentation features and adaptive bandwidth features, and the detailed features have been separately validated as well. Hypothesis 1.2, addressing rich user models, and their role in users' acceptance via recommendations have also been validated taking into consideration the accepted numerical values generated and statistical significance for the proposed sample size. Hypothesis 1.3, examining the different sources of data collected, showed no significant difference between the different data collection approaches, so the assumption that the different data sources will allow for comparison between these sources of user model data for adaptive advertising has therefore been confirmed. This is an indication that for the purposes of the proposed research questions and the proposed research approach there is no difference between the two methods. Using either of these methods will render similar results.

For Hypothesis 3, the users were not decisive in their feedback in the descriptive statistics. However, the results were mainly positive and all the questions generated statistical significance and therefore, the hypothesis have been confirmed. The validation of the entire hypothesis has been explored in Section 7.5.

The chapter has achieved all the objectives stated earlier in Section 7.l and help in answering the set of research questions Q1: **can adaptive e-advertising lead to users' acceptance in terms of being usable and useful from a user perspective?, Q1.1: What features from adaptive hypermedia users would want to have in adaptive advertising and how are they related to**

users' acceptance?, Q1.2: How can user modelling contribute to users' acceptance of the e-advertising experience? Q1.3: What are the main sources of user information that can be explored for adaptive e-advertising? And Q3: What technology is acceptable for e-advertising?

Chapter 8

8. Conclusions and Recommendations for Future Work

All the research presented in this thesis aimed at addressing the research problem discussed in the beginning of the work, which is the *acceptance of e-advertising*.

The outcome of the research has eventually led to the exploration and creation of a novel research approach to deliver e-advertisements, using a technological method that has not been well-explored before. This approach is based on *classical adaptation features*, an updated set of *user modelling techniques* and the *use of different adaptation features* with an *Amazon-like appearance*, which, eventually, leads to users' *acceptance*.

The theoretical aspect has also been an imperative issue. Thus, a proper, structured, conclusive *theoretical framework* can be presented in the domain of e-advertising, as previous work has not been rooted in *adaptation theories*.

Finally, exploring different *data sources* and their reflection on the users' experience has also been investigated.

The research process has been based on a user-centric methodology for design and evaluation, among other methodological approaches, as described in Chapter 3. Hence, in each iteration users have contributed to the design and validation of the proposed research.

The research used an e-advertisement delivery tool called MyAds. It has been developed during the research for this thesis, based on the theoretical framework also developed and presented in this thesis.

MyAds has gone through two versions. The first version had basic adaptation and user modelling features, to explore the user acceptance of this kind of approach. Based on the feedback of the first version, the second version was developed, to include a more advanced and detailed set of features to provide e-advertisements.

This chapter aims at providing the final and conclusive remarks of the general research progress and demonstrating the overall research contribution. As it is a research-based work, there is space for enhancement. Thus, potential directions for future research will be presented.

The chapter is organised as follows. The first section will summarise the research process in relation to the research questions and answer these questions. The next section then discusses how well the proposed research objectives have been achieved. In Section 8.3, the difference between the proposed approach and other commercial - and research approaches is discussed, to better highlight the novelty of the work. Section 8.4 summarises the original contributions of the work presented in this thesis. Section 8.5 articulates the challenges and limitations faced throughout the work. Finally, Section 8.6 gives recommendations for future work and enhancements.

8.1. Answers to Research Questions

The research deliberated about the problem of rejected e-advertisements and tackled users' acceptance of e-advertisements, by providing the users with more personalised and adaptive e-advertisements. For the research problem to be investigated and evaluated, it was transformed into research questions. Each question addressed a certain and specific element of the research problem.

In the following, these research questions are revisited, and the answer to them (as derived from this thesis) is presented.

Q1. Can adaptive e-advertising lead to users' acceptance in terms of being usable and useful from a user perspective?

Answer: The overall answer resulting from the different experiments is yes. Adaptive hypermedia offers a comprehensive approach for the personalisation process. Not only does it provide a solid theoretical background, but it also contains different frameworks and systems that inspired the work presented in this thesis. Adaptive hypermedia can also be used with different methodologies, so the applicability of AH within different disciplines was smoothly achieved. Answering this question required 5 different experiments, to be properly addressed. The first experiment was an exploratory one that generated a generic requirements list, to be used for the proposed system, as discussed in details in Chapter 4. Next, this requirement list, alongside other features extracted from the state-of-the-art, was used to generate the first version of the MyAds adaptive e-advertisements system. The results from the follow-up experiments, using the MyAds system, suggested an overall acceptance of the approach, as well as stressed some drawbacks and issues to be considered in the updated version. Details of the experiment based on the first version of MyAds can be found in Chapter 5. Although the researcher had insight about the problems related to the first version of MyAds from this experiment, she further strengthed her ideas with another focus group experiment, to extract an updated requirements list, and features to be used within the updated version of MyAds. The outcome of the new set of requirements, alongside the output from the first MyAds experiment, allowed the researcher to formulate new ideas, in order to produce a novel system design and algorithms, as described in details in Chapter 6. The final two evaluations addressed this research question directly, by posing a high level hypothesis, stating that, on a general level, the answer for this research questions is “yes”. This hypothesis has been confirmed by our experiments, within the frame of the limitations described, as can be found in Chapter 7 Sections 7.5. Detailed answers to this question are found as answers to the following questions below.

Q1.1. What features from adaptive hypermedia users would want to have in adaptive advertising and how are they related to users’ acceptance?

Answer: The features that the users within the used sample stated to find acceptable are the *adaptive navigation support*, including link sorting, general guidance, link annotation and link hiding / showing. For general guidance, *buttons guidance* was found more acceptable than *stretch-text* and *shortcuts*. For adaptive navigation support, *hiding unnecessarily link* and the *logical grading of the recommendations* were found more acceptable than *link annotation*, *bandwidth adaptation* and *link sorting*. For adaptive *presentation*, extending the text was found more acceptable than hiding the text; however, both features generated relatively similar results. An *adaptive story line* was also found acceptable by the users, as well as the ability to allow both the adaptive and adaptable approach. All the system features, including the ones found highly acceptable or not at all acceptable, are described in Chapter 6. Results from the users' perception are discussed thoroughly in Chapter 7.

Q1.2. How can user modelling contribute to users' acceptance of the e-advertising experience?

Answer: User modelling is discussed from two angles: *richness* and *control*. Rich user models can contribute to e-advertising, through ordering, providing products based on user interests and constantly updating the user model, based on user behaviour and feedback. The results showed that, within the used sample, adding social features for users to give their direct feedback to the recommendations was highly accepted. From a user richness point of view, users didn't accept the features of collecting untraditional features, such as religion, as they possibly found them invading their privacy. From the angle of user control, allowing for scrutable user models, changing the recommendation location and appearance, all contribute to the acceptance, rather than simply relying on static user models, based on the initial data collected. The user model algorithms and features were discussed in details in Chapter 6 (Sections 6.5, 6.6 and 6.7). The evaluations of the user modelling features are described in Chapter 7.

Q1.3. What are the main sources of user information that users would want to have for adaptive advertising?

Answer: Both explicit data collected directly from the user and implicit data sources, such as the ones harvested from social networks and users' direct input on registration forms, have the same impact on user perception and acceptance. In the outcomes of this research, there was no clear distinction between the users' preferences about the initial data source, as long as they received the personalised content. Chapter 7 (Section 7.4) addresses this research question.

Q2. How can online adaptive advertising be generated theoretically?

Answer: Adaptive advertising is an interdisciplinary domain that intersects with different research areas. It can be generated theoretically by creating a theoretical framework, based on extensive study of the previous state of the art from various disciplines. In this work, extensive research was conducted, as illustrated in Chapter 2, to cover the domains of e-commerce, adaptive hypermedia, information retrieval, artificial intelligence and data mining.

Although the purpose of this question is theoretical, throughout the thesis, the theoretical framework created worked as the backbone for any technical implementation, and each component in the practical development was a reflection of one in the framework. The initial design of the framework was discussed in Chapter 4, followed by the first practical testing of it in Chapter 5. Chapter 6 addressed the pitfalls encountered in the previous chapter, allowing a new version of the system to be developed, for the final practical testing in Chapter 7.

Q3.What technology is acceptable for e-advertising?

Answer: Throughout the thesis, the technological approach used was the standalone system. This approach has proven to be useful and usable in some cases. However, other evaluations indicated that users were undecided about such approaches especially in relation to the usefulness and the amount of recommendations provided. Nevertheless, it was found to be more flexible and allowed for more control, compared to other e-commerce approaches. The use of this approach was the result of the exploratory study discussed in Chapter 4. The concrete evaluation of this technological approach was discussed in detail in Chapter 7.

8.2. Research Objectives

In order to answer the research questions, they have been mapped into six different Objectives (as in Chapter 1 Section 1.4). Below, the way each of these objectives was implemented in this thesis is explained.

Objective 1: *Conduct an extensive theoretical background study, to investigate the area of research that needs further exploring, by extracting the main gaps found in the literature and focusing on the contribution on this area.*

This objective has been addressed in the early stages of the research. However, it remained as a continuous process, as the need for updated knowledge emerged with each new aspect in the research. The chapter that includes the detailed relevant theoretical background and related work description is Chapter 2. It was not surprising that, while investigating the area of personalised e-advertisement, which it is derived from e-commerce, it was found that it is a highly competitive field. It is competitive from a commercial point of view, as the companies are looking into expanding their business, gaining more customers, keeping existing ones, increasing the click-through rate and decreasing the blocking of e-advertisements. On a research level, this area has also been explored, as it has been described as a "hot area" of research, because of its continuous evolution [169]. However, the research area has been heavily focused on user profiling (based on previous purchasing or browsing history), and providing recommendations based on filtering techniques, such as collaborative filtering and content-based filtering. User modelling techniques in relation to adaptation techniques have not been well explored in e-advertisements and no e-advertising platform is rooted in adaptation features and user modelling theory, compared with (for example) e-learning, such as the adaptation taxonomy proposed in [19, 23] and the user modelling standard approached described in [51, 64].

The limitations and gaps found in the theoretical background and related work served as a starting point for the research investigation and the following gaps have been highlighted. Personalised e-advertisements mostly do not utilise adaptive content, and therefore do not use adaptive hypermedia techniques, such as adaptive navigation support or adaptive presentation. Instead, it bases user profiling upon 'traditional' approaches (such as harvesting previous purchasing history, or using cookies). It therefore cannot construct rich user models that reflect upon the users' interests through implicit or explicit user models. Instead, most of the research focuses on banner advertisements, as the most common approach for e-advertisement, neglecting other types of e-advertisements, such as classified ads. Only commercial platforms, such as Craigslist, Gumtree and Groupon, have explored this model, albeit with minimum personalisation. The Information Retrieval (IR) literature provides a concrete theoretical and technical basis for this research, as the framework researched relies on different approaches for design, implementation and evaluation of IR.

Conducting and achieving research **Objective 1** provides background knowledge for answering the research questions **Q1**, Q1.1, Q1.2, Q1.3, **Q2 and Q3.**

Objective 2: *Conduct a series of experiments that investigate the appropriate approach and features to design adaptive e-advertisements, and then test the practical development of these features in an adaptive e-advertising system, addressing the acceptance of this form of ads in the targeted evaluations.*

This research objective has been implemented as an on-going process, since the beginning of the design phase in Chapter 4, to the final evaluations in Chapter 7. It has been achieved through five different experiments: two design-based ones and three implementation-based ones. The first experiment conducted was the exploratory study, found in Chapter 4. In the exploratory study, a *user centric design methodology* was deployed, with the help of different thinking techniques, such as the *six thinking hats* and *brainstorming*. Users generated a *requirement list*, as a qualitative outcome of the experiment. They also answered a questionnaire, which served as an indication of the platforms the users found popular. The results showed that users were in favour of using different adaptation techniques, adaptation approaches, as well as the general principle of building a standalone system that generates advertisements. The findings from this work have been published in [170]. Also, the results from the experiment, alongside with the related literature, have inspired the first version of the theoretical framework and system architecture, found in Chapter 4 (Section 4.7) and Chapter 5 (Section 5.2). The proposed framework has been published in [157].

The second experiment was the actual implementation of version one of MyAds. The users evaluated the delivery tool for adaptation. The system included basic user modelling and adaptation techniques, with the main focus on scaling user interests and giving recommendations based on gender, age and interests. The user model was constructed only from explicit data sources (as described in Chapter 5, Section 5.4). The results collected were from two different sources: the users' feedback via the questionnaires and the information harvested from the log-files, as described in Chapter 5 Section 5.5.4. The results were positive, as the users indicated that the approach was personal and easy to use. However, the main drawback was the look-and-feel of the system, some usability issues were raised as well as the need for more sophisticated user models and personalisation approaches. The results of this work were published in [160].

The third experiment was a focus group design experiment that aimed at re-visiting and improving the look-and-feel and functionality of the delivery tool, to ensure the best possible user experience. A focus group experiment was conducted, where users provided another set of requirements that they would like to explore in an adaptive e-advertisements system. Additionally, they highlighted the *Amazon* case study, as an example of a good platform to build upon. This was due especially to the look-and-feel of it, since it has been one of the most common and well-accepted platforms. The results of this work have been published in [171].

The fourth experiment was a large scale evaluation, for a rich and updated adaptive e-advertisement delivery system. The system had rich user modelling features, based on well-defined algorithms. It has also included rich adaptation techniques, as well as many of the adaptation techniques proposed by Brusilovsky [19, 47]. The techniques selected were the ones that fit with the application area of e-advertising. Some other techniques were found more suitable for other areas, such as e-learning. The results from the experiment showed which features were considered better than others, as described in detail in Chapter 7. For example, adaptive presentation (involving showing and hiding text and content) achieved better feedback than adaptive bandwidth and adaptive link annotation. The overall acceptance in terms of *usability* and *usefulness* has been mostly positive. Especially, users found the approach quite innovative, simple, easy to use and personalised. The main drawback was that the users criticised the lack of products available to be explored. Due to the fact that this is a research-based system, the crawlers within the system were not able to find enough free products to match the rich categories designed, so not many products could be collected. The free dataset that was found did not completely match the requirements of the system, detailed in Chapter 6, to have multiple categories, as the dataset offered many products, but with two or three categories only. Another drawback was that the implicit user modelling data source could not be evaluated during this experiment, as the connection between the Facebook API and the server was not working at the time. The results of this experiment are published in [172]. Although the results were positive, further evaluation of implicit data sources, as well as finding the correlation between implicit and explicit data sources, and determining if they have a different impact upon the users' experience, was required. Moreover, some adaptation features have not been explored enough in the previous experiment, so a follow-up experiment was required.

The fifth and final experiment was conducted through the same evaluation delivery system, MyAds, with the added Facebook login token and the activation of implicit user modelling features, allowing users to choose between two different login approaches. The login approaches included the direct user registration (system registration) and the login via Facebook (single sign-on OAuth). The results from this experiment were positive and indicated user acceptance of the implicit data modelling approach. However, as the two approaches, implicit and explicit, were evaluated separately, the results do not definitively show a preference towards one and the other. This experiment additionally indicated that usability was not as successful as usefulness. This meant that, whilst users found the adaptive features useful, they believed the implementation of these features can be improved. Furthermore, some non-traditional user modelling features were not highly appreciated by the users. These features include information about religion that was found unnecessary, possibly as users saw it as an invasion into their privacy. To address this, an explanation on the purpose of such data - here, to allow for special celebrations to be taken into account in the system - should possibly be added in the future.

This research objective has provided answers to the research questions, as follows in Table 8.1.

Table 8.1: Research Questions and their relationship to experiments

Research Question	Experiment	Comments
Q1	Experiments 1, 2, 3, 4 and 5	This is an overall question about adaptation features, so each experiment contributed to answering it.
Q1.1	Experiments 4 and 5	This question is more specific, for adaptation features that were well explored in experiment 4 and 5. The initial experiments were more generic.
Q1.2	Experiments 2, 4 and 5	This question is specific for user modelling features, which were well explored in experiments 4 and 5. However, experiment 2 did also include modelling features.
Q1.3	Experiment 5	This question is focused on the comparison between different data sources, which was only done in experiment 5.
Q2	Experiments 1, 2 and 4	The first two experiments allowed for a first development of the theoretical framework and architecture. As the initial implementation and design didn't achieve the necessary acceptance level, the need to revisit the whole theoretical background emerged, and eventually led to an enhanced framework, reflecting well on the users' experience, as evaluated in experiment 4.
Q3	Experiments 2, 4 and 5	All the system implementation evaluation experiments have adopted the standalone system approach. Therefore, this question is indirectly answered in a constructive way, as part of all implementation experiments.

Based on the above, it is shown that this research **Objective 2** did indeed provide answers to all the research questions, as initially planned, albeit on different levels.

Objective 3: *Propose a suitable (new or extended) theoretical framework/model for adaptive features necessary in advertising, such as a layered model.*

This research objective has been thoroughly explored via two different approaches. The first approach was through the extensive study and work on the related literature and theoretical background, to understand the different personalisation theories. In the area of e-commerce, personalisation theories are highly focused on the work of information retrieval. There has not been a distinct theoretical framework to depend on, as a solid background, compared with (for example) the many suggested for the area of e-learning. Therefore, the theoretical framework proposed was derived from the concepts and theories found in the domain of e-learning and general hypermedia, like the Dexter framework [65], by deploying them in the area of e-commerce.

In particular, the theoretical framework was formed based on the users' perceptions and input on the experiments. The first two experiments were critical to the formation of the theoretical framework, because it set the foundations for the research features and the communication and correlations between them. Experiment one, the exploratory study in Chapter 4 (Section 4.3), created an understanding of the different stakeholders, layers and personalisation approaches. Experiment two in Chapter 5 (Section 5.4) was also important, as the initial implementation of MyAds was based on the theoretical framework produced, and the reflection on the results had informed the redesign and formation of the framework. In experiment four in Chapter 7 (Section 7.3), the system was built on the latest updated version of the framework and the results reflected how well this framework had functioned in real-life applications.

Based on the above, research **Objective 3** has been implemented, in order to answer research Question **Q2**.

Objective 4*: Design, implement and update a dedicated system for testing the adaptive e-advertisement and measure the level of acceptance achieved by the end users through the evaluation of their subjective and objective feedback.*

This research objective has been realised via the designed and implemented versions of MyAds, serving as an adaptive delivery system for e-advertisements. MyAds is a standalone adaptive e-advertisement website that provides personalised products to users. This form of advertisements is not widely used in this domain. However, it is gaining more and more popularity, due to the rise of famous platforms, such as Groupon. As a result, the first live experiment, which was experiment two in Chapter 5 (Section 5.4), did evaluate the users' opinions about this approach. Experiment 4 and 5 in Chapter 7 had well-defined evaluation measures and thus addressed this objective directly. The results from all experiments were positive in many aspects. Especially, the users found this approach personal, easy to use and not as intrusive as other approaches. Therefore, **Objective 4** has been reached, in order to answer research Question **Q3**.

Objective 5*: Ensure that each research question is represented in the framework and in the delivery system.*

All the research questions have been mapped onto the research features and evaluations. Associated with this research objective, evaluations have been performed via three different experiments: experiment two, four and five found in Chapters 5 and 7. In each experiment, users were asked to evaluate their experience in using the adaptive delivery system MyAds. During the evaluation, they were asked questions involving the measures of *usability* and *usefulness*. Experiment 5 was more specific in this sense, as it also specifically collected answers about the measures of *satisfaction* and *desire*. Further quantitative feedback was collected from the users, as a selected focus group was interviewed. Log-files were studied and analysed, because they are a form of objective feedback, which allows for the study of the users' behaviour, without any subjectivity of perceptions. Therefore research **Objective 5** was addressed.

Objective 6: *Ensure that each step of the research is conducted based on established research methodology.*

This is one of the objectives that have influenced all other objectives. The methodological choices within this thesis formed the blue print for the research. The methodological approach was many divided into four different ones. The first one was the theoretical studies that have been fulfilled in Chapter 2, as the theoretical knowledge has been established the research could start going into the practical part. The second methodological approach was the user centric design methodology. Within this methodology both the design experiments were conducted. Other supportive approaches were used such as focus groups, brainstorming and six thinking hats to generate rich qualitative feedback. The qualitative feedback was analysed through the content qualitative feedback analysis method. For the practical experiment the user centric evaluation methodology was used. The method was use to evaluate the acceptance of users' in terms of the perceived usability and usefulness. In some very specific cases the needs and desires were examined. Based on the above Objective 6 has been addressed.

8.3. Comparison between MyAds and other Adaptive Systems

To further validate the proposed approach in this thesis, a theoretical comparison with other popular platforms is conducted. Because this is research-based work, it is difficult to compare it against commercial websites and services, as the amount of time (person-months) and money (funds) invested are extremely different. However, it is still valid that this comparison is performed, and it is important to highlight the contribution of the proposed work.

The main aspects that are compared are:

- The type of technological approach (as this is one of the discussed problems);
- The type of adaptation or personalisation presented;
- The user modelling features;
- The specific adaptation and personalisation features.

The comparison includes one research platform discussed extensively in Chapter 2, which is AdRosa by Kazienko and Adamski [15]. AdRosa is discussed because it is the one that focuses on adaptation using data mining techniques and focuses on user modelling. Although it uses traditional approaches of data collection and is different, as it uses banner e-advertisements, it is similar in the research approach. The commercial platforms included are Google, since it is one of the most common platforms for personalised recommendations and advertisements, and it also has a dedicated service to advertisements, making it one of the main competitors in the field [43]. Facebook is discussed, as one of the most successful platforms in recommending user personalised ads, due to the fact that it has a lot of information about its users [8]. Amazon is also one of the most successful e-commerce systems and provides personalised recommendations to users, so using it and comparing against its approach is important [40]. Groupon is the platform that has the least personalisation amongst the above. However, it is very important to this research as it has the same technological approach as the one adapted in this research. Groupon is a standalone system that provides recommendation (e-advertisements) based on geographical location.

With regards to the technological approach, MyAds serves as a standalone system, to present personalised products. It functions as a brokerage system and uses the registration approach and the Facebook login approach. Groupon is also a standalone system, to provide discounted products and personalised products and services. It also functions as a brokerage system and uses the registration approach as a way to start using the platform. However, AdRosa, whilst also research-based as well as a brokerage system, it is instead embedded as a plug-in within other websites, and advertises through banner advertisements. Facebook is a social network platform that is an intermediate space for companies to advertise, as well as providing personalised ads. Amazon is a warehouse and a traditional e-commerce website that conducts all its transaction within its environment. Finally, the famous Google is a search engine that works with advertisements via the recommendations it provides and via the sponsored search dialog on other websites.

User modelling and user profiling are a key aspect in personalisation for all the platforms. MyAds uses both implicit and explicit user modelling, via scaling user interests and considering all the information the user provides, to construct the model and recommend products. AdRosa focuses only on implicit modelling, by building the user profiles based on the users' behaviour online. It does not save any information about the user. The personalisation approach consists of data mining on the content and the usage, as well as filtering the ads, before presenting them to users. User modelling is quite simple in Groupon, as it is only based on geographical location, and it does not track user behaviour on the system, so it is quite static. The personalisation is based on different categories and does not change or update when the users perform different tasks on the platform. In Facebook, it is all about user modelling, as the users in social networks tend to volunteer a lot of information about themselves, opening the window for other companies to retrieve this information, personalise products to it and then re-present it on Facebook. It relies on cross-domain integration and external companies to provide these ads [173]. The way Facebook performs its personalisation is quite advanced and very business-oriented. Facebook sell users information to companies that are keen to provide personalised advertisements. These companies then target the users based on their interests. Google is another big player in the personalisation domain, as it works within the personalisation of recommendations – based on (amongst other things) the search terms users provide– and the personalisation of ads on both Google and other platforms that use the Google search box. It uses both AdSense and AdWords for keyword matching. The algorithms used involve filtering and ranking. Filtering is also popular in Amazon, as it uses both collaborative filtering and content-based filtering. Additionally, Amazon provides adaptive storylines, as it recommends any item as a set of other complementary and similar ones. For the user profiles, it can save products for later and create a wish list, which also affect the recommendations provided. However, the main influence in recommendations is the frequently searched and clicked-on items. MyAds clearly uses adaptive navigation support, adaptive presentation and adaptive bandwidth. As noticed from the above, MyAds combines features from popular platforms, especially from Amazon and Facebook, and also uses the technological approach of a stand-alone system, as the one of Groupon. However, it remains distinct, as it functions within a structured framework and uses research-based algorithms and rules, to determine the proper adaptation to the user.

A detailed and summarised description can be found in Table 8.2 below.

Table 8.2: Comparison between MyAds and other approaches

System / Features	**MyAds**	**AdRosa**	**AdSense/ AdWords**	**Facebook**	**Amazon**	**Groupon**
Type of technological approach	Standalone adaptive delivery system – products	Plug-in – banner advertisement / Remote open site agents	Plug-in – banner advertisement Search engine	Social Network – banner advertisements Advertising pages	Warehouse System – banner advertisements and products	Standalone personal product / service recommendation system - Brokerage system
Platform base	Research	Research	Commercial	Commercial	Commercial	Commercial
Adaptation / personalisation	Personalised products based on different variables – depending on how rich the user model is	Personalised ads based on previous browsing history	Three approaches: *AdSense for publisher* *AdSense for content* *AdWords*	*Sponsored ads* Do not change *Personalised ads* based on users' information and previous browsing history	*Sponsored ads* Do not change *Adaptive storyline* *Filtering techniques*	Personalises the recommendation based on location
User Modelling Features	*Explicit user modeling* through registration *Implicit user modeling* based on users' behaviour on	*Implicit user modelling* only – users' behaviour	*Previous search history* *Keywords matching*	*Implicit modelling through* previous browsing history *Explicit modelling* via directly asking for users' feedback on blocked ads	*Previous searched* and *click-on items* User profiles are only for completing sale	*Explicit user modelling* Request e-mail registration to send data Recommend based on location only
Adaptation / personalisation features	Adaptive navigation support Adaptive presentation Adaptive bandwidth	Uses content and usage mining to provide personalisation and filtering of content	Filtering through Ranking algorithms Keyword matching ephemeral personalisation, as it is done per session, or per search	Cross domain integration External services and 3d party-sites	Using collaborative and content based filtering to recommend items	No changing of system recommendations based on users' behaviour or clicked-on items

8.4. Original Contributions

The major contribution of this research is to answer the research question **Can adaptive e-advertising lead to users' acceptance, in terms of being usable and useful from a user perspective?** The research has extensively investigated theories, frameworks, techniques and technologies to provide both a theoretical and a technical answer for the question.

The theoretical contribution was through the structuring of a conclusive, well defined theoretical framework for adaptive e-advertisements. The theoretical framework was inspired from previous work in adaptation and pitfalls found in e-advertising and e-commerce frameworks.

In addition, it contributed to generating a dynamic architecture that is built upon the framework that can adapt to the different needs of e-advertising.

On the technical contribution level, a new and previously unexplored approach of a standalone system that works as an adaptive brokerage portal was explored. Two main novelty aspects have been covered by the technical approach; the user models and the adaptation techniques. The user models constructed in the proposed approach were based on algorithms that have been developed by the researcher to fit to the research needs. Also the user models included novel and new features that have not been used in other systems, such as sub-profiles, connecting events and celebrations with user profiles and scrutable user models. Furthermore, from a user modelling point of view, users' information has been updated dynamically using data mining techniques to adapt to their varying needs. The adaptation techniques for e-advertisement used were integrated in a novel way: specifically, there has been a logical grading of the recommendations. The logic of recommending products was based on the theoretical framework.

The research has also investigated the different data sources of information collected. Contrary to the traditional approaches of using the user's browsing history or cookies, the novelty in the proposed approach focused on collecting data from users, by retrieving their interests and tracking the user's behaviour within the system itself.

8.5. Challenges and Limitations

The challenges of this research have arisen since the early beginnings of the work. The area of e-commerce is wide and very challenging, due to the reality of the commercial competition. The comparison between the research approach and the commercial approach will always happen, regardless of the differences in the amount of investments, whether financially, mentally or in other resources. Moreover, commercial platforms are like plain "black boxes" – publications are few, and researchers can only guess what is going on there, unless the companies allow direct and privileged access to information.

Furthermore, this is an interdisciplinary research that combines two well developed areas: e-commerce and adaptive hypermedia. The combination of these two areas required a lot of theoretical background research in both domains, as well as related ones, in order for a coherent knowledge representation to be generated. However, the literature lacks a structured and well-developed approach to link e-advertising to adaptation, through theories, models and approaches. In fact, this thesis is one of the first attempts to provide this link.

Choosing to implement a standalone system was also a challenging aspect, due to the fact that, this is not a traditional approach for advertising – compared with frequently used technologies, such as banner advertisements and plug-in tools embedded within other websites. Justifying this selection and highlighting the contribution has always been an issue.

Datasets were also another obstacle, as this approach needed to collect as many products as possible, which at the same time also belonged to different categories, to create a rich database. Free datasets usually contained two to three categories only, with many products on them. Crawlers were blocked after harvesting some products from commercial websites, limiting the product data collection at times. This challenge has been reflected in the evaluations presented in the results chapter, as the users highlighted this issue as one of the least favoured features of the system.

Moreover, during the work on the thesis, social networks (such as Facebook) have started a stricter privacy policy about releasing their user information. As a result, no valuable information can be harvested for free, as used to be possible when this work was planned. Now, only specialised companies can currently buy the users' data, for other commercial uses, which clearly affects research-only projects. Moreover, this privacy policy does not protect the users, as their data can still be released – it merely helps to ensure new income revenues.

The sample size posed another limitation of the work. E-commerce is widely used online, so the number of users exposed is relatively large. The limitation was posed in getting the exact number that can reflect significantly over the population of internet users. Moreover, the demographics and different cultural backgrounds were also a limitation within the sample size. The researcher did not have access over different age groups with multi-cultural background users to provide a more comprehensive outcome. All the results generated were specifically addressed within the context of the sample size, in terms of number and demographics.

8.6. Recommendations for Future Work

It has been discussed in detail that the proposed approach is novel and extensively researched through the work on this thesis. However, there is always an area of improvement, especially in this rich and wide domain. Some of the recommendations for future work are as follows:

- Firstly, affiliating follow-up work with large companies, or research-oriented organisations, which are interested in adopting this approach to further develop their commercial potential, is useful. This would solve such issues as the need for a larger pool of products. Collaborating with a large scale warehouse online shop would allow for real-world shopping data to be used, and for the evaluations to measure whether such adaptive e-advertising improves revenues. Moreover, professional branding and launching can also be pursued.

- From a technical point of view, other more innovative, non-interfering, objective ways of collecting data from the users can be achieved, such as tracking users' eye movements, measuring the time spent browsing a product, and touch pad or mouse movement. Evaluations can be performed through monitored labs, where privacy issues are not a problem.
- In cooperating, the social element has been one of the initial ideas that there was not deployed to its full potential. Thus, social shopping and integrating with social networks and platforms could also be another avenue of further research.
- For evaluation purposes, it is worth exploring other measures, such as reliability, scalability and privacy. The privacy concern would also be worth exploring, especially with the amount of data available online.
- Cooperating with Social Network providers and building the system as an API on top of a popular platform can also be explored, due to the fact that these networks are highly exposed and have a huge amount of users.
- From an evaluation point of view, using Amazon's Mechanical Turk[8] for further extended large scale evaluations, so the data collected and analysed can have a higher degree of statistical significance, and potentially a higher degree of objectivity.

[8] https://www.mturk.com/mturk/welcome

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Annex I : XML files and Database Schema

An example of the XML File is as follow:


```
<?xml version="1.0" encoding="utf-8"?>
<!--
- phpMyAdmin XML Dump
- version 4.0.10deb1
- http://www.phpmyadmin.net
-
- Host: localhost
- Generation Time: Nov 12, 2014 at 04:04 PM
- Server version: 5.5.37-0ubuntu0.14.04.1
- PHP Version: 5.5.9-1ubuntu4.2
-->

<pma_xml_export version="1.0"
xmlns:pma="http://www.phpmyadmin.net/some_doc_url/">
  <!--
  - Structure schemas
  -->
  <pma:structure_schemas>
    <pma:database name="myads" collation="latin1_swedish_ci" charset="latin1">
      <pma:table name="events">
        CREATE TABLE `events` (
          `event_id` int(3) NOT NULL AUTO_INCREMENT,
          `user_id` int(3) NOT NULL,
          `event_name` varchar(100) NOT NULL,
          `event_date` date NOT NULL,
          PRIMARY KEY (`event_id`)
        ) ENGINE=InnoDB AUTO_INCREMENT=69 DEFAULT CHARSET=latin1;
      </pma:table>
      <pma:table name="products">
        CREATE TABLE `products` (
          `product_id` int(3) NOT NULL AUTO_INCREMENT,
          `category` varchar(100) NOT NULL,
          `product_name` varchar(300) NOT NULL,
          `price` varchar(100) NOT NULL,
          `description` text NOT NULL,
          `image` varchar(200) NOT NULL,
          `url` text NOT NULL,
          `meta` text NOT NULL,
          PRIMARY KEY (`product_id`)
        ) ENGINE=InnoDB AUTO_INCREMENT=57 DEFAULT CHARSET=latin1;
      </pma:table>
      <pma:table name="sub_profiles">
        CREATE TABLE `sub_profiles` (
          `subprofile_id` int(3) NOT NULL AUTO_INCREMENT,
          `user_id` int(3) NOT NULL,
          `name` varchar(100) NOT NULL,
          `electronics_intrest` int(3) NOT NULL,
          `furniture_intrest` int(3) NOT NULL,
          `beauty_intrest` int(3) NOT NULL,
          `toys_intrest` int(3) NOT NULL,
```

```
      `woman_intrest` int(3) NOT NULL,
      `men_intrest` int(3) NOT NULL,
      PRIMARY KEY (`subprofile_id`)
    ) ENGINE=InnoDB AUTO_INCREMENT=88 DEFAULT CHARSET=latin1;
  </pma:table>
  <pma:table name="users">
    CREATE TABLE `users` (
      `user_id` int(3) NOT NULL AUTO_INCREMENT,
      `fname` varchar(100) NOT NULL,
      `lname` varchar(100) NOT NULL,
      `birth` date NOT NULL,
      `gender` enum('1','0') NOT NULL,
      `email` varchar(100) NOT NULL,
      `password` varchar(200) NOT NULL,
      `occup` varchar(100) NOT NULL,
      `country` varchar(100) NOT NULL,
      `live` varchar(100) NOT NULL,
      `electronics_intrest` int(3) NOT NULL,
      `furniture_intrest` int(3) NOT NULL,
      `beauty_intrest` int(3) NOT NULL,
      `toys_intrest` int(3) NOT NULL,
      `woman_intrest` int(3) NOT NULL,
      `men_intrest` int(3) NOT NULL,
      `religion` varchar(100) NOT NULL,
      `color` varchar(100) NOT NULL,
      PRIMARY KEY (`user_id`)
    ) ENGINE=InnoDB AUTO_INCREMENT=247 DEFAULT CHARSET=latin1;
  </pma:table>
  <pma:table name="user_behaviour">
    CREATE TABLE `user_behaviour` (
      `user_id` int(3) NOT NULL,
      `product_id` int(3) NOT NULL,
      `behave` int(3) NOT NULL,
      `refuse_reason` int(3) NOT NULL
    ) ENGINE=InnoDB DEFAULT CHARSET=latin1;
  </pma:table>
  <pma:table name="user_feedback">
    CREATE TABLE `user_feedback` (
      `user_id` int(3) NOT NULL,
      `product_id` int(3) NOT NULL,
      `rate` int(3) NOT NULL,
      `comment` text NOT NULL
    ) ENGINE=InnoDB DEFAULT CHARSET=latin1;
  </pma:table>
  <pma:table name="user_log">
    CREATE TABLE `user_log` (
      `user_id` int(3) NOT NULL,
      `product_id` int(3) NOT NULL,
      `date` date NOT NULL
    ) ENGINE=InnoDB DEFAULT CHARSET=latin1;
  </pma:table>
 </pma:database>
</pma:structure_schemas>

<!--
```

```
- Database: 'myads'
-->

</table>
    <!-- Table users -->
    <table name="users">
        <column name="user_id">1</column>
        <column name="fname">Salameh</column>
        <column name="lname">Yasin</column>
        <column name="birth">2004-09-06</column>
        <column name="gender">0</column>
        <column name="email">salameh.yasin@yahoo.com</column>
        <column name="password">123</column>
        <column name="occup">student</column>
        <column name="country">JO</column>
        <column name="live">JO</column>
        <column name="electronics_intrest">10</column>
        <column name="furniture_intrest">2</column>
        <column name="beauty_intrest">8</column>
        <column name="toys_intrest">7</column>
        <column name="woman_intrest">5</column>
        <column name="men_intrest">1</column>
        <column name="religion">muslim</column>
        <column name="color">red</column>
    </table>
    <table name="users">
        <column name="user_id">2</column>
        <column name="fname">Salameh</column>
        <column name="lname">Yasin</column>
        <column name="birth">0000-00-00</column>
        <column name="gender">1</column>
        <column name="email">salameh.yaseen@gmail.com</column>
        <column name="password">123</column>
        <column name="occup">student</column>
        <column name="country">null</column>
        <column name="live">null</column>
        <column name="electronics_intrest">7</column>
        <column name="furniture_intrest">6</column>
        <column name="beauty_intrest">5</column>
        <column name="toys_intrest">3</column>
        <column name="woman_intrest">5</column>
        <column name="men_intrest">0</column>
        <column name="religion">muslim</column>
        <column name="color">white</column>
    </table>
    <table name="users">
        <column name="user_id">3</column>
        <column name="fname">Dana</column>
        <column name="lname">Qdah</column>
        <column name="birth">2014-10-24</column>
        <column name="gender">0</column>
        <column name="email">dana@gmail.com</column>
        <column name="password">123</column>
        <column name="occup">student</column>
        <column name="country">JO</column>
```

```
    <column name="live">JO</column>
    <column name="electronics_intrest">6</column>
    <column name="furniture_intrest">5</column>
    <column name="beauty_intrest">4</column>
    <column name="toys_intrest">3</column>
    <column name="woman_intrest">6</column>
    <column name="men_intrest">0</column>
    <column name="religion">muslim</column>
    <column name="color">white</column>
</table>
<table name="users">
    <column name="user_id">8</column>
    <column name="fname">salameh</column>
    <column name="lname">yas</column>
    <column name="birth">0000-00-00</column>
    <column name="gender">1</column>
    <column name="email">sss@ssss.com</column>
    <column name="password">123</column>
    <column name="occup">student</column>
    <column name="country">BS</column>
    <column name="live">BH</column>
    <column name="electronics_intrest">10</column>
    <column name="furniture_intrest">0</column>
    <column name="beauty_intrest">0</column>
    <column name="toys_intrest">0</column>
    <column name="woman_intrest">0</column>
    <column name="men_intrest">0</column>
    <column name="religion">muslim</column>
    <column name="color">white</column>
</table>
<table name="users">
    <column name="user_id">9</column>
    <column name="fname">aa</column>
    <column name="lname">aa</column>
    <column name="birth">0000-00-00</column>
    <column name="gender">0</column>
    <column name="email">dd@hotmail.com</column>
    <column name="password">123</column>
    <column name="occup">student</column>
    <column name="country">AM</column>
    <column name="live">AU</column>
    <column name="electronics_intrest">0</column>
    <column name="furniture_intrest">10</column>
    <column name="beauty_intrest">0</column>
    <column name="toys_intrest">0</column>
    <column name="woman_intrest">0</column>
    <column name="men_intrest">6</column>
    <column name="religion">muslim</column>
    <column name="color">white</column>
</table>
<table name="users">
    <column name="user_id">10</column>
    <column name="fname">rawan</column>
    <column name="lname">almasri</column>
    <column name="birth">0000-00-00</column>
```

```
    <column name="gender">0</column>
    <column name="email">rawanalmasri231@yahoo.com</column>
    <column name="password">password</column>
    <column name="occup">student</column>
    <column name="country">null</column>
    <column name="live">null</column>
    <column name="electronics_intrest">10</column>
    <column name="furniture_intrest">10</column>
    <column name="beauty_intrest">10</column>
    <column name="toys_intrest">10</column>
    <column name="woman_intrest">10</column>
    <column name="men_intrest">10</column>
    <column name="religion">muslim</column>
    <column name="color">white</column>
</table>
<table name="users">
    <column name="user_id">11</column>
    <column name="fname">sara</column>
    <column name="lname">alhmade</column>
    <column name="birth">0000-00-00</column>
    <column name="gender">0</column>
    <column name="email">soso_smart2012@hotmail.com</column>
    <column name="password">123456789</column>
    <column name="occup">student</column>
    <column name="country">JO</column>
    <column name="live">JO</column>
    <column name="electronics_intrest">5</column>
    <column name="furniture_intrest">9</column>
    <column name="beauty_intrest">9</column>
    <column name="toys_intrest">10</column>
    <column name="woman_intrest">10</column>
    <column name="men_intrest">9</column>
    <column name="religion">muslim</column>
    <column name="color">black</column>
</table>
```

The Database schema is as follows:

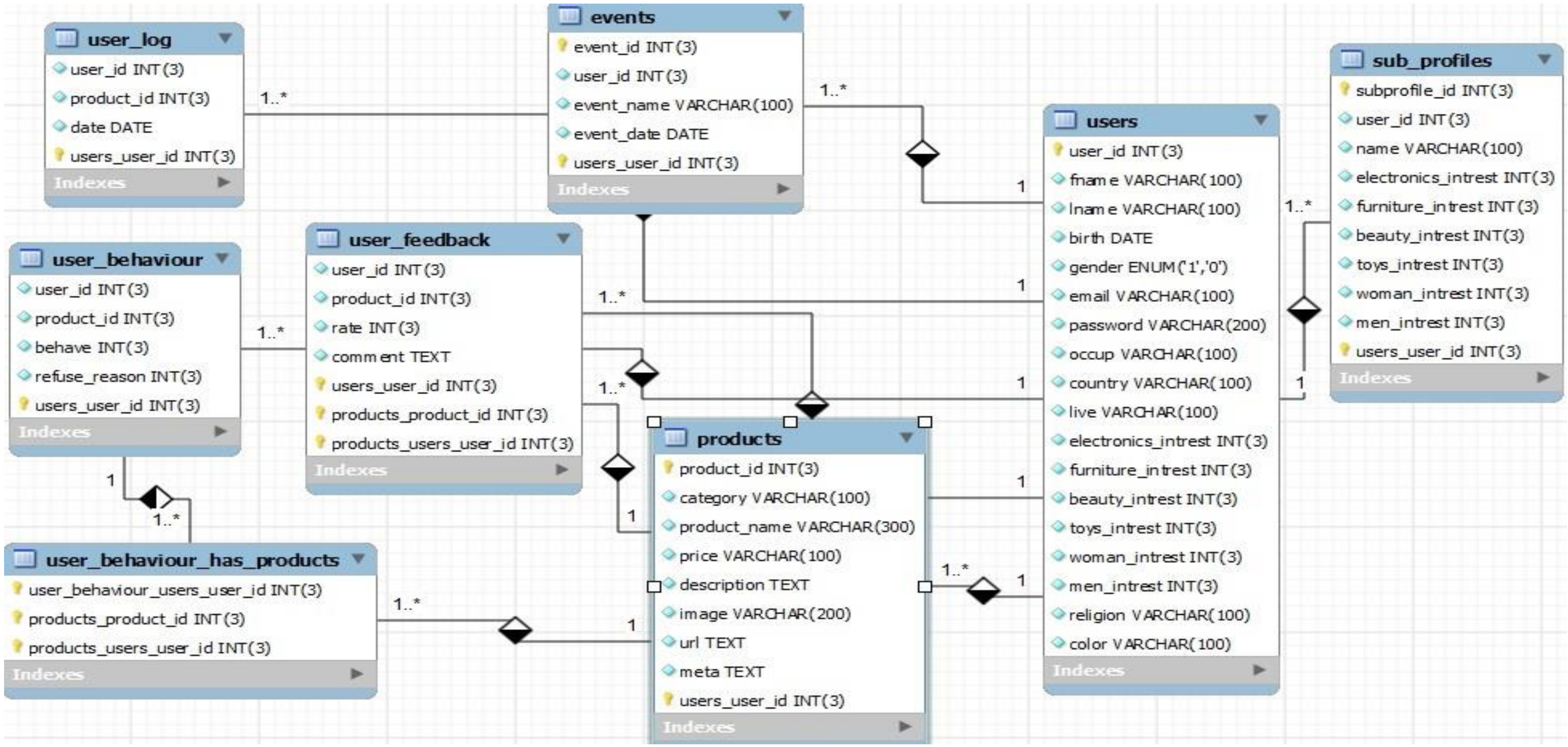

Figure I.1: Database Schema

Annex II: Snippet code for various algorithms

User modelling Algorithms and Snippet Code

Algorithm #1. ***Initialise the Explicit User Model***

```
Input: a set of all users' information collected through the registration process.
Output: procedure (initiate user model when n=1)
2:     if user = male [Exclude female categories] Else [Exclude male categories]
3:        For each interest = 1 to 5 calculate Euclidian Distance
4:           Distance = Sqr(pow(10 – [user interest value],2));
5:             if distance ≥ 5 then GENERATE kNN { Dis = 9-10 get 3 products of category, Dis = 7-8                get 2 products, Dis = 6 or 5 get 1 product} Else {exclude category}
6:             if favourite colour = "colour value" get product tagged "colour"
7:           if religion = "religion value" get product tagged "religion"
8:           Array_set = SELECT * FROM products WHERE category = category
9:           print 9 recommendations,  end for, end procedure
```

```php
<?php require_once 'items.php'; ?>
<?php
// UM
if(isset($_GET['redirect'])){
    $userId = $_SESSION['user_id'];
    $userModel = new user();
    $userSet = $userModel->fetchById($userId);
    $userSet = $userSet[0];
    $gender = $userSet['gender'];
    $catRecomended = array();
    // Generic Select Function
        function maleProductWeight($category,$limit){
            global $itemModel;
            $sql = "SELECT * FROM products WHERE category = '$category' "
                    . "AND product_id NOT IN(32,33,20,21,24,28) ORDER BY RAND() LIMIT $limit";
            return $itemModel->fetchBySql($sql);
        }
        function femaleProductWeight($category,$limit){
            global $itemModel;
            $sql = "SELECT * FROM products WHERE category = '$category'"
                    . "AND product_id NOT IN(22,23,25,30,31) ORDER BY RAND() LIMIT $limit";
            return $itemModel->fetchBySql($sql);
        }
    // remove unnecassary category according to gender
    if($gender == 1){
       // male Check
        // calculate Euclidian distance
        $electronics = sqrt(pow(10 - $userSet['electronics_intrest'],2));
        $furniture   = sqrt(pow(10 - $userSet['furniture_intrest'],2));
```

```
    $beauty      = sqrt(pow(10 - $userSet['beauty_intrest'],2));
    $toys        = sqrt(pow(10 - $userSet['toys_intrest'],2));
    $men         = sqrt(pow(10 - $userSet['men_intrest'],2));
    // generate Recomendation Category Arrays
    if($electronics >=0 && $electronics <=5){
       $catRecomended['electronics'] = $electronics;
    }
    if($furniture >=0 && $furniture <=5){
       $catRecomended['furniture'] = $furniture;
    }
    if($beauty >=0 && $beauty <=5){
       $catRecomended['beauty'] = $beauty;
    }
    if($toys >=0 && $toys <=5){
       $catRecomended['toys'] = $toys;
    }
    if($men >=0 && $men <=5){
       $catRecomended['men'] = $men;
    }
    // calculate product weight & apperance frequency
    asort($catRecomended);
    $catCount = count($catRecomended);
    if($catCount == 5){
       $electSet  = maleProductWeight('electronics', 1);
       $furnSet   = maleProductWeight('furniture', 1);
       $beautySet = maleProductWeight('beauty', 1);
       $toysSet   = maleProductWeight('toys', 1);
       $menSet    = maleProductWeight('men', 1);
       $calcultedProducts = array_merge($electSet,$furnSet,$beautySet,$toysSet,$menSet);
    }elseif ($catCount == 4) {
       // find the Strongest Category
       $forthOption = array_keys($catRecomended);
       $setOne   = maleProductWeight($forthOption[0], 3);
       $setTwo   = maleProductWeight($forthOption[1], 1);
       $setThree = maleProductWeight($forthOption[2], 1);
       $setFour  = maleProductWeight($forthOption[3], 1);
       $calcultedProducts = array_merge($setOne,$setTwo,$setThree,$setFour);
    }elseif ($catCount == 3) {
       // find the Strongest Category
       $threeOption = array_keys($catRecomended);
       $setOne   = maleProductWeight($threeOption[0], 3);
       $setTwo   = maleProductWeight($threeOption[1], 2);
       $setThree = maleProductWeight($threeOption[2], 1);
       $calcultedProducts = array_merge($setOne,$setTwo,$setThree);
    }elseif ($catCount == 2) {
       // find the Strongest Category
       $twoOption = array_keys($catRecomended);
       $setOne   = maleProductWeight($twoOption[0], 3);
       $setTwo   = maleProductWeight($twoOption[1], 3);
       $calcultedProducts = array_merge($setOne,$setTwo);
    }elseif ($catCount == 1) {
       $firstOption = array_keys($catRecomended);
       $setOne   = maleProductWeight($firstOption[0], 6);
       $calcultedProducts = $setOne;
    }
}else{
  //female Check
  // calculate Euclidian distance
    $electronics = sqrt(pow(10 - $userSet['electronics_intrest'],2));
    $furniture   = sqrt(pow(10 - $userSet['furniture_intrest'],2));
    $beauty      = sqrt(pow(10 - $userSet['beauty_intrest'],2));
    $toys        = sqrt(pow(10 - $userSet['toys_intrest'],2));
    $woman       = sqrt(pow(10 - $userSet['woman_intrest'],2));

    // generate Recomendation Category Arrays
    if($electronics >=0 && $electronics <=5){
       $catRecomended['electronics'] = $electronics;
```

```
    }
    if($furniture >=0 && $furniture <=5){
        $catRecomended['furniture'] = $furniture;
    }
    if($beauty >=0 && $beauty <=5){
        $catRecomended['beauty'] = $beauty;
    }
    if($toys >=0 && $toys <=5){
        $catRecomended['toys'] = $toys;
    }
    if($woman >=0 && $woman <=5){
        $catRecomended['woman'] = $woman;
    }

    // calculate product weight & apperance frequency
    asort($catRecomended);
    $catCount = count($catRecomended);
    if($catCount == 5){
        $electSet  = femaleProductWeight('electronics', 1);
        $furnSet   = femaleProductWeight('furniture', 1);
        $beautySet = femaleProductWeight('beauty', 1);
        $toysSet   = femaleProductWeight('toys', 1);
        $womanSet  = femaleProductWeight('woman', 1);
        $calcultedProducts = array_merge($electSet,$furnSet,$beautySet,$toysSet,$womanSet);
    }elseif ($catCount == 4) {
        // find the Strongest Category
        $forthOption = array_keys($catRecomended);
        $setOne   = femaleProductWeight($forthOption[0], 3);
        $setTwo   = femaleProductWeight($forthOption[1], 1);
        $setThree = femaleProductWeight($forthOption[2], 1);
        $setFour  = femaleProductWeight($forthOption[3], 1);
        $calcultedProducts = array_merge($setOne,$setTwo,$setThree,$setFour);
    }elseif ($catCount == 3) {
        // find the Strongest Category
        $threeOption = array_keys($catRecomended);
        $setOne   = femaleProductWeight($threeOption[0], 3);
        $setTwo   = femaleProductWeight($threeOption[1], 2);
        $setThree = femaleProductWeight($threeOption[2], 1);
        $calcultedProducts = array_merge($setOne,$setTwo,$setThree);
    }elseif ($catCount == 2) {
        // find the Strongest Category
        $twoOption = array_keys($catRecomended);
        $setOne   = femaleProductWeight($twoOption[0], 3);
        $setTwo   = femaleProductWeight($twoOption[1], 3);
        $calcultedProducts = array_merge($setOne,$setTwo);
    }elseif ($catCount == 1) {
        $firstOption = array_keys($catRecomended);
        $setOne   = femaleProductWeight($firstOption[0], 6);
        $calcultedProducts = $setOne;
    }
}   }
```

Algorithm #2. ***Track User Behaviour***

```
Input: a set of all the user's behaviour, clicked on – ads,
frequent search items
Output: procedure (update user model when n > 1)
2:    fetch "User_Session" // calculate Product Session
Array
3:      For each product =0; product <total number product;
Product++)
4:      [product_id = logSet[product][product_id];
    product_category = logSet[product][category];
    product_meta_tag =logSet[product][meta_tag]; ]
5:      Calculate TF/IDF
             {output .= (total_retrevied_documents
/value_certain_term_appearnce) * log(total / value,10);] Get
output
6:       Calculate Jaccard Similarity between output,
foreach (itemFrequency ≥ value)    Jaccard_Similarity =
((tf_idf_value ∩ total number)/ (tf_idf_value U total
number))
7:     Get products with highest out,   Recommend products
8:     End for, End Procedure
```

```php
<?php require_once 'includes/header.php'; ?>
<?php require_once 'includes/userlog.php'; ?>
<?php require_once 'includes/items.php'; ?>
<?php
$userLog = new userLog();
$logSet  = $userLog->fetchById($_SESSION['user_id']);
$total = count($logSet);
// calculate Product Session Array
for($i=0;$i<$total;$i++)
// calculate repeated products in Session
foreach ($product as $item){
   $items[] = $item['product_id'];
}
$itemFrequency = array_count_values($items);
// calculate TF
$product = new product();
$output = '';
foreach ($itemFrequency as $key=>$value){
   $productName = $product->fetchNameById($key);
   $output .= "<br><p><u>$productName : </u></p>";
   $output .= " <p>(TF) = ";
   $output .= $total / $value;
   $output .= "</p>";
   $output .= "<p>";
   $output .= " (IF) = ";
   $output .= log($total / $value,10);
   $output .= "</p>";
   $output .= " <p>(TFIDF) = ";
   $output .= ($total / $value) * log($total / $value,10);
   $output .= "</p><br>";
}
```

```
// Jaccerd Similarity:
$joutput = " ";
$recommended = array();
foreach ($itemFrequency as $key2=>$value2){
   $tfidf = ($total / $value2) * log($total / $value2,10);
   if($tfidf > 1){
    $productName = $product->fetchNameById($key2);
    $jcarrt = 4/($total * 4);
    $joutput .= "<p>$productName  = ";
    $joutput .= "$jcarrt</p><br>";
    $recommended[] = $key2;
   }
}

if(isset($recommended)){
    foreach ($recommended as $recomProduct){
        $productSet[] = $product->fetchById($recomProduct);
    }
}
?>
<div class="main">
    <div class="wrap">
        <div style="clear: both"></div>
        <div>
            <h3 class="m_3" style="margin-top: 100px;color: green">TFIDF : </h3>
        </div>
            <?php
            if(isset($output)){
                echo $output;
            }

            ?>
        <div>
            <h3 class="m_3" style="margin-top: 100px;color: green">Jaccerd Similarity: </h3>
            <?php
            if(isset($output)){
                echo $joutput;
            }

            ?>
        </div>
        <?php if(isset($productSet)) : ?>
        <!-- Start Similar Products Slider -->
                <div class="clients">
                    <h3 class="m_3">Other Suggestions According to your interest</h3>
                    <div class="nbs-flexisel-container">
                        <div class="nbs-flexisel-inner">
                            <ul id="flexiselDemo3" class="nbs-flexisel-ul" style="left: -178.8px; display: block;">
            <?php foreach ($productSet as $image) : ?>
                   <a href='product.php?id=<?php echo $image[0]['product_id'] ?>'>
                   <li class='nbs-flexisel-item' style='width: 178.8px;'>
                   <img src='items/<?php echo  $image[0]['image'] ?>'></li></a>
            <?php endforeach; ?>
                            </ul>
                        </div>
                    </div>
                    <script type="text/javascript">
                        $(window).load(function() {
                            $("#flexiselDemo1").flexisel();
                            $("#flexiselDemo2").flexisel({
                                enableResponsiveBreakpoints: true,
                                responsiveBreakpoints: {
                                    portrait: {
                                        changePoint: 480,
                                        visibleItems: 1
                                    },
                                    landscape: {
```

```
                        changePoint: 640,
                        visibleItems: 2
                    },
                    tablet: {
                        changePoint: 768,
                        visibleItems: 3
                    }
                }
            });

            $("#flexiselDemo3").flexisel({
                visibleItems: 5,
                animationSpeed: 1000,
                autoPlay: true,
                autoPlaySpeed: 3000,
                pauseOnHover: true,
                enableResponsiveBreakpoints: true,
                responsiveBreakpoints: {
                    portrait: {
                        changePoint: 480,
                        visibleItems: 1
                    },
                    landscape: {
                        changePoint: 640,
                        visibleItems: 2
                    },
                    tablet: {
                        changePoint: 768,
                        visibleItems: 3
                    }
                }
            });
        });
    </script>
    <script src="js/jquery.flexisel.js" type="text/javascript"></script>
  </div>
  <!-- End of Slider -->
 <?php endif; ?>
 </div>
</div>
<?php require_once 'includes/footer.php'; ?>
```

Adaptation Algorithms and Snippet Code

Algorithm #3. ***Create Storyline***

```
Input: a set of all users' information from the UM.
Output: procedure creates storyline for users
1:   Launch function = NavigationSupport.Guidance{  /setting
up the function.navigation support
32:     foreach item = i sort in descending order based on
output of kNN
3:                 i++;
4:                  Print product ={item['product_id']}
title={item['meta_tag']
                     Display "stretch-text" // general
guidance navigation support
5:                  if ($i % 3 == 1)  // Number of button
clicked
                        { show
6:                      "newbutton" id='like'>I Do not Like
Any< if click ==true, select new
                          products, else {keep list}
7:                       "newbutton">Go To Home Page< if
click ==true, redirect to "index.
                          Page", else  {keep list}
8:                       "newbutton">See Different Set< if
click ==true, select new products,
                          else {keep list}} end if,  End for
}
9:    Get bandwidth=value, use Lazy loader,  Get related
items ==JQuery calls }
10:  end procedure }
```

```
<?php require_once 'includes/items.php'; ?>
<?php require_once 'includes/header.php'; ?>
<?php require_once 'includes/userlog.php'; ?>
<?php require_once 'includes/userBehaviour.php'; ?>
<?php require_once 'includes/subprofile.php'; ?>
<?php
$product_id = $_GET['id'];
$itemModel  = new product();
$productSet = $itemModel->fetchById($product_id);
$category   = $productSet[0]['category'];
$imageSet = $itemModel->fetchByCat($category);
// log user actions
$userLog = new userLog();
$userLog->productId = $product_id;
$userLog->userId = $_SESSION['user_id'];
$userLog->insert();

// log user behavoiur
if (isset($_POST['submit'])) {
    $behave = new userBehaviour();
    $behave->userId = $_SESSION['user_id'];
    $behave->productId = $product_id;
    $behave->behave = isset($_POST['behave']) ? $_POST['behave'] : 0;
    $behave->refuseReason = isset($_POST['never']) ? $_POST['never'] : 0;
    $behave->insert();
}
// see all subprofiles
$sub = new subProfile();
$subSet = $sub->fetchAll($_SESSION['user_id']);
?>
<script>
    $(document).ready(function() {
        $("#buy").click(function() {
            $("#watchme").show('slow');
        });
        $("#consider").click(function() {
            $("#watchme").hide('slow');
            $("#considerpara").show('slow');

        });
        $("#never").click(function() {
            $("#watchme").hide('slow');
            $("#considerpara").hide('slow');
            $("#neverpara").show('slow');

        });

    });

</script>
<hr>
<div class="main">
    <div class="wrap">
        <ul class="breadcrumb breadcrumb__t">
            <a href="index.php" class="home">Home</a> / <a href="index.php?cat=<?php echo
$productSet[0]['category'] ?>" class="home"><?php echo $productSet[0]['category'] ?></a> /
        </ul>
        <div class="section group">
            <div class=" span_2_of_2">
                <h2 class="head"><?php echo $productSet[0]['product_name'] ?></h2>

                <div class="grid images_3_of_2">
                    <div id="container">
                        <div id="products_example">
                            <div id="products">
```

```
                <img src='items/<?php echo $productSet[0]['image'] ?>' width='200' height='350' />
                <div>
                    <button class="newbutton">Share It</button>
                </div>
            </div>
        </div>
    </div>
</div>
<div class="desc1 span_3_of_2">
    <h3 class="m_3"><?php echo $productSet[0]['product_name'] ?></h3>
    <p class="m_text2"><?php echo $productSet[0]['description'] ?></p>
    <div class="btn_form">
        <form action="product.php?id=<?php echo $product_id ?>" method="post">
            <p><input type="radio" value="1" name="behave" id="buy"> I Will definetly consider buy this
product .</p>
            <p><input type="radio" value="2" name="behave" id="consider"> I May consider buy this
product .</p>
            <p><input type="radio" value="3" name="behave" id="never"> I Will never buy this product
.</p>
            <div id="watchme" style="margin:40px 0;display: none">
                <p class="m_5"><?php echo $productSet[0]['price'] ?></p>
                <p class="m_5"><a href="<?php echo $productSet[0]['url'] ?>" target="blank"><u>Product
Link</u></a></p>
                <h3 class="m_3" style="margin-top:20px;">Why This Recommended for you ?</h3>
                <p class="m text">Based in your Specified Interest </p>
                <p>In <?php echo $productSet[0]['category'] . " (" . $productSet[0]['meta'] . ")" ?></p>
            </div>
            <div id="considerpara" style="margin:40px 0;display: none">
                <p class="m_5"><?php echo $productSet[0]['price'] ?></p>
                <p class="m_5"><a href="<?php echo $productSet[0]['url'] ?>"><u>Product
Link</u></a></p>
            </div>
            <div id="neverpara" style="margin:20px;display: none">
                <h3 class="m_3" style="margin-top:20px;">Can you please tell us why?</h3>
                <p><input type="radio" value="1" name="never">It wasnt to my taste . </p>
                <p><input type="radio" value="2" name="never">This is not i had in mind. </p>
                <p><input type="radio" value="3" name="never">I dont need this product. </p>

            </div>
            <br>
            <input value="Submit" title="" type="submit" name="submit">
        </form>
    </div>
</div>
<div class="clear"></div>
<div class="clients">
    <div style="float:left">
        <h3 class="m_3">Is This product for the sub profile you selected  ? </h3>
    </div>
    <div style="float:left">
        <a href="" style="margin:10px;"><button class="newbutton">YES</button></a>
        <a href="" style="margin:10px;"><button class="newbutton">No</button></a>
        <select class="register_account">
            <option>Please choose your sub profile</option>
            <?php
            if(isset($subSet) && count($subSet) !=0 ){
                foreach ($subSet as $subprofile){
                    echo "<option>{$subprofile['name']}</option>";
                }
            }
            ?>
        </select>
    </div>
    <div style="clear:both"></div>
</div>
<!-- Start Similar Products Slider -->
<div class="clients">
```

```
<h3 class="m_3">Other Suggestions According to your interest</h3>
<div class="nbs-flexisel-container">
    <div class="nbs-flexisel-inner">
        <ul id="flexiselDemo3" class="nbs-flexisel-ul" style="left: -178.8px; display: block;">
            <?php
            foreach ($imageSet as $image){
                echo "<a href='product.php?id={$image['product_id']}'>"
                . "<li class='nbs-flexisel-item' style='width: 178.8px;'>"
                     . "<img src='items/{$image['image']}'></li></a>";
            }
            ?>

        </ul>

    </div>
</div>
<script type="text/javascript">
    $(window).load(function() {
        $("#flexiselDemo1").flexisel();
        $("#flexiselDemo2").flexisel({
            enableResponsiveBreakpoints: true,
            responsiveBreakpoints: {
                portrait: {
                    changePoint: 480,
                    visibleItems: 1
                },
                landscape: {
                    changePoint: 640,
                    visibleItems: 2
                },
                tablet: {
                    changePoint: 768,
                    visibleItems: 3
                }
            }
        });

        $("#flexiselDemo3").flexisel({
            visibleItems: 5,
            animationSpeed: 1000,
            autoPlay: true,
            autoPlaySpeed: 3000,
            pauseOnHover: true,
            enableResponsiveBreakpoints: true,
            responsiveBreakpoints: {
                portrait: {
                    changePoint: 480,
                    visibleItems: 1
                },
                landscape: {
                    changePoint: 640,
                    visibleItems: 2
                },
                tablet: {
                    changePoint: 768,
                    visibleItems: 3
                }
            }
        });

    });
</script>
<script src="js/jquery.flexisel.js" type="text/javascript"></script>
</div>
<!-- End of Slider -->
<div class="toogle">
<div class="btn_form">
```

```
                    <form action="feedback.php?product_id=<?php echo $product_id; ?>" method="post"
style="border: 2px solid #ccc;padding: 10px">
                        <h3 class="m_3">Feedback</h3>
                        <div style="float:left">
                            <h3>Rate :</h3>
                        </div>
                        <div>
                            <input name="star1" type="radio" class="star" value="1"/>
                            <input name="star1" type="radio" class="star" value="2"/>
                            <input name="star1" type="radio" class="star" value="3"/>
                            <input name="star1" type="radio" class="star" value="4"/>
                            <input name="star1" type="radio" class="star" value="5"/>
                        </div>
                        <div style="clear: both"></div>
                        <br>
                        <textarea rows="5" cols="60" name="comment" placeholder="Comment \ Review
Tags"></textarea>
                        <br><br>
                        <input value="Submit" type="submit" name="submit">
                    </form>
                </div>
            </div>
            <div class="toggle">
                <div style="float:left;margin-bottom: 20px;">
                    <h3 class="m_3">Do you like to go back to your product list ? </h3>
                </div>
                <div style="float:left">
                    <a href="index.php?redirect=true" style="margin:10px;"><button
class="newbutton">YES</button></a>
                    <a href=""style="margin:10px;"><button class="newbutton">No</button></a>
                </div>
                <div style="clear:both"></div>
                <div style="float:left">
                    <h3 class="m_3">Do you like to start new search ? </h3>
                </div>
                <div style="float:left">
                    <a href="index.php?redirect=true" style="margin:10px;"><button
class="newbutton">YES</button></a>
                    <a href=""style="margin:10px;"><button class="newbutton">No</button></a>
                </div>
                <div style="clear:both"></div>


            </div>
        </div>
    </div>
  </div>
</div>
<?php require_once 'includes/footer.php';
```