An Adaptive e-Advertising Delivery Model: The AEADS Approach

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Abstract: e-Advertising adaptation plays a main role in delivering personalised advertisements to internet users. In this time of the Internet revolution, many websites need to use the adaptation process to adapt their advertisements. This paper focuses on a lightweight delivery model, easy to integrate into wide range of existing websites. This model includes three engines, in order to deliver personlised advertisements to Internet users easily. It also presents a study that assesses the effectiveness of a tool based on this model, called AEADS, via a trial run of a model prototype with users.

1 INTRODUCTION

Providing suitable content and products for different users meets the needs of both businesses and customers. It increases business profit and allows greater customer satisfaction. Recently, there has been a rapid growth of e-commerce and web applications (Abu-Taieh, 2009; Al Qudah et al., 2014; Kazienko and Adamski, 2007), and thus the improvement of the delivery systems is important, to match such growth. E-commerce has given customers the power to choose from a variety of options offered by different companies, and thus competition has emerged (Puntambekar, 2008). Adaptation attempts to match content and products to profiles of targeted customers. Delivering adaptive advertising will support this process, by both maximising the profits of businesses and increasing customer satisfaction. Still, adaptation has not been applied consistently and effectively in e-advertising. Moreover, whilst businesses large and small may wish to add adaptive advertisement to their sites, the process currently is too cumbersome for an easy transition. Currently, there is no solution that can be added in a lightweight fashion to existing websites of businesses. Thus, our research targets the following main research question:

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

To answer this question, we recommend a collection of tools, *Adaptive e-Advertising Delivery System (AEADS)*, which facilitate the creation of adaptive e-advertising. This paper focuses on a vital component in adaptive delivery systems, the *Delivery Model (DM)*. Here we propose a lightweight DM, with a set of features that we consider essential to adaptive advertising, and which can be easily added to wide range of static commercial websites. This model is implemented and evaluated with real Internet users and customers.

2 RELATED RESEARCH

Many methods of modelling delivery specification have been proposed. The following were selected based on their similarity to AEADS.

ADE (Scotton et al., 2011) is written in Java, using Servlets and JSP technology, and can be run on a standard Tomcat server, to display any content which can be described using standard web mark-up languages. The delivery processes in ADE are located in the adaptation and presentation layers. Based on user model, domain model, and adaptation strategies, ADE delivers the appropriate course contents for users. ADE is able to adapt to the type of device being used. In addition, ADE uses AJAX, to track the network status and update the bandwidth variable in the user profile, to tailor adaptation.

AdROSA (Kazienko and Adamski, 2007) extracts knowledge stored in the web content page and the historical user sessions, and recent behaviour of online users, via data-mining techniques. Banners visited by users are stored in the form of vectors of

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user behaviour. The delivery part of AdRosa applies advertising policy and priority features to advertisements alongside user behaviour, to display the most appropriate advertisements for each user.

Based on the LAOS framework (Cristea and de Mooij, 2003), the MyAds system (Al Qudah et al., 2014) encapsulates the delivery part in the adaptation model - where the connection between the user model and the appropriate advertisement is established - and the presentation model - where the personalised advertisement is displayed to the users. The Personalisation and Decision Making Engine delivers adaptive advertisements, matching the UM with the appropriate product, to show adaptive advertisements to each user.

Although ADE delivers adaptation content efficiently, it mainly targets course adaptation, meaning that there are certain limitations for its use in the delivery of adaptive advertisements. The parameters applied to introduce adaptive advertisements and adaptive courses are different, since, for example, the course adaptation depends mainly on experience, as well as has a more narrative structure. Moreover, it is a standalone system and cannot be easily incorporated into existing websites. The AdROSA and MyAds systems are designed to be used in the portal model of advertising, since they match the publishers' interests and many advertisers' interests. The delivery tool in AEADS controls and adapt advertisements located and owned by businesses. Finally, the delivery engine in AEADS is superior to AdROSA and MyAds, as it allows businesses to control the number and location of advertisements on each webpage automatically. Additionally, it can be integrated easily into a wide range of websites.

3 AUTHORING ADAPTIVE E-ADVERTISING

The overall Authoring model of Adaptive e-Advertising, informed by prior research, includes:

1. The *Domain Model* - used by businesses to organise, label and categorise advertisements (Qaffas and Cristea, 2014b).
2. The *Adaptation Model* (Qaffas and Cristea, 2014a) - enabling businesses to adapt the advertisements they have organised, using the domain model tool for their customers’ needs.
3. The *User Model* - representing the personal data of an individual user, to base adaptive changes on system behaviour (Qaffas and Cristea, 2015).

These tools are used to author personalised advertisements via XML files, used by the delivery model to deliver personalised advertisements.

4 DELIVERING ADAPTIVE E-ADVERTISING

The *delivery model (DM)* (Figure 1) is resident on the same website server, in order to deliver advertisements to Internet users. This part parses the contents of the XML files and uses adaptation strategies to send appropriate advertisements to the respective users, based on a user model. It consists of three engines: *inference*, *decision* and *modifier*.

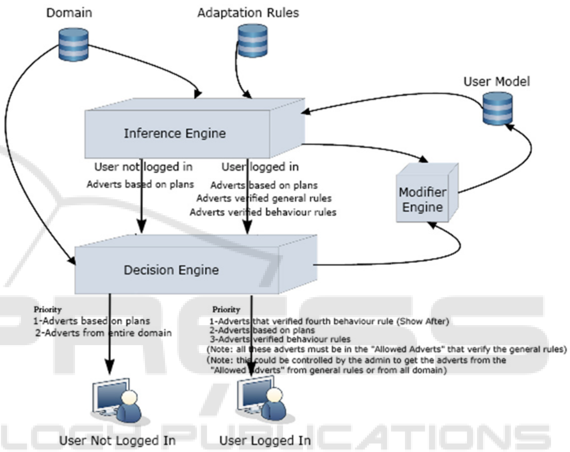

Figure 1: Delivery Engines of the AEADS System.

4.1 The Inference Engine

The *inference engine* gathers data from the domain model, the adaptation model and the user model, to infer multiple sequences of advertisements, to be sent to the decision engine. First, it checks whether or not the current user is logged in. If not, the inference engine only applies the *plan recognition* process. This will depend on the *plan libraries*, which the businesses create in the authoring part. The inference engine checks the clicked items and the plan libraries, to acquire a sequence of advertisements to send to the decision engine (Figure 2). An XML file contains the library of plans. Using XML files should enhance the portability, easy processing and generalisation of the system, as discussed. Each node represents an advertisement, and inside this node, an edge will be inserted with the advertisement ID referring to the linked advertisement. The simple structure of the XML file allows authors to easily add plans.

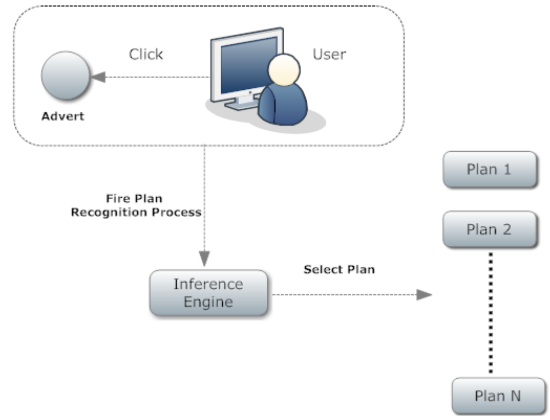

Figure 2: Plan Recognition in the Inference Engine.

If the current user is logged in, then *general rules* will be applied by the inference engine, to assign a group of advertisements to the current user, according to features, e.g., gender and age - based on stereotypes created. This data is sent to the modifier engine, to update the user model. Next, *behaviour rules*, representing adaptation strategies, are next applied. A sequence of advertisements is also retrieved and passed to the decision engine, based on these rules. The inference engine also applies the plan recognition process and passes it to the decision engine. Finally, all of these advertisements must apply the general rules from the first step (Figure 3).

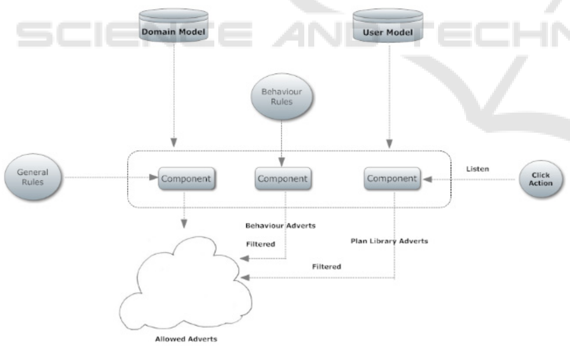

Figure 3: Inference Engine Process (User Logged In).

4.2 The Decision Engine

The *decision engine* is responsible for displaying advertisements to the current user. Firstly, a flexible method that allows businesses to put any number of advertisements anywhere they want, is used by the decision engine. The businesses are only assigned the ID of the html element that contains the advertisement image with a fixed name "Image_Universal_AdLocation". As shown in Figure 4, the ID of the link that represents this advertisement will be assigned the name "A_Universal_AdLocation", and this code is to be repeated on all webpages. This allows businesses to add any number of advertisements in any location on the webpage (Figure 5). Furthermore, the number and location of advertisements can vary from page to page, based on businesses views.

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

Figure 4: Advertisements Location Determination Code.

When a user loads a webpage, the decision engine searches for the IDs, which represent the advertisements, and changes their names, by giving them a number in increasing order. The decision engine then determines the number of advertisements, which will appear on the current webpage. This process is aimed at allowing the system flexibility and usability for businesses to insert advertisements, since the business owners have the ability to control the number of advertisements and the location of each advertisement on the webpage (Figure 5).

Figure 5: Advertisements on the Webpage.

If the current user is not logged in (Figure 6), then higher priority advertisements will be displayed first. The decision engine arranges the available advertisements, as per following algorithm.

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

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

1. The fourth behaviour rule, “show after” explained in (Qaffas and Cristea, 2014a), has first priority, if it exists.
2. If there are advertisements from the plan recognition, display them. If they are exhausted, display advertisements, which meet the other behavioural rules.

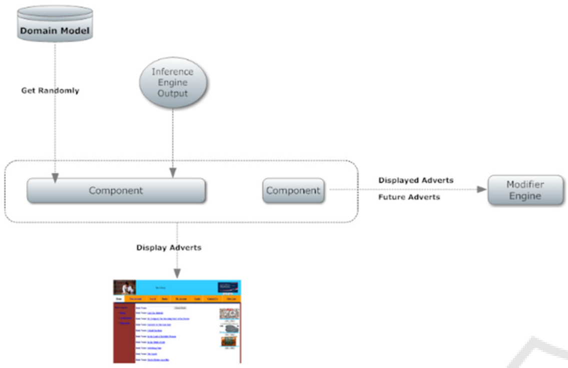

Figure 6: Decision Engine Process (User not Logged In).

4.3 The Modifier Engine

The *modifier engine* acquires information from the inference and decision engines, to update the user model. The user model is updated based on certain events; for example, during the user’s login, the modifier engine detects whether or not the device type and bandwidth have changed and it updates the user model. When the decision engine delivers advertisements to be shown, the modifier engine also updates the user model.

5 CASE STUDY

To test the AEADS system and obtain feedback with regards to its *effectiveness* (usefulness) and *efficiency* (ease of use), the AEADS system was integrated with an online bookstore. To evaluate the AEADS system, samples of Internet users were asked to use the system. The user modelling profile attributes of the AEADS system was integrated into the online bookstores user profiles (Figure 7). In the figure, the ‘name’, ‘user name’, ‘password’ and ‘email’ attributes form the online bookstores user profile attributes, while the attributes ‘age’, ‘gender’, ‘bandwidth’, ‘education level’, ‘education type’ and ‘hobbies’ are the AEADS user modelling profile attributes. The user modelling tool in AEADS has been designed to be simple—i.e., to possess only a few user model features and have an XML data structure — the latter so that it is lightweight and can be integrated with any potential website user model (Qaffas and Cristea, 2015). AEADS includes two methods of login: registering (explicit data retrieval) and Facebook login (implicit data retrieval), as discussed in (Qaffas and Cristea, 2015).

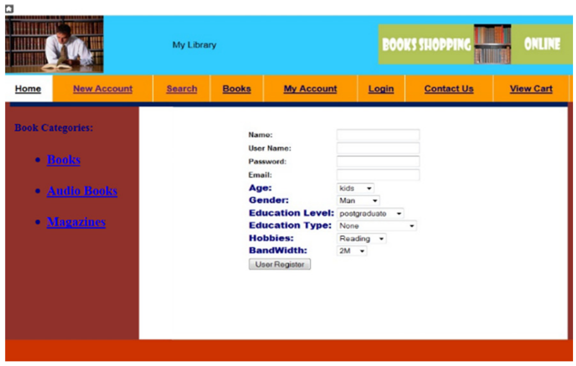

Figure 7: Book Store Registration.

The main aim of this survey was to determine whether Internet users responded favourably to the new lightweight advertising delivery system. Currently, there are around three billion worldwide Internet users (InternetWorldStats, 2012). Thus, a suitable sample group requires 267 participants at a confidence level of 90; alternatively, we can use a sample group of 377 participants, at a confidence level of 95 (raosoft). Aiming at international applicability (confidence level 90-95), 450 different Internet users were sent the user questionnaire.

5.1 Hypotheses

Hypotheses have been defined to evaluate the AEADS system, from Internet users’ perspective:

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

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

H0x are the basic hypotheses. Specific hypotheses were also tested via the questionnaire method:

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

H2: *AEADS has a shallow learning curve.*

H3: *AEADS overcomes the privacy concerns.*

H4: *Users prefer to login via Facebook account rather than register.*

H5: *The collected data is enough and acceptable for users.*

H6: *The AEADS system interface is user-friendly.*

H7: *The AEADS system performance is adequate.*

H8: *The AEADS system reliability is achieved.*
H9: *The AEADS system increases the clicking behaviour on advertisements.*

5.2 Case Study Setup

The AEADS system was tested by a number of students who were studying a variety of disciplines at the King Abdul-Aziz University in Saudi Arabia. They were studying Principles of Marketing, Introduction to Business, Management Information Systems and e-Marketing. These students were chosen as suitable system testers, as they were frequent Internet users and often made online purchases. In effect, these students were familiar with online platforms and had first-hand knowledge of existing online providers. Additionally, students were representing a diverse range of subjects, to obtain generalisable results and avoid focusing only on computer science students. However, evaluating with students presents drawbacks, as, whilst they represent the young population knowledgeable of the Internet and its tools, especially e-business tools, they do not represent the population at large.

All users were required to use, assess and evaluate AEADS. This process involved a number of different stages, as outlined below.

Table 1: AEADS System Features.

1	Registration process
2	Logging in using Facebook account
3	Managing the user profile
4	Automatic extraction of device information (location, device type, device software, bandwidth)
5	The advertisements that are appropriate for users
6	The personalised advertisements is acceptable for users
7	I notice that the advertisements were personalised
8	The system collects enough information from you
9	Your behaviour on the website is tracked to give you suitable advertisements

The participants were first given a general overview of the AEADS system and the concept of adaptive advertising. They were then asked to use the system and evaluate its functionality. At this stage, a five-part survey was distributed, to facilitate the assessment process. The opening section of the questionnaire asked participants to provide personal demographic details, e.g., age, gender, level of education, etc. The following section asked participants to answer system usability scale (SUS) questions. The next step required users to general questions, while the fifth section required them to offer more in-depth responses. This section utilised a Likert scale for responses, as participants were required to analyse and evaluate the effectiveness and applicability of the system. Numerical data was used to represent feelings or opinions: for instance, 1 = 'not at all useful' / 'very difficult'; whereas 5 = 'very useful' / 'very easy to use'. The last section then asked a number of qualitative questions.

5.3 Results

A total of 381 questionnaires were completed accurately and returned to the researcher. The number of completed surveys is impressive, considering that students were assured that participation was completely voluntary. From respondents, almost two thirds were aged between 18 and 24 while a further 22.8% were aged between 25 and 34. In terms of gender, over two thirds of those who took part in the survey were male, while only 27% were female. Finally, in terms of education level, the majority of participants held a Bachelor's degree, while only 14.2% were pursuing a post-graduate qualification. This indicates that the data may be skewed towards younger, well-educated males. Nonetheless, this demographic is crucial for web providers, as they are the most prolific Internet users, likely to maintain a high rate of Internet usage in the future. It is therefore imperative that web providers meet the needs of this niche social group.

For SUS results, the majority agreed that the system is simple to understand and use by Internet users, without specialised training or advanced knowledge, which support hypothesis H2. They also considered the system well integrated, and stated that they would like to use the system on a frequent basis, which support hypothesis H1. They strongly agreed that AEADS is easy to use, with 96.9%, and 95.6% stating that they felt very confident using it. Most users understood how to use the system from the presentation given at the beginning of the evaluation. They were confident when they used the system. Additionally, they further backed up these statements via open-ended question (section 5.4). Furthermore, the overall SUS score for AEADS is 87.70 out of 100. Cronbach's Alpha for SUS scores is $0.93 \in [\geq 0.9]$, meaning the results of the SUS questionnaire were at an 'excellent' level of reliability. These findings support hypothesis H0b, which posits that AEADS is easy to use.

The second section of the survey posed a series of general questions about the functionality of AEADS and its overall effectiveness. This section focused primarily on the influence of AEADS in encouraging users to click on sponsored links or make purchases on the basis of personalised advertisements. It also focused on the degree to which participants were concerned about their online security and the safety of their personal information. Of those questioned, 93.5% stated that the system would encourage them to click on more links and make more purchases, while 90.9% claimed that they were largely unconcerned about their privacy and online security. This supports hypothesis H9, which posits that the AEADS system increases the clicking behaviour on advertisements. Furthermore, these findings also substantiate hypothesis H5, as 90.2% of participants felt that the system was justified in collecting private information and were willing to offer such data in exchange for a more effective adaptive advertising mechanism, as the AEADS system collects only the data that is needed to personalise the advertisement. In addition, 85.7% of the participants stated that they would login via Facebook, if they were to use this system regularly, which substantiates hypothesis H4, on preferring to login into the system using their Facebook account.

A significantly large proportion of participants (95.9%) strongly agreed that the information requested by the system overcomes privacy concerns, by collecting only data needed for personalisation of advertisements, which left users feeling confident with the AEADS system. These findings support hypothesis H3. Generally, the majority of users were extremely satisfied with the effectiveness of the system and believed that it performs exceptionally well. In addition, the majority of those questioned had faith in the reliability of the system. These findings support hypothesis H8. The Cronbach's Alpha score was 0.96$\in$ [$\geq$ 0.9], meaning that the reliability of the psychometric test is excellent.

A comparatively low score was obtained in relation to the user interface of the system, as only 79.5% of those questioned considered the system interface to be user-friendly. This relatively low level of satisfaction could be attributable to the interface of the website on which the assessment was performed. Though the design of the website was beyond our control, the system nonetheless scored highly in terms of usability and ease of use, supporting hypothesis H6, positing that the user interface of the AEADS system is user-friendly.

Participants were next asked to evaluate the various features and functions of the AEADS system on a Likert scale. The main functions of the system were generally well-received by users, with more than 84.8% of participants stating that they found the various features extremely useful. The standard deviation values in this instance were between .46-.54 and a mean value of 4.24-4.69. Thus, the system can be considered 'useful'. The Cronbach's Alpha score is 0.90 $\in$ [$\geq$ 0.9], meaning that the reliability of the psychometric test is excellent.

In terms of which features proved the most popular, the majority of those questioned agreed that the advertisements shown were suitable, given their interests and preferences. In addition, the majority found the advertisements shown to be acceptable, and were satisfied that their behaviour on the website was monitored, in order to generate the most relevant advertisements. The participants clearly enjoyed the advertisements they were shown during the evaluation processes because the advertisements had been personally adapted, through methods based on the personal data found within the user profiles, along with the participants' behaviour, which had been monitored by the system. These findings substantiate hypothesis H0a, as the AEADS system and its functions is useful for adaptive advertising.

The least-liked features included 'automatic extraction of device information (location, device type, device software, bandwidth) is useful' and 'logging in using a Facebook account is useful'. Nonetheless, as these features still scored above 4, they cannot be considered as disliked features. In fact, the lower score obtained by these features could be attributable to the user's lack of understanding of the purpose of each feature. Another interpretation is that they might have been worried about the system extracting information without their knowledge (as in the extraction of the device information). Additionally, they might have been worried about the information that the system would have access to, if they were to login via their Facebook accounts. In the open-ended question section, one user questioned whether the system would continue to track their online activities once they had closed the webpage, as is further discussed in section 5.4. Nevertheless, as both rules achieved a minimum rate of 4, they can still be deemed useful (Figure 8).

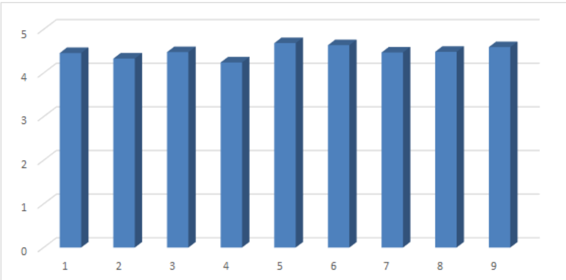

Figure 8: Usefulness (Ox axis detailed in Table 1).

These findings substantiate hypothesis H0a, which posits that the AEADS system and its functions is useful for adaptive advertising.

The usability of the distinct features was separately evaluated through questionnaire questions (1-9, defined in Table 1). In terms of usability and ease of use, the mean values fell between 4.17-4.74. In addition, the standard deviation values for usability fell between .45-.51. These results indicate that AEADS can be considered usable, as it can be easily operated by any user, without the requirement for formal training, or an existing knowledge of online platforms. In addition, the Cronbach's Alpha score is $0.91 \in [\geq 0.9]$, meaning that the reliability of the psychometric test is excellent. These findings were then subject to analysis and it was discovered that the most popular elements in terms of usability were 'Your behaviour on the website is tracked to give you suitable advertisements' and 'login via Facebook is easy to use'. Obviously, users preferred to receive personalised advertisements based on their characteristic and preferences, as the personalised advertisements were presented to them during the evaluation processes based on their data contained within the user profiles, along with their behaviour, which was monitored by the system. Moreover, in 2005, 80% of Internet users were interested in receiving personalised content on sites that they visited (ChoiceStream, 2005) and the percentage has only increased since then.

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

5.4 Qualitative Answers and Discussion

One user made the commented that it was clear how each of the displayed advertisements were linked. In other words, they understood how each advertisement related to one another as well as related to the interests or preferences of the users. Basically, the users acknowledged the effectiveness of the system in customising the selection of advertisements based on the unique details of each user. Another user also highlighted how the advertisements that were displayed reflected aspects of the user's profile, which again indicates that the system worked effectively for the majority of participants. In fact, many of those questioned expressed their appreciation of personalised advertisements and were impressed with how the system tailored the advertisements displayed, based on their profile, user preferences and online behaviour. The system also allows the user to accept or reject the use of cookies, which was highlighted by one user as a useful feature. However, another user stated that the system did not include their personal hobbies in their list of common interests. This fell in line with the quantitative data, as they considered the registration and managing of their profiles as their least popular features. It should be noted that the attributes are a changeable list that can be modified, based on the business owner's view. More details about attributes are discussed in (Qaffas and Cristea, 2015).

Another issue highlighted by the users within the qualitative section of the questionnaire concerns the security of private data and the system's monitoring of online activity. For instance, one user wondered whether the system would continue to track their online activities once they had closed the webpage. This implies that some users might be concerned about the possibility of the system monitoring all of their online behaviour. Thus, measures should be taken to ensure that the system's users are fully aware of how the system operates and when the system is tracking activity, in order to deliver the most relevant and user-specific advertisements. Another user commented that the user interface of the website needs to be more attractive. Again, this relatively low level of satisfaction could be attributed to the interface inherited from the website, upon which the assessment was performed. Though the original design of the website was beyond our control and the AEADS extensions were applied in a manner that was true to the principles of our research, in a lightweight manner, without changing the look&feel of the original website, the system nonetheless scored highly overall in terms of usability and efficiency.

In terms of usefulness and usability, one user simply stated that they 'liked the system', which indicates their full overall satisfaction with the system's features and functionality. Within the analysis of the quantitative data process, users revealed the belief that AEADS had aided them in receiving personalised advertisements much more than any normal e-business system would have. The users stated that they had been confused by Google advertisements when attempting to find certain content and most especially when trying to download specific software. One user also stated that they liked the location of the advertisements, which indicates that the AEADS system displays advertisements in an eye-catching, yet unobtrusive manner. Another user claimed that the frequent display of different advertisements was both convenient and effective. In addition, another user stated that the system pushed them to think about developing their own online business, as the features and functions of the system facilitated the marketing and advertising required for their company.

These insights into the system reflect the effectiveness and functionality of the current system from the perspective of Internet users, while highlighting possible areas in which future versions of the system could be modified.

6 CONCLUSIONS

The delivery model is introduced in this paper, its design and internal processes are described in detail. It consists of three engines: inference, decision, and modifier engines. The system, its features and usability have been evaluated by real users, and the overall outcome has been positive. Based on this outcome, it can be seen that the delivery model in AEADS is necessary and introduces flexible adaptation.

REFERENCES

Abu-Taieh, E. M. 2009. Utilizing Information Technology Systems Across Disciplines: Advancements In *The Application of Computer Science: Advancements in the Application of Computer Science*, IGI Global.

Al Qudah, D., Cristea, A. I., Shi, L., Al-Sayyed, R. M. & Obeidah, A. 2014. Myads: A Social Adaptive System for Online Advertisement from Hypotheses to Implementation.

Choicestream. 2005. Choicestream Personalization Survey: Consumer Trends and Perceptions. Available: Http://Www.Choicestream.Com/Pdf/Choicestream_Pe rsonalizationsurveyresults2005.Pdf [Accessed 10 March 2014].

Cristea, A. I. & De Mooij, A. 2003. Laos: Layered Www AHS Authoring Model and their Corresponding Algebraic Operators. *WWW03 (The Twelfth International World Wide Web Conference), Alternate Track on Education*, Budapest, Hungary.

Internetworldstats. 2012. World Internet Usage and Population Statistics. Available: Http://Www. Internetworldstats.Com/Stats.Htm [Accessed 25 September 2013].

Kazienko, P. & Adamski, M. 2007. Adrosa—Adaptive Personalization of Web Advertising. *Information Sciences*, 177, 2269-2295.

Puntambekar, A. A. 2008. Data Structures and Files, *Technical Publications*.

Qaffas, A. & Cristea, A. 2014a. How to Create An E-Advertising Adaptation Strategy: The Aeads Approach. In: Hepp, M. & Hoffner, Y. (Eds.) *E-Commerce and Web Technologies. Springer International Publishing*.

Qaffas, A. & Cristea, A. 2014b. How to Create an E-Advertising Domain Model: The Aeads Approach. *The 2014 International Conference on e-Learning, E-Business, Enterprise Information Systems, and E-Government (EEE'14)*. Las Vegas, United State.

Qaffas, A. A. & Cristea, A. I. 2015. An Adaptive E-Advertising User Model the Aeads Approach. *The International Conference on E-Business (Ice-B)*. Colmar, Paris.

Raosoft. Sample Size Calculator [Online]. Available: Http://Www.Raosoft.Com/Samplesize.Html [Accessed 25 September 2013].

Scotton, J., Stewart, C. & Cristea, A. I. 2011. Ade: The Adaptive Display Environment for Adaptive Hypermedia. *Proceedings of the ACM Hypertext 2011 International Conference*, Eindhoven, The Netherlands.