Journal of Universal Computer Science, vol. 24, no. 7 (2018), 935-974
submitted: 11/10/17, accepted: 20/7/18, appeared: 28/7/18 © J.UCS

Lightweight Adaptive E-Advertising Model

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Abstract: Adaptive online advertising is a rapidly expanding marketing tool that delivers personalised messages and adverts to Internet users. At a time when the Internet is burgeoning, many websites use an adaptation process to tailor their advertisements, however, often in an ad-hoc manner. Thus, a new model that guarantees a *systematic integration of adaptive features on existing business websites* has become an urgent requirement to satisfy customers. This paper aims to solve this issue, by presenting an innovative model for e-advertising adaptation: *the Layered Adaptive Advertising Integration (LAAI)*. LAAI is building upon previous models and frameworks from different domains, by selecting and adding novel features appropriate for e-advertising. Based on this model, a new adaptation system *–AEADS –* is developed, to test and evaluate the LAAI model. This research also reports on the perception on the methods towards obtaining generalisation, portability and efficiency, as proposed by the LAAI model, by evaluating how a range of businesses are enabled to adapt their advertisements based on user profiles and behaviours.

Keywords: Adaptation Model, Adaptation Strategy, Adaptive Advertising, Authoring System, Delivery System, E-advertising, E-commerce, Personalisation.
Categories: H.5.4, J.4, M.0, M.4, M.5

1 Introduction

Adaptive hypermedia systems are known to improve the efficiency and accuracy of the information distribution [Brusilovsky, 2012], by displaying or concealing the content to be adapted. The systems rely on storing user data that is represented by the user model, and adaptation specifications that are represented by the adaptation model [Zhang, 2000]. The user model is initialised by user registration and updated by the observation of user behaviour. The content owner manages the adaptation model, which is modified. It contains the author's rules and strategies for managing the adaptation processes.

Technology advances and the emergence of new ways of selling products – such as online marketing – have allowed organisations to develop advertisements that enable them to adapt to changes in the environment [Bauer and Lasinger, 2014]. As

such, these methods challenge the traditional modes of advertising, in which advertisements are presented to a general audience, with little processing of any feedback. Adaptive advertising has, therefore, improved the ability of companies to present the right product to the right customer base, by enhancing the level of feedback which can be received and processed for each advertisement [Bauer and Lasinger, 2014].

Today, a great proportion of online advertising systems apply *customer-based targeting* [Kazienko and Adamski, 2007]. Adaptation in this field aims to increase advertising effectiveness, by ensuring that the right person receives the right message at the right time and in the right context [Adams, 2004, Chutijirawong and Kanawattanachai, 2014].

However, the process of creating adaptive advertising is complex [Qaffas, et al., 2013], since there are many criteria that must be considered. When determining the most suitable advertisements for a particular user, several factors must be considered. These may include: web page content, user interests, user location, search and buying history, advertisement format, current user activity, advertisement homepage content, and the history of advertisements that the user has already seen [Kazienko, 2005, Nayak, et al., 2017].

Thus, small commercial websites which want to join the general trend and wish to find an adaptive solution that is appropriate for them don't have an easy task. What we believe they need is a *lightweight adaptive advertising approach*. Here, we name 'lightweight' advertising - advertising that is easily integrated into any given commercial website, starting from the given status quo – to differentiate from stand-alone, dedicated adaptive commercial websites (such as, e.g., Amazon). However, whilst adaptive hypermedia has been the focus of many studies, the functioning of lightweight adaptive advertising is a less explored area. Clearly, this concept is important, especially for small businesses, since it could potentially easily support the integration process and transition to a personalised, adaptive approach. However, whilst the majority of small businesses may require some level of adaptation, they are either unaware or uninterested in the techniques, definition or background of the process. In addition, they want to preserve the performance of their website, without modifying the structure.

To address the need of such small businesses, a supporting model is necessary. However, most adaptive hypermedia models are dedicated to the field of education, or strongly influenced by it [Brusilovsky and Peylo, 2003, Cristea and de Mooij, 2003, De Bra, et al., 1999, Ghali and Cristea, 2009]. The models used in adaptive advertising are few and are limited in terms of the lightweight approach. Thus, the research presented in this paper aims to address the following umbrella research question:

How can we create a model for lightweight adaptive advertising that can be integrated with most websites?

To answer this question, the paper presents a new theoretical model, called: **Layered Adaptive Advertising Integration (LAAI)**. This model supports delivery of personalised advertisements to Internet users, in line with lightweight personalisation specifications. In summary, the research aims to *identify how the previous frameworks and models can be built on and, importantly, how they can be expanded and renewed to enhance the generalisation, portability and efficiency of the*

user and delivery models, to enable a range of businesses to adapt their own website advertisements based on users' profiles and behaviours.

To evaluate the LAAI model, a new system, AEADS, has also been developed based on LAAI, which allows adaptation of advertisements on a range of websites. This system was evaluated with business owners (presented here) and Internet users [Qaffas and Cristea, 2016]; the evaluation found that the AEADS system, which is based on the LAAI model, successfully chooses the most appropriate advertisements for users based on their data. This paper focusses on the system evaluation with *business owners (providers)* of the *LAAI model*, which it also describes in details for the first time. The paper contains additionally a first description of the *personalisation and adaptation algorithms*. The evaluations with *internet users (consumers)* and a more detailed AEADS system description can be found in [Qaffas and Cristea, 2014, Qaffas and Cristea, 2014, Qaffas and Cristea, 2015, Qaffas and Cristea, 2015].

The remainder of the paper is organised as follows. After reviewing related research, the Layered Adaptive Advertising Integration (LAAI) model is introduced, together with its individual sub-models, including delivery algorithms. This is followed by the results of the evaluation with business owners. Finally, conclusions are drawn.

2 Related Research

In this study, prior studies from the fields of Adaptation in education, e-commerce, and e-advertisement are built upon, by introducing a *new, systematic way of building adaptation advertising systems, based on solid theoretical foundations*.

There are several models and frameworks based on which adaptation of information may be authored and delivered. For instance: the Dexter Hypertext Reference Model [Halasz, et al., 1994], AHAM [De Bra, et al., 1999, Wu, 2002], Munich Reference Model [Koch and Wirsing, 2002], LAOS [Cristea and de Mooij, 2003], and SLAOS [Ghali and Cristea, 2009]. When analysed from the perspective of lightweight adaptive advertising, each of these models or frameworks has benefits and limitations. For example, AHAM [De Bra, et al., 1999, Wu, 2002] is a Dexter-based reference model. As such, AHAM focuses on the information nodes as well as the link structures that connect the nodes. AHAM consists of three major elements, which are: domain model, user model, and adaptation model [Brusilovsky, et al., 2000]. However, whilst AHAM was one of the original and most well-known adaptive hypermedia models, it does have its drawbacks. The contents in the domain model are concepts or composite concepts, and therefore can't represent related elements that are not a concept. For instance, location on the webpage, location on the media, and description of the advertisement cannot be easily represented. Importantly for our research, any attribute that describes advertisements cannot be added easily in this model. In addition, the user model relies on a rigid table structure. Finally, the model is designed mainly for adaptation in education fields and is not well-tuned for advertising purposes.

The Munich Reference Model [Koch and Wirsing, 2002] is similar to AHAM; however, it uses object-oriented specification written in UML. Overall, it suffers from similar problems as the AHAM model.

LAOS [Cristea and de Mooij, 2003] is a theoretical framework for flexible authoring of adaptive hypermedia, which attempts to resolve the issue of concealed adaptation information. LAOS is a universal representation of a layered model for generic authoring of adaptive hypermedia [Cristea, et al., 2007]. [Cristea and Stewart, 2006] claim that functionality and semantics guide the separation of adaptive hypermedia components into layers, in order to group the components based on their potential usage – primarily for later use and reuse. Although the LAOS framework represents a gigantic leap towards the development of a reusable adaptation system, its structure restricted the model's authors. Like AHAM, LAOS is also mostly applied in the education field. Its goal model is especially useful for representing pedagogical goals, but less so for representing advertisement goals, which are less structured. Furthermore, it is adapted to enable standalone applications and is not aimed at supporting portability and easy integration, which are the main goals of our research.

The SLAOS framework [Ghali and Cristea, 2009], based on LAOS, additionally supports the representation of collaborative activities of users – authors and learners. The social activities in this framework drive the delivery and authoring process, by introducing adaptive materials based on communities of practice. The social layer in SLAOS interacts with the five other layers of the LAOS framework. For instance, the user model layer contains new entities that describe the roles that will be assigned for these groups. The social aspect is relevant in adaptive advertising as well. However, previous issues with the LAOS framework with respect to applicability to e-advertising are inherited by the SLAOS framework.

In addition to the models and frameworks that are designed for the educational field, there are some frameworks that are intended to adapt advertisements.

AdSense [Davis, 2006], AdRosa [Kazienko and Adamski, 2007] and more recently MyAds [Al Qudah, et al., 2015] are examples of systems coming with their own advertisement adaptation frameworks. AdSense specialises in banner advertisements and uses location to personalise content. This system allows users to control the delivered ads. It changes the ads presentation and text formats to fit the author's website. Additionally, the categories of ads can be chosen by authors to reflect their rules and website type [Davis, 2006]. AdRosa creates automatic personalised web banners, which are based on the specific browsing behaviours of a user. AdRosa uses a portal model of advertising to deliver the advertisements. The more recent system, MyAds [Al Qudah, et al., 2015], is a social adaptive hypermedia system used for online advertising. MyAds is a standalone system that is based on a theoretical framework, which consists of five core components. The concept of this system is different from the AEADS system concepts, since they concentrate on collecting advertisements from advertisers across the web and organising these advertisements according to certain criteria.

Concludingly, none of the aforementioned models' primary objective is the *lightweight integration of adaptive features on websites*, however. Additionally, user models tend to be generic, and thus non-specific, and normally contain hence no subdivisions (or sub-models). Furthermore, a substantial proportion of the existing frameworks are designed for the educational field, which is not directly related to the research presented in this paper. AdSense [Davis, 2006], unlike our approach, cannot provide advertisements to clients directly, it just allows for advertisers in the Google Network to deliver advertisements to the content site, which is then presented to

users, automatically. However, this process does not utilise any form of user modelling, or the assimilation of user information for personalisation purposes. The last two models mentioned, AdRosa and MyAds, are more closely linked to this research, as they are designed for the advertising field. AdRosa, however, employs a model based solely on user behaviour, whilst MyAds has only recently been developed and has a different purpose – that of a standalone system – and is therefore not directly applicable to this research, where the main aim is portability and generalisation.

Finally, there are various advertising networks that deliver advertisements based on user features, which are to some extent similar to AdSense. The most used one being Amazon Associates Web Service [AmazonWebService, 2017], which processes a large amount of data and supports most functionality used by Amazon. Items for sale, customer reviews, seller reviews are examples of these data, whilst finding items, or finding similar items are examples of Amazon functionality. The system also divides the items into multiple categories, like Baby, Magazines, Beauty, etc. PropellerAds [PropellerAds, 2011] is another advertising network example, which claims to create a bridge between publisher and advertiser, by sending adverts from the latter to the former. It formats the advertisements based on the type of target device (mobile, desktop, etc.). Additionally, it displays the most relevant advertisements for users based on their characteristics. However, all of these advertising networks' algorithms are proprietary and thus not available for analysis or comparisons.

It needs noted that, at best, state-of-practice business solutions can be 'reverse-engineered' from their behaviour, in order to establish the principles of their functioning, as there is little or no information about the algorithms and processes used. This is even more so in the case of authoring for such systems, as even the systems themselves are not open to the public (or research audience) to study.

In this paper, therefore, we address the gap by *introducing a new model for adaptive advertising*, which contains a few features inherited from existing adaptive frameworks, as well as several novel features, as explained in the following.

3 The Layered Adaptive Advertising Integration Model (LAAI)

Based on the above summarised analysis of existing models and frameworks, resulting in accepting the fact that they cannot be directly applied to the current work, this research proposes instead a new adaptation model, named the *Layered Adaptive Advertising Integration (LAAI)*, which can be used to disseminate advertising, and which is extracts from previous hypermedia adaptation models only the elements which are appropriate for this purpose. This model seeks to introduce common abstractions, in order to provide a basis for the development of advertising adaptation applications and to support the portability of these applications. LAAI ensures *'separation of concerns'* [Cristea and de Mooij, 2003, De Bra, et al., 1999, Ghali and Cristea, 2009] for an adaptive advertising application, i.e., content, adaptation requirements and delivery are kept separate. This is important for higher-level strategies, as it enables content to be *reusable*. The high-level structure of the LAAI model is illustrated in Figure 1 and comprises four layers: *domain model (DM), adaptation model (AM), user model (UM),* and *delivery model (DM)*. In proposing

these layers, the LAAI model aims to reuse, as said, certain features from previous models, such as AHAM [De Bra, et al., 1999] and LAOS [Cristea and de Mooij, 2003], whilst increasing specificity for advertising, and simplicity and portability for lightweightedness. The layers it uses appear also in previous models and frameworks, but the way they are used is somewhat different, to cater for the advertisement world, as is further explained here in brief, and in more details in the subsequent sections. Moreover, some elements of previous models, such as LAOS's Goal Model, have been discarded: as the Goal Model is most appropriate for the pedagogical narrative, and thus not as useful for adapting advertising content. Furthermore, user model options that are advertisement-specific, which may be allowed by other models, but are implicit, have been integrated as an explicit sub-model in the User Model, known as 'Future Advertisements'. For example, in LAOS, concepts could be shown to the users based on their experience, but this is not specifically illustrated by the framework. In LAAI, instead, the 'Future Advertisements' component is part of the model. It can be used, for instance, at users' logout, when advertisements that are appropriate for the current user have not yet been shown to the user; these will be saved to be shown at the next user login, saving the current user state and saving search time upon revisit.

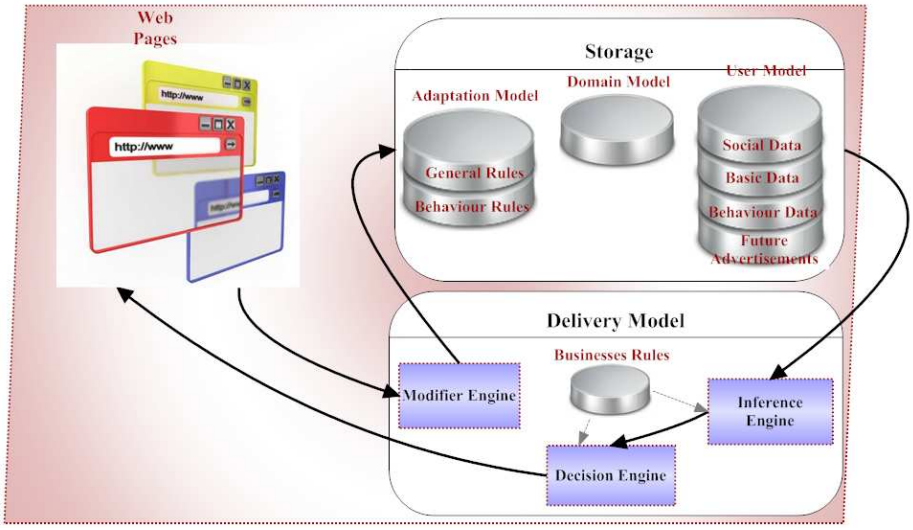

Figure 1: The Layered Adaptive Advertising Integration (LAAI) Model

The first layer, the *domain model (DM)*, unlike previous models, describes entities in an application that represent advertisements and the relationships between them. This is represented by grouping the advertisements into levels, each category of advertisements belonging to one level and having a relation to its parent level, as further explained below (Section 4). The next layer, the *adaptation model (AM)*, describes the adaptation rules that adapt advertisements for each user (Section 6). The *user model (UM)* layers store four different types of data: social data, basic data, behaviour data, and 'future advertisements' data (Section 5). The final layer, the

delivery model (DM), uses the data stored in the other layers to generate adapted advertisements (Section 7). This layer also monitors user behaviour and updates the other layers with the current user status. The business rules that are stored within the delivery model layer are a new concept within adaptation models and frameworks, and are aimed at enabling businesses to modify (Section 7.2) the priorities and actions of the inference (Section 7.1) and decision engines (Section 7.3). This component - the business rules – informs the delivery model what to do with data retrieved from the user model. These rules can be used to customise inference and decision engine actions and priorities. They are isolated in the delivery model, to encapsulate data, in order to enhance the delivery model process and to allow easy extension for the adaptation system, in a plug-and-play manner: e.g., having websites with the same business rules, but with different adaptation rules, or vice-versa as further discussed below (Section 7).

Next, we describe each of the component models of LAAI in more details.

4 Domain Model (DM)

Generally, in adaptive hypermedia applications, the *domain model (DM)* consists of concepts and of the relation
ships between these concepts [Wu, et al., 2001]. The most common relationship type is the hypertext link, although conceptual structures which are separate from the hypermedia delivery itself have also been proposed [Cristea and de Mooij, 2003, Wu, et al., 2001]. Concepts have been classified within two categories – atomic or composite – with respect to the information structure [Wu, et al., 2001]. Atomic concepts represent a fragment of information, while composite concepts include a (potentially ordered) subset of these fragments. If the children of a composite concept are all atomic in nature, then, in the past, such a composite concept has been used to represent a page in the browser window.

The domain models in previous adaptation models or frameworks, such as AHAM [De Bra, et al., 1999], the Munich Reference Model [Koch and Wirsing, 2002], the Dexter Hypertext Reference Model [Halasz, et al., 1994], XAHM [Cannataro and Pugliese, 2002], WebML [Ceri, et al., 2000], and LAOS [Cristea and de Mooij, 2003] are similar, but structured slightly differently, each proposing some improvements over the previous models. In the Dexter Hypertext Reference Model, *the hypertext link* relationship is the only type of relationship between components of hypermedia systems. In AHAM, in addition to the hypertext link relationship type, a *prerequisite* type is added – for instance, users must read C1 before C2 if C1 is a prerequisite for C2. The latter type is originally clearly of a pedagogical nature. Thus, LAOS also includes these two types, as well as others, and, additionally, divides them across two layers – domain model and goal and constraint model – in order to separate behavioural links (such as prerequisites) and presentation-related information (the fragments which will form the pages) from domain-specific information (such as concepts and their inherent relations).

As there have been many models proposed in the past for design, authoring and delivery of adaptive e-content, it seemed natural and logical to either use one of the existing models for the new application area of business, specifically, adaptive advertising, or to extend an existing one. Nevertheless, it quickly became evident

existing models were too 'heavyweight', in that, whilst offering a great level of flexibility, they became too complex to handle, especially for our primary target, the author. Moreover, existing models, even the flexible ones, didn't correctly cater for adaptive advertising. Thus, instead of expanding further an existing model, and thus adding more complexity, the solution selected was to 'pick & choose' features appropriate for adaptive advertising, whilst keeping the complexity low.

Features borrowed from other models are as follows. In order to allow for flexible adaptation, and independent reuse of components, similar to other domain structures, such as, e.g., LAOS, AHAM, etc., a *conceptual* structure was selected for LAAI. Please note that this structure is of a theoretical nature, and its implementation constitutes a separate decision. In principle, it could be implemented as an ontology, or a basic XML structure, or a database structure. Furthermore, further following previous models and frameworks, each basic item in LAAI (concept: here, advert) has attributes: an advertisement in the domain model contains a number of attributes, such as the *location* of the advertisement in the storage medium and its *name* and *description*. The implementation can use these or expand on them. However, any expansion has to keep in mind that simplicity is key when creating authoring tools which are to be used by busy business managers. These attributes form a model of the advertisement and include thus independently reusable information pieces about the advertisement that will be used by the delivery layer (see Section 7), to carry out the adaptation of the advertisements. For example, the (brief) 'description' of an advertisement may be used on its own, to show a user a brief version of the advert, which could possibly be expanded by clicking, if the user desires it. Similarly, it can be used in many other processes in the delivery layer, in addition to the adaptation rules, that are carried out to match advertisements to users. The 'name' attribute can be used to create, on the fly, a list of adverts recommended for a user. These attributes could, in principle, also be easily extended by any application (i.e., new attributes can be added or deleted), to reflect its particular requirements, or in response to changes (changes in a business may require some changes in advertisement's attributes). Thus, flexibility is made possible – however, any expansion should consider the principles of lightweightedness and ease of use for authors. In short, advertisements can be considered to correspond to atomic concepts in other adaptive hypermedia models, like AHAM, or to concept attributes in LAOS.

Unlike some of the previous models, like AHAM or LAOS, however, as said, the focus in LAAI is on building a *simple* model, which is not attempting to be exhaustive, but comprises adaptive advertising basics, and, most importantly, should lead to easy authoring for the *business owners*.

As illustrated in Figure 2, based on our research results [Qaffas, et al., 2013], which showed that all businesses interviewed had a clear preference to control the classification of advertisements, in LAAI, advertisements can be further grouped into categories on multiple levels, based on the author's decision. The number of categories can be also determined by the author. The strength of this categorisation lies in allowing the adaptation model (Section 6) to apply various adaptation rules on a specified group at once. This grouping process allows enriching the domain model and helps to overcome authoring difficulties, as authors don't need to apply the same rule separately for each advert for which they judge it as appropriate. For example, the author can divide advertisements into groups, based on certain user characteristics

– e.g., based on age, such as advertisements for children. This division is introduced by our model, to allow for extra control for authors in dividing their domain. Moreover, this division is further used by authors in the adaptation model, to apply rules on the domain model. This type of processing on a larger scale is aimed specifically at commercial advertising, where commonalities between adverts are to be expected [Hsieh, et al., 2016]. Moreover, in this model, the author can connect advertisements via relationships, which, to the best of our knowledge, hasn't been proposed before, by constructing *plan libraries* that represent a *sequence of advertisements*. These libraries can be later used by inference engines to display advertisements in sequence, based on clicks (see Section 7.1).

Figure 2: Domain Model Structure in LAAI

Thus, the domain model in LAAI can be summarised as a single root concept, grouping categories of ads, containing many composite/ group concepts. These composite concepts (representing categories) can contain other composite concepts, as well as atomic concepts, as children. Advertisements are here the atomic concepts, and do not have any child-concepts, only a set of attributes that describe each advertisement, which are used in diverse ways by subsequent layers, as explained above. This summarisation is illustrated in Figure 3, which also illustrates the attributes of adverts; these attributes are illustrated in the current implementation via three items: description, name, and location; however, as said, these can be extended,

depending on the requirements of the application – with the caveat that simplicity is to be further promoted, for ease of use for the authors.

Moreover, the LAAI model is unlike most adaptation models, as it targets adaptation in the e-advertising field, which uses a different domain and thus determines a different domain model structure. This is starting with the advertisement being a concept in this domain, requiring a different granularity, and different narrative than, for instance, pedagogically-structured material. Advertisements determine further some specific attributes that must be associated with them in the domain model structure, such as the advertisements description, advertisement label/name, etc. As adverts are often visual, other specific attributes include: size of ads (depending on screen size of devices or bandwidth).

Next, we describe the User Model in LAAI.

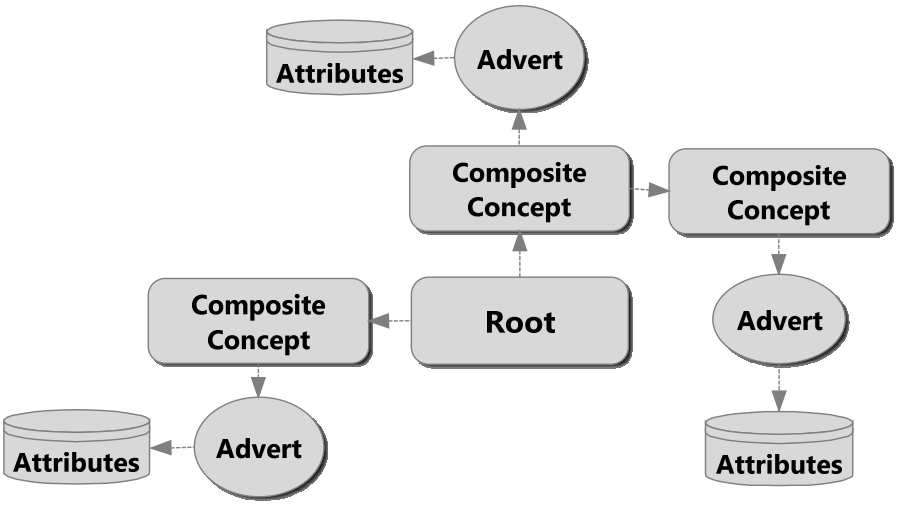

Figure 3: Composite and Atomic Concepts in LAAI

5 User Model (UM)

It is accepted in the literature that users have unique behaviours, characteristics, interests, goals and so on [Brusilovsky, 2001]. In order to personalise advertisements, these must be modelled, and a user model is a basic component in any system offering personalisation [Brusilovsky, 2001]. All adaptive hypermedia frameworks and models have a user model as one of their components [Cannataro and Pugliese, 2002, Ceri, et al., 2000, Cristea and de Mooij, 2003, De Bra, et al., 1999, Halasz, et al., 1994, Wu, 2002]. A user model is a collection of data that describes a user's characteristics explicitly at a certain time, while user modelling is the process that manipulates the user model, by creating and updating its components. In the following, we describe the basis of user model data and representations, and then we present our user modelling approach for LAAI.

5.1 User Model Data

User model contents can be classified into user data, usage data, and environment data [Kobsa, et al., 2001]. According to [Brusilovsky and Millán, 2007], an adaptive model is one which takes into consideration all the relevant features of the user, who is at the core of any model development.

The most common *user data* that have been used in a user model are knowledge and background, interests, goals and tasks, individual traits [Brusilovsky and Millán, 2007]. Knowledge and background represent what the user knows, while interests can represent, for the business domain, the information, services or products that the user prefers. The aim is to establish what the user wants to do exactly, and what individual traits are the characteristics that define them (i.e., personality, cognitive styles, other cognitive factors).

The second category of user model data - *usage data* - is data regarding user interaction with the application, which is recorded directly from observations, like selective actions and ratings, or acquired by analysing observable data, like action sequences. Usage data is considered a source for adaptation, since it deals with the interactions of the user and this allows the system to be tailored to the user as much as possible.

Finally, *environment data* is about the user's environment, hardware, software, and location. Software information may include browser version and platform, while hardware information may include bandwidth, processing speed, and input devices [Kang and Bear, 2016]. User location, like noise level and brightness of the surroundings, can be recorded in a user model.

5.2 Representation of the User Model

Many formats can be used to represent a user model, for example attribute-value pairs, Booleans, lists, references to external objects, and so on. The knowledge in a user model can be represented in different ways [Ghorab, et al., 2013, Rich, 1979], such as overlay models, semantic nets, user profiles and stereotype-based models, to name but a few. For example, in an overlay model [Carr and Goldstein, 1977, Kobsa, 2007], the user's knowledge is represented as a subset of the domain model of the application.

5.3 User (Customer) Model in LAAI

In AHAM [De Bra, et al., 1999], the user model includes a set of entities associated with a number of attribute-value pairs. Some attributes are typical for domain-related concepts, while others represent a user's background, preferences, and general data. Every concept in the domain model has a user model counterpart defining the user's knowledge about that concept. LAOS [Cristea, 2003] views the user model as a concept map, since the relationships between variables in the user model can be explicitly expressed and do not need to be "hidden" within adaptive rules.

The *user (customer) model* in LAAI was designed based on the LAOS model. However, we extended the LAOS model, by adding components relating to social input and 'future advertisements' and by expressing several functions, such as the inference function, in the delivery layer, in order to support portability and easy integration as follows.

The first component (*basic data*) contains basic user (customer) data, which is acquired directly and does not require inference or tracking of user behaviour. This component includes customer characteristics, such as age, gender, interest, bandwidth, device type, etc. The characteristics that are considered here must be appropriate for the adaptation of advertisements. Demographic information, interests, education level, age, gender and so on are all required, in order to efficiently adapt advertising content. For example, gender data typically allows advertisers to increase advertising accuracy, by targeting differences in interests and tastes between gender – or simply not advertise inappropriate items to the wrong gender (such as dresses to males). Moreover, some characteristics, like bandwidth and device type, could (and should) be acquired automatically, in order to decrease the burden on the system and to maximise portability and generalisability.

Social networks are useful sources of user information and may be used to obtain customer characteristics to personalise advertising. Over the past six years, social networks have become a fundamental part of life, with numbers of users rising dramatically. Social networks reflect and record the social practices, preferences, and concerns of their users. Social networking sites vary greatly in form – some simply share content, while others allow users to take an active role in content creation. In general, however, a large amount of user data can be acquired from these sites, including gender and geographic region.

For this component of the LAAI model, basic data can be acquired via three ways: (1) the *manual registration process*, (2) from *social websites* or (3) *automatically*, as illustrated in Figure 4. 'Manual' registration, where the user inserts at registration point all data required by the system's adaptation, is an arguably precise, albeit, potentially, burdensome process. The second alternative, gathering data from social websites, entails extracting profile information – age, gender, etc. – without any burden to the user from social networking sites – just by permitting login access to that specific social network. The one-stop-shop approach via one single login can allow integration of the proposed work into any website, establishing the basis of portability and generalisability in the creation of adaptation systems for advertising content. However, if users are concerned about potential privacy infringements, they can always have as fall-back the other two methods. Thirdly, the automatic acquisition of some basic data, such as bandwidth, and device type, returns accurate data (as in data which has been verified, e.g., by other systems), and is also a low overhead method. For instance, software and hardware environment data can be automatically extracted. Additionally, by using a plan recognition process, prediction of future actions, based on reoccurring patterns, can be automatically obtained. Further customer characteristics or environment data can be obtained automatically by using various techniques. For example, information about the web client can be obtained from the header of the HTTP requests that are received by the server. Moreover, Global Positioning System (GPS) technology can be used to retrieve locality information.

Figure 4: Methods to Collect Basic Data

The second component of the user model – *behaviour data* – contains information about the behaviour of each user. This information varies, according to the actions of the user. In order to design an application to effectively adapt advertising content, actions such as the number of displays and clicks for each advertisement, in addition to actions such as searching for and purchasing items, must be tracked and saved [Puglisi, et al., 2017]. This is illustrated in Figure 5. The application developed for the LAAI model monitors user actions and stores binary values (clicked or not clicked, sequence of clicks, etc.) for each user.

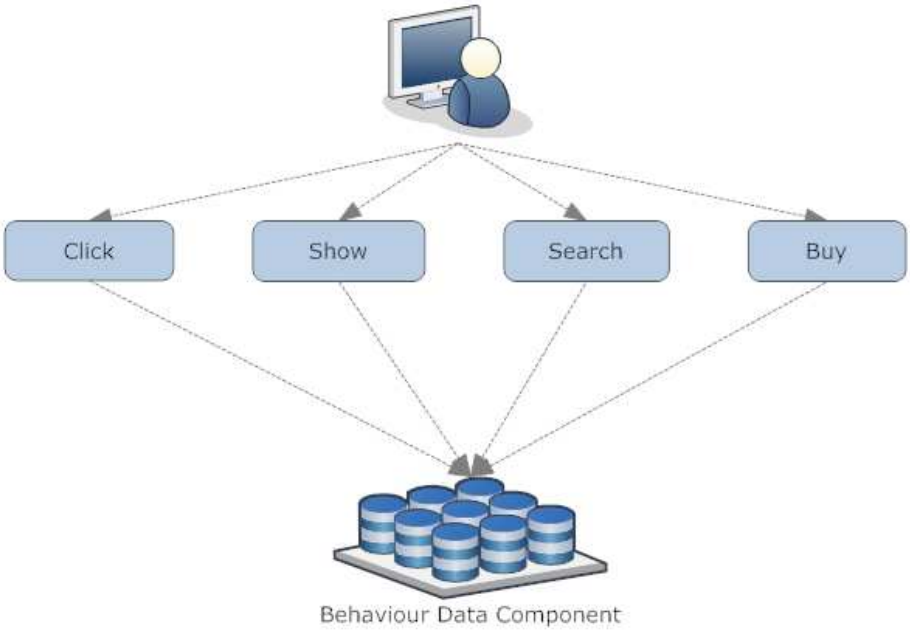

Figure 5: Method to Collect Information on the User's Behaviour

The third component – *social data* –has been added to the user model, based on more recent models, such as SLAOS, taking into account the major impact of social interaction on today's web. Specifically, this component allows users to control advertisements in the domain model and to identify them with social data, such as *likes* and *stops*. Businesses may decide what happens based on this data – for instance, if a user stops an advertisement, the business may choose to remove or change this particular advertisement, or to hide all advertisements within the same category, for a fixed number of log-ins. The advertisements in the domain model are attached to the user model that represents a user's actions, such as click, search, and so on. Additionally, as an application of the social features in our model, the advertisements can be marked with 'like', 'stop', and so on, to support the adaptation process. In order to apply business decisions, this social data has been implemented in the delivery process.

The fourth component, a novel component, proposed here for the first time as a separate entity, to the best of our knowledge – *future advertisements* – includes advertisements that are to be shown to each user in the future, based on their previous interaction. The delivery model stores the remaining advertisements that will be shown to the user at their next log-in, based on the decision engine (Section 7.3), which is a component of the delivery model (Section 7). Thus, first, the advertisements that are shown to a user are organised based on priority, as established by the application of the rules. Next, this list is saved in the 'future advertisements' component, during log-out. Cookies and other similar techniques are commonly used in existing adaptation systems, but the implementation of the 'future advertisement' component introduces a more accurate, machine-independent and persistent process, since cookies can be blocked by many users.

Next, we describe the Adaptation Model in LAAI.

6 Adaptation Model (AM)

In general, an *adaptation model (AM)* [Brusilovsky, 2003, Brusilovsky, 2012, Cartmell, 2012] will describe how the AHS should carry out adaptations, in order to select appropriate information to each user. These adaptations are performed based on domain models and user models; and thus represent the connection between these models. Concretely, the adaptation model can consist of a set of rules and functions that are used to perform adaptations, which are defining the *adaptation method*, as per adaptive hypermedia literature [Brusilovsky, 1998, Wang, et al., 2016]. Each method can be applied via a number of *adaptation techniques*. These techniques can be defined based on information that is stored in the user model, via an adaptation algorithm. For instance, in order to hide the links to the adverts which are not appropriate to be presented, several different techniques can be implemented, such as link removal, or link greying out, etc. Brusilovsky [Brusilovsky, 1998] summarises these different adaptation techniques that are used in adaptive hypermedia, in his well-known taxonomy. These technologies are classified into two groups, based on *adaptive presentation* and *adaptive navigation*. LAAI uses both, in a lightweight manner, as follows: adaptive presentation techniques are used to adapt the content (advertisements) of each webpage, based on the characteristics of each individual

user. Furthermore, with adaptive navigation, users find their paths (sequence of related advertisements), based on their behaviour.

The adaptation model in AHAM [Wu, et al., 2001], e.g., is defined as a set of adaptation rules – condition-action rules – that establish a connection between domain model, user model and the presentation that will be generated. The adaptation rule language in AHAM is based on database query languages, and can be quite difficult to use by novice authors or busy business people. By contrast, in LAOS [Cristea, 2003, Cristea and de Mooij, 2003], the adaptation model consists of three layers, in order to overcome both the limitations of the inexperienced author and, at the same time, allow adequate flexibility for the advanced author. These layers, Adaptive Assembly Language, Adaptive Language and Adaptive Strategies, are distinguished by the type of rules they allow. The first layer, Adaptive Assembly Language, represents traditional techniques, like the insertion/removal of fragments, sorting of fragments and links, link hiding/removal/disabling, as defined by Brusilovsky's taxonomy [Brusilovsky, 1998]. The second layer groups the elements from the previous layer, to create adaptation mechanisms and constructs, and can be represented as a higher-level adaptation language, which can be defined by the designer. The third layer uses the building blocks from the previous layer to build higher-level programs and, potentially, reusable strategies.

Thus, previous adaptation models bring interesting ideas and approaches. However, most of the existent adaptation models are targeting the adaptation in the education field. Moreover, the majority try to be comprehensive, e.g., as in covering the whole of Brusilovsky's taxonomy, as the authoring language LAG does [Cristea and Verschoor, 2004, Scotton, 2013]. This often leads to quite complicated authoring models (and their respective tools), which further means that only experienced authors could write efficient adaptation strategies for them.

In this research, instead, *businesses* are at the centre, and are supported to apply adaptation strategies to their own advertisements in a manner which is *lightweight*, and, presumably, easier. In other words, instead of opting for a complicated adaptation model, the lightweight approach introduced is intended to ensure adaptive flexibility, whilst keeping the choices of strategies extremely simple.

The specification of adaptation in the LAAI model can be thus described by an advertisement-oriented adaptation model. Concretely, the adaptation model layer contains the adaptation rules, which specify different styles of adaptive behaviour for adverts. This layer describes the relationships between adverts domain models and customer (user) models, and, based on these relationships, a group or sequence of groups of advertisements can be assigned to each user.

Moreover, in contrast to previous models, the adaptation rules in the adaptation model are further categorised into two newly defined, original categories, which are proposed as part of the LAAI model (as described by [Qaffas, et al., 2013]) – *general* and *behaviour* – in order to ultimately facilitate authoring, by further supporting the principle of 'separation of concerns' [Laplante, 2007]. The idea is to separate adaptation of stable versus volatile user (customer) model components, as is explained below. Furthermore, template adaptation rules are to be prescribed within these categories, to preclude the need to write complex adaptation rules by hand.

Specifically, *behaviour rules* assign advertisements to users, based on the user behaviour, the volatile, changeable characteristic of a user. In the implemented

version of LAAI, this process involves a number of prewritten strategy templates that the author may choose from and control. This method is aimed at overcoming the difficulties encountered by inexperienced authors, such as not knowing how to start, which have been highlighted in prior research [Foss and Cristea, 2009, Foss and Cristea, 2010]. The author (here, a website and business owner) controls these strategies, by updating them to meet specific requirements. For instance, by using an adaptation system based on the LAAI model, it should be straightforward to add a behaviour rule that will instruct the delivery layer to display an advertisement, after a user has clicked on another specified advertisement. As shown in Figure 6, after defining a sequence of rules, the author must then assign or unassign advertisements to these rules. In this way, the process of what advert follows what rule is completely under the control of the website owner. Moreover, the figure also shows that rules can be reused (e.g., 'Behaviour Rule *2*' is used both by Advert *2* and Advert *n*), thus answering the concern raised in adaptive hypermedia about the necessity of reuse of information [Cristea and Stewart, 2006].

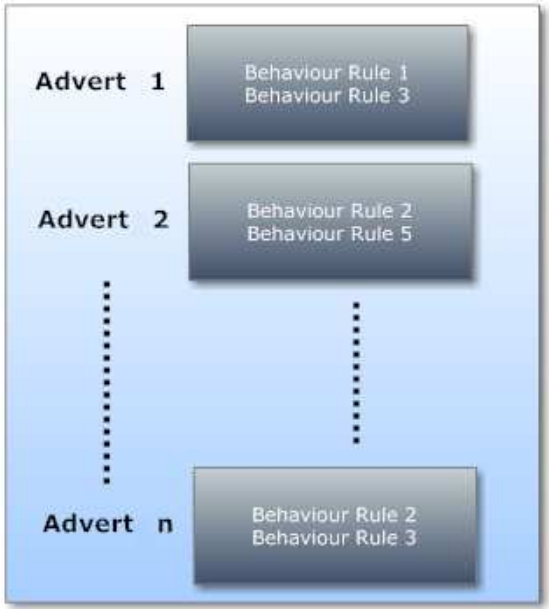

Figure 6: Behaviour Rules in LAAI

With respect to the nature of advertisements, in addition to grouping advertisements into levels within the domain model, the behaviour rules also establish links between advertisements, from the same or even a different group in the domain, which allows the system to present them in an arguably smooth sequence. Thus, user behaviour can create units, based on otherwise unrelated adverts. For example, when using an application that has been developed founded on this model, the author can add a behaviour rule, to display two advertisements from a specified subgroup, if another specified advertisement in the same subgroup is clicked. In order to ensure

flexibility, the application should allow the author to control the number of clicks to fire, as well as the number of advertisements that will be shown.

By contrast, *general rules* assign advertising content to a user, by exploiting basic data from the user model, such as age, gender, etc. Adaptation to this kind of parameters can be considered relatively mainstream in adaptive hypermedia [Al Qudah, et al., 2015]. From an authoring perspective, the author must be able to add or remove these characteristics if they so desire, in order for the application to maximise the portability and generalisability of the adaptation system. This type of adaptation rules have some similarity to stereotyping, as, for example, an adaptation rule may assume that, if a user is employed as a judge, they are likely to be over the age of forty and well educated, and could potentially assign advertisements based on this reasoning.

Furthermore, general rules in LAAI can make use of two types of data – *discrete* or *range*. The data type can be determined by businesses, allowing thus for further flexibility and potential efficiency. As illustrated in Figure 7, businesses could, for example, add a general rule named 'Gender', by using discrete data that will retrieve the gender of users. According to this rule, advertisements could be categorised by businesses to differentiate between those targeting male or female users. Moreover, general rules can also be assigned based on range-type data. Figures 8 and 9 illustrate a general rule called 'Age', written in two ways, which use different data types. In other words, a business could create this general rule, 'Age', and then could assign the appropriate data type for this rule, according to their marketing policy.

Finally, the adaptation model should allow for an easy match between rules and domain models, as rules only need to be written once and then could be assigned to any number of advertisements. With regard to flexibility, generalisability and portability, for any application based on LAAI, the adaptation model is considered as a storage layer of adaptation specifications, and any implementation of adaptation is isolated within the inference engine in the delivery model (described in the following). Thus adaptation specification and adaptation implementation are also separated, allowing for an enhanced level of reuse.

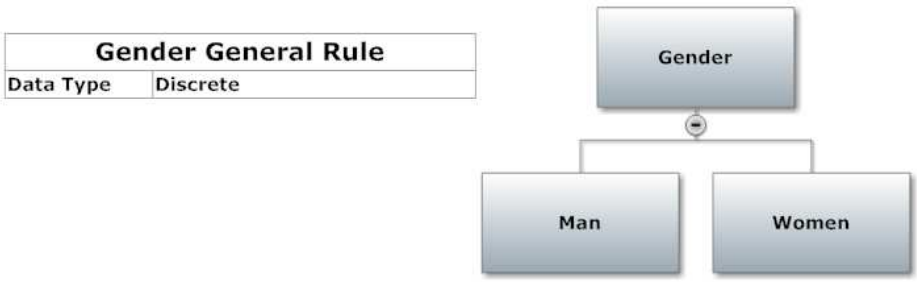

Figure 7: Gender Rule with Range Data Type

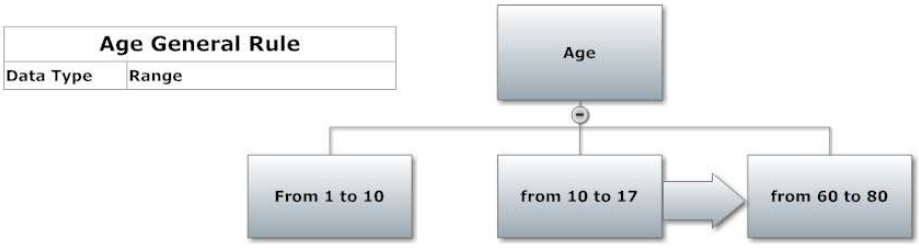

Figure 8: Age Rule Example with Range Data Type

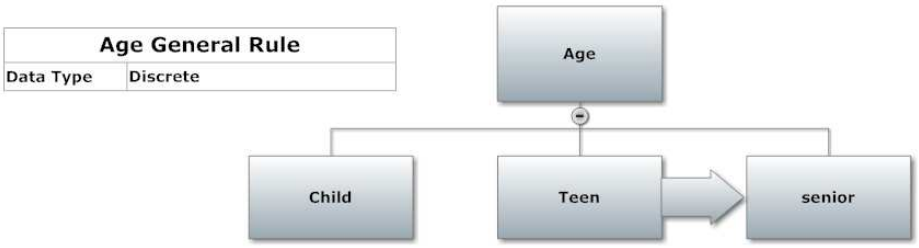

Figure 9: Age Rule Example with Discrete Data Type

7 Delivery Model (DM)

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

This focus is additionally supported by the *delivery model (DM)* developed for the LAAI model being further separated into three engines: *inference, decision,* and *modifier*. The reason for introducing this expanded level of 'separation of concerns' is to separate important stages in the delivery of appropriate adverts to a client, as explained below. Using these three engines, the delivery model generates advertisements that are suitable for the current user. The first engine, inference, carries out reasoning processes about the state of the user. The decision engine is based on adaptation rules, domain items and data generated by the inference engine, and retrieves appropriate advertisements for each user and displays these advertisements. Finally, the modifier engine updates the user model with current data. The modifier engine determines how to make transitions to the user model, and

updates the data in the user model, based on the behaviour of the user. The following subsections describe the structure and functionality supported by each of these three engines.

7.1 Inference Engine

As illustrated in Figure 10, the *inference engine* obtains data from the domain, adaptation and user models, and carries out a series of processes based on this data, in order to generate multiple sequences of advertisements to send to the decision engine. Adaptation rules from the adaptation model are executed in the inference engine. The latter first determines whether the current user is logged into the website. If the user accesses anonymously, the inference engine will only apply the *plan recognition* process, based on the current session and behaviour data only. *Plan recognition* refers to the task of inferring the plan of an intelligent agent (here, customer) from observations of the agent's actions or the effects of those actions [Ramırez and Geffner, 2009, Seidman, 2013]. This helps pinpoint the aim of the customer, based on their actions in a specific environment, thus narrowing the number of possible goals, by observing the actions performed. For example, in message centres and information systems, customers often have specific goals, such as listening to new messages or getting billing information.

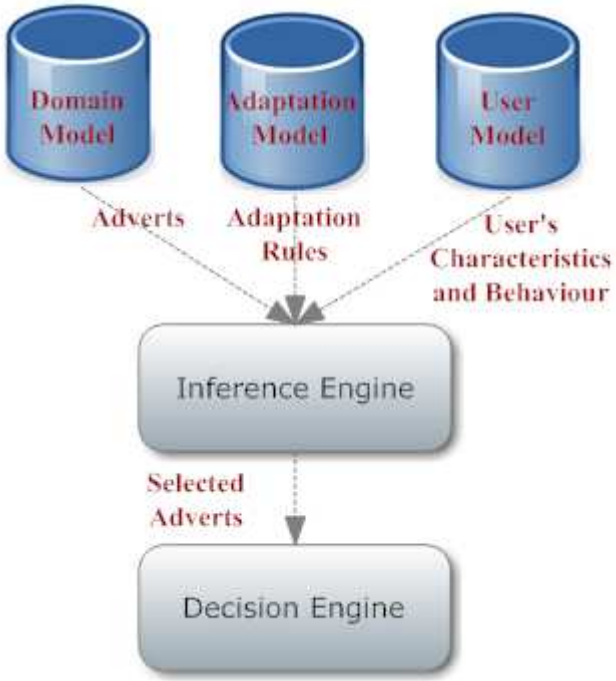

Figure 10: Inference Engine

The plan recognition process depends on the plan libraries (Figure 11), which the business will have previously created. The inference engine checks clicked items and then checks the plan libraries, with a view to generate a sequence of advertisements, to be dispatched to the decision engine. For example, as shown in Figure 11, the author may construct a plan, such as follows: *Advert 1* followed by *Advert 3* and then *Advert 6*. This plan will be recognised by the inference engine when *Advert 1* is clicked by a user. In this situation, the inference engine will place *Advert 3* and *Advert 6* in a queue (list) that will be sent to the decision engine.

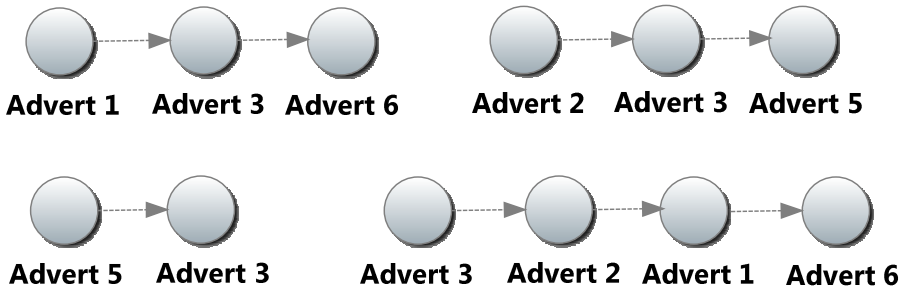

Figure 11: Plan Libraries from the Domain Model

On the other hand, if the current user is logged in, the user can be identified by the system, and Algorithm #1 below is triggered.

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

If the user is logged in, loop as long as the user is using the website

a. Retrieve advertisements from the inference engine that match and do not match the general rules for the current user (unsuitable adverts).
   i. Send this information to the modifier engine to update the user model.
b. Retrieve advertisements from the inference engine that were stopped based on the 'stop' social networking data.
c. Retrieve advertisements from the inference engine that were retrieved based on the 'like' social networking data.
d. Retrieve advertisements from the inference engine as per applied behaviour rules.
e. Monitor advertisement clicks to apply the plan recognition process, then send the results to the decision engine.

End if

Then, the general rules from the adaptation model will be applied by the inference engine first, in order to assign a group of advertisements from the entire domain to the user, based on features such as gender, age, and so on. The group of data relating to the current user will be sent directly to the modifier engine, which will update the user model with 'suitable' and 'unsuitable' advertisements. It is important to have the latter together with the suitable adverts, due to the fact that these rules may only apply

to a subset of adverts, leaving still a (potentially large) number of adverts which are 'indifferent' at this stage, to be processed via other rules. Moreover, these could be further applied to dynamic systems, where ads keep dynamically being added to the system.

Next, the behaviour rules, representing adaptation strategies, are applied. The user model data that represents the user's behaviour – for example, advertisements they clicked – is used by the inference engine, to apply the behaviour rules. This process will yield a list of advertisements, which will then be sent to the decision engine.

Another list of advertisements is also retrieved and passed on to the decision engine, based on the plan recognition process. For the logged in user, the inference engine will also apply the plan recognition process and pass the results to the decision engine. Moreover, the inference engine will apply a series of processes, based on criteria developed by the business, relating to user actions – such as searches, likes and purchases.

The social networking data component of the user model will cause the inference engine to exclude certain advertisements based on 'stop' data (dislikes of a user) and to display other advertisements based on 'like' data. The customised business rules included in the delivery model also help to determine how the inference engine deals with social networking data.

The resulting recommended advertisements for each customer must have been validated by the general rules.

7.2 Modifier Engine

The *modifier engine* updates the user model based on the connections between the modifier, inference and decision engines (as illustrated by Algorithm #2 below).

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

while not (logged out)

a. Listen for decision engine to update the number of shows for advertisements.
b. Listen for user behaviour to update:
   - Advertisements that are clicked, and number of clicks.
   - Advertisements that are searched.
   - Advertisements that are bought.
   - Advertisements that are viewed and not clicked.
c. Update user model with information obtained by the inference engine by applying general adaptation rules.
d. Update user model with information that describes inference engine actions on advertisements.

end-while;

if user is logged out

- The modifier engine stores the remainder of the advertisements in the 'future advertisements' component of the user model for the next login.

end if

The modifier engine receives two groups of advertisements for the current user from the inference engine, which has applied general rules to generate these groups. The modifier engine then updates the current customer's user model with 'suitable' and 'unsuitable' groups of advertisements, based on these general rules. In addition, the modifier engine can monitor the user's behaviour, to update the user model with new data, such as clicks, searches, likes, and so on. By collecting this data and updating user models, the modifier engine is designed to contribute to the portability and generalisability of the overall application design. Next, the decision engine is described.

7.3 Decision Engine

The *decision engine* is responsible for displaying advertisements to the current user (see Algorithm #3 above).

First, the decision engine must check whether the current user is logged in or not. If the user is not logged in, the decision engine will randomly display advertisements from the entire domain. In addition to displaying these advertisements, the decision engine obtains the user's click data, so that it can trigger the plan recognition process generated by the inference engine. This click data represents in this case the only personal information known about the user, which is then used to generate new advertisements with the highest priority.

On the other hand, if a user is logged in and thus identifiable, the decision engine will retrieve first the business rules strategy saved in the delivery model, in order to assign the priority levels determined by the business to the advertisements yielded by the inference engine. The decision engine will now also load the advertisements previously saved in the 'future advertisements' component of the user model. This engine also retrieves advertisements that match data from the inference engine, such as 'like' and 'stop' social networking data, behaviour rules, general rules, and user actions (search and buy), and uses the priorities as set by the business, in order to arrange them in a list. For the logged-in user, the decision engine also uses the user's clicks, to fire the plan recognition process from the inference engine. However, advertisements that are generated by this process will be assigned to the tail of a list, as they represent only indirectly retrieved customer preferences, unlike the previous data, where the user expressed preferences directly.

The decision engine is now ready to display the advertisements from the list (created via the prioritisation process of the various lists received from the other engines) to the current customer. The engine displays advertisements from the list, until the sequence is completed, and then, if the recommended list is finished, it further selects advertisements that match the general rules, appropriate for the user's characteristics. If the user logs out while there are advertisements remaining in the list, the decision engine will save these advertisements in the 'future advertisements' component of the user model, to be loaded as a first priority at the user's next log-in.

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

If the user is logged in:

a. Load previous advertisements which were assigned to the user at the last login, but were not displayed (these are stored in the *future advertisements* section of the user model).
b. Find the advertisements from the user model which do not match the general rules for the current user (unsuitable adverts).
c. Call the inference engine (General Rules part) one time only at login, to find advertisements which match or not the general rules, adding them to two lists labelled 'suitable' and 'unsuitable', respectively.
d. Call the inference engine (Social part) to retrieve the advertisements that are stopped based on 'stop' social data.
e. Call the inference engine (Social part) to retrieve the advertisements based on different social data ('like'); add them to the social data list.
f. Call the inference engine (Behaviour Rules part) to retrieve advertisements, and add them to the behaviour rules data list.
g. Remove all advertisements listed in the 'unsuitable' list.
h. Apply the priority algorithm determined by the business rules, in order to arrange advertisements according to the type of criteria used by the inference engine to obtain the advertisements.
i. Loop while the user is logged in:
    1. Display the advertisements from the list on the current page (with the condition of no duplication of advertisements within the same page).
    2. If advertisement is clicked, the advertisement clicks-listener fires the inference engine to retrieve list of advertisements, based on the click, and shows the results to users.
    EndIf
    3. Call the Modifier Engine to update the user model based on all above changes (ads displayed, clicks, unclick).
    End loop

Else (for the anonymous user)

j. Load all advertisements in list.
k. Loop
    1. Display an advertisement randomly from the list on the current page.
    2. If advertisement is clicked, the advertisement clicks-listener triggers the inference engine, to retrieve the list of ads, based on the click, showing the results to users.
    EndIf
    End loop

End if

8 Evaluation

In order to test the LAAI model, the AEADS system [Qaffas and Cristea, 2014, Qaffas and Cristea, 2014, Qaffas and Cristea, 2015, Qaffas and Cristea, 2015], which was implemented based on the above proposed LAAI model, was integrated with an online bookstore.

For evaluating the AEADS system, a number of business owners were asked to utilise the system in its current format. Next, we present the hypotheses for this study.

8.1 Hypotheses

The following umbrella hypotheses have been defined to evaluate the AEADS system, from a *business owner*'s perspective:

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

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

H0x above are the basic hypotheses, which are further refined into more specific hypotheses, corresponding to the AEADS system features, as defined below (with hypotheses labelled with 'a' and 'b' being a subset of H0a and H0b, respectively):

H1a: *The various functions in the AEADS system are well integrated.*

H1b: *The AEADS system has a shallow learning curve.*

H2a: *The clicking process (to reach desired ads) is more effective in the AEADS system, when compared to other online ads systems.*

H2b: *The clicking process (to reach desired ads) is easier in the AEADS system, when compared to other online ads systems.*

H3a: *Buying is more effective in the AEADS system, when compared to other online ads systems – in terms of increasing the buying opportunity.*

H3b: *Buying is easier in the AEADS system, when compared to other online ads systems.*

H4a: *The AEADS system allows the control of the location of advertisements within the web page effectively.*

H4b: *The AEADS system allows the control of the location of advertisement within the web page easily.*

H5a: *Controlling the number of advertisements on each webpage in AEADS is effective.*

H5b: *Controlling the number of advertisements on each webpage in AEADS is easy.*

H6a: *The AEADS system allows the application of the general rules effectively.*

H6b: *The AEADS system allows the application of the general rules with ease.*

H7a: *The AEADS system allows the application of behaviour rules effectively.*

H7b: *The AEADS system allows the application of behaviour rules with ease.*

H8a: *The AEADS system allows the application of the plan recognition process effectively.*

H8b: *The AEADS system allows the application of the plan recognition process with ease.*

H9a: *The overall authoring part is useful.*

H9b: *The overall authoring part is usable.*

H10a: *The overall delivery part is useful.*

H10b: *The overall delivery part is usable.*

H11a: *The Facebook login is more useful than the fill-in (manual registration) data process.*

H11b: *The Facebook login is more usable than the fill-in (manual registration) data process.*

H12a: *The user information acquisition via system registration is useful.*

H12b: *The user information via system registration is usable.*

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

8.2 Evaluation Methodology and Setup

Several entrepreneurs were chosen to participate in this data collection phase - the *structured interview* - composed of four parts. This form of interview is known to provide valuable information and understanding regarding companies' opinions of the implemented model and system [Seidman, 2013]. It was also believed that the structured interview would enable discovering clients' perspectives, raise issues and generate tips related to the implementation of the model and offer information about the system's appropriateness.

Participants were selected from *various industries*, in pursuance of obtaining results that are representative of a broader business scene. Thus, a total of *seventeen business owners* were invited for participation, and all of them accepted. They were requested to test the authoring of the AEADS system from various aspects.

The interview was structured as follows. First, at the beginning of the interview, the idea of adaptive advertising was presented and explained to all participants, individually. Next, participants were provided with a basic understanding of the AEADS system and how to use it. This explanation session took about 30 minutes, including questions Once participants sufficiently understood the information provided during this initial stage, after agreeing that they are comfortable to use the system, they were required to test the AEADS system in practice. All of the respondents then assessed the system, in order to offer feedback, in the form of answering a questionnaire, enabling us to gain the required information to answer the research questions and improve the model and the system. They were also asked, where necessary, to explain their decisions and discuss freely about the system.

The questionnaire itself consisted of four subsections. The first section asked participants to provide generic information, such as the type of business, size of business, etc. The second part requested that respondents offer their own personal feedback on the overall function of the AEADS system. This questionnaire section also included ten system usability scale (SUS) standard questions [Bangor, et al., 2008].

The third section of the questionnaire required participants' feedback on the AEADS system's practical implementation, specifically, on its main features (see Table 1). This section included a Likert scale for respondents' answers. Here, numerical data was used to represent a certain feeling or opinion: for instance, *1 = 'not at all useful'* to *5 = 'very useful'* for questions related to the a-series of hypotheses; or *1='very difficult to use'* to *5 = 'very easy to use'* for questions related to the b-series of hypotheses.

Additionally, in the fourth and concluding section of the questionnaire, a number of open questions were asked. These questions were created to obtain qualitative

information from the entrepreneurs regarding the implementation of the AEADS system, and are:

1. What are your suggestions for improving AEADS? Please list below.
2. What other features/ functions would you like to see in AEADS? Please list/comment below.
3. What else you want to tell us? (Anything please).

To understand the numerical feedback from the interviews, firstly, question reliability was computed with Cronbach's Alpha. Next, the average scores obtained for the various questions were compared with the neutral response (3, on the Likert scale of 1-5). This was done via T-tests in a first instance. As the T-test assumes normality of the data, a non-parametric Mann-Whitney test, which avoids this assumption, was also performed. For both tests, the $p<=0.05$ significance threshold was used, which is the one most commonly used in significance research.

NO	Feature	Hypotheses
1	Clicking on Advertisements process	H2a, H2b
2	Buying process	H3a, H3b
3	Controlling the location of Advertisements on the webpage	H4a, H4b
4	Controlling the number of Advertisements on each webpage	H5a, H5b
5	Applying General Rules	H6a, H6b
6	Applying Behaviour Rules	H7a, H7b
7	Applying the Plan Recognition Process	H8a, H8b
8	Overall Authoring	H9a, H9b
9	Overall Delivery	H10a, H10b
10	Facebook login (against the Fill-in Data Process)	H11a, H11b
11	Information Acquisition via System Registration	H12a, H12b

Table 1: AEADS System Features and their mapping over Hypotheses

8.3 Numerical Results and Discussion

The aim of this evaluation was to gather the perspective of the business owners on the AEADS system. Here, the sheer numbers were less important, than the spread of business types (on the Internet), as well as the qualitative feedback. As illustrated in Table 2, the respondents selected for participation in this study were representative of several sectors. Specifically, the respondents represented the construction industry, online education industry, telecommunications industry, retail industry, consultation industry, transportation sector and the media industry. Figure 12 depicts the mix of companies by size, with most companies (41%) being small and medium-sized enterprises (SMEs), around one third (35%) being medium-sized enterprises and around one quarter (24%) being large-sized enterprises. Thus, an arguably broad representation in terms of business size is also achieved. As shown in Figure 13, the company participants involved in this study were also representative of two different

countries, with 29% being located in the UK and the remaining 71% in Saudi Arabia, as these were the two countries the main researcher had access to. By selecting such a mix of participants, with as varied characteristics as possible, the aim was that the findings of this study will allow improved insight into the perspectives of individuals from a variety of sectors, company sizes and countries, making the findings more applicable to a wider range of businesses.

Table 3 below summarises the validation results for all hypotheses, based on the answers from Sections 2 and 3 of the questionnaire. As can be seen, all responses regarding all hypotheses have both means and medians well above 3 (actually, above 4), with standard deviations of around half a point. Thus, when computing the probability of this value of being by chance above the indifferent response of 3, all probabilities are at $p=0.0001<0.05$, confirming that results are significant. In addition, the Cronbach's Alpha score is 0.92 [$\geq$ 0.9], meaning that the reliability of the psychometric test is excellent [Cronbach, 1957]. This confirms that the business owners found the functionality as implemented in AEADS and prescribed by the LAAI model as *useful*, as well as *usable*. This confirms the (cumulative) basic hypotheses **H0a** and **H0b**, respectively.

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

Table 2: Types of Business

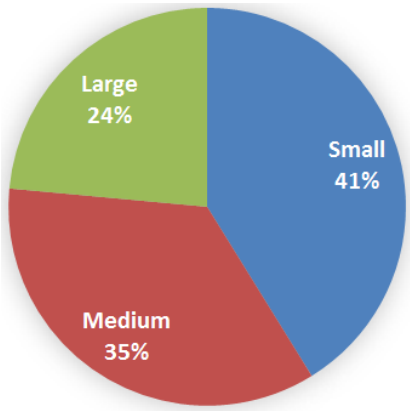

Figure 12: Size of Businesses

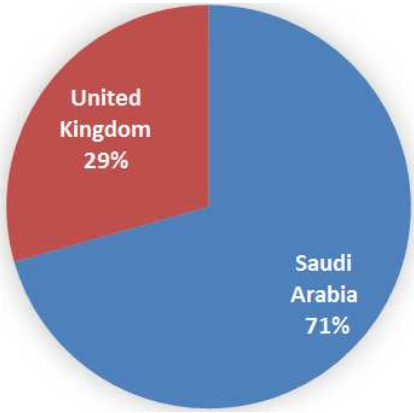

Figure 13: Country

Hypothesis	Mean	Median	SD	p
H1a	4.76	5	.43	.0001
H1b	4.41	4	.62	.0001
H2a	4.71	5	.46	.0001
H2b	4.53	5	.50	.0001
H3a	4.35	4	.48	.0001
H3b	4.41	4	.49	.0001
H4a	4.82	5	.38	.0001
H4b	4.35	4	.48	.0001
H5a	4.76	5	.42	.0001
H5b	4.53	5	.50	.0001
H6a	4.41	4	.49	.0001
H6b	4.82	5	.38	.0001
H7a	4.47	4	.50	.0001
H7b	4.47	4	.50	.0001
H8a	4.24	4	.42	.0001
H8b	4.88	5	.33	.0001
H9a	4.41	4	.49	.0001
H9b	4.47	4	.50	.0001
H10a	4.53	5	.50	.0001
H10b	4.29	4	.46	.0001
H11a	4.53	5	.50	.0001
H11b	4.53	5	.50	.0001
H12a	4.24	4	.55	.0001
H12b	4.35	4	.48	.0001

Table 3: Hypotheses revisited

Furthermore, the SUS score for AEADS is 87.90 out of 100 (with a score of above 68 being above average [SystemUsabilityScale(SUS), 2018]), while the Cronbach's Alpha score is 0.93 [≥ 0.9], meaning that the reliability of the psychometric test is excellent [Cronbach, 1957]. These findings also suggest that the validity and reliability of the findings are positive. The answers of business owners are presented in Figure 14, with the negative questions[1] mapped onto the positive domain, via the following formula (eq. (1)).

$$new_question_value = 6 - old_question_value \quad (1)$$

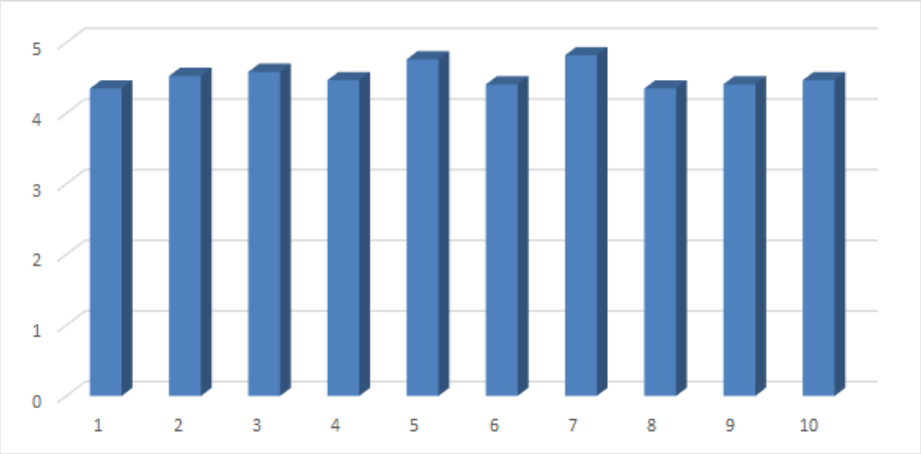

Figure 14: System Usability Scale (SUS)

As illustrated in Figure 14, a score of at least 4 was achieved for every item in the system evaluation questionnaire. All company representatives involved in the study reported thus high levels of satisfaction with the AEADS system. The value of the SUS score shows, additionallly to the self-designed questions on usability modelled on the hypotheses H1b-H12b, that, based on a common instrument used in software analysis, business owners found the AEADS system, rooted in the LAAI model, to be useful.

The analysis of the participants' questionnaire responses offers further various insights into businesses' opinions of the AEADS system. These findings will now be outlined. Firstly, from one of the SUS questions, it emerged that most respondents stated that they would have a preference for utilising the AEADS system on a regular basis. Furthermore, also from SUS we found out that many respondents thought that every element of the AEADS system was effectively integrated, making it streamlined and well-functioning, which supports hypothesis **H1a**. They also stated that they felt very confident when using the AEADS system.

[1] SUS alternates positive and negative questions. To compare them with the neutral state, they need all transformed into questions with the same polarity (here, positive).

The questionnaire results also indicate that the majority (96.5%) of businesses believed that the AEADS system could be implemented effectively within actual companies, without the need for extensive system training, as they further comment via the open-ended questions (see Section 8.4). This means that employees should find the system relatively easy to install and use without many complications, which additionally supports hypothesis **H1b**.

The results above are further confirming the **basic hypothesis H0b**, i.e. supporting the fact that the majority of the participants felt satisfied (91.8%) with the usability of the system (another result extracted from the SUS questionnaire).

Overall, for the SUS questions, the T-test rendered values of 37.75 (p= .0001<.05), pointing to a significantly greater average than the neutral response. This is further supported by the Mann-Whitney test (with Z-score 15.67, U-value 170, p=.0001< .05). The distribution is approximately normal, because of the U-value.

Further analysis of feature-related results suggest that the business owners involved in testing the system for the purposes of this study considered it to be highly useful. This argument is further supported by the standard deviation values of 0.38 - 0.55 and mean value of 4.24 - 4.82 (see Table 3). For example, the results clearly indicate that business owners highly valued the systems' effectiveness in terms of the clicking process, of the management of the advertisements' placement and of the control of the number of advertisements on each page, which support hypotheses **H2a, H4a and H5a** (see Table 3).

Although the information acquisition via the system registration method (related to **H12a**) received a rating of 4 or more, this nonetheless appears to be considered the least important element of the AEADS system among participants. It is possible that the reason behind the lack of emphasis on this particular element is that business owners may have preferred the Facebook login approach. They also may have considered that other system components were more important than this particular feature. Nevertheless, this feature still rated highly, thus indicating its perceived usefulness for many businesses, which supports hypothesis **H12a**.

This overall positive attitude about the usefulness of the functionality of the AEADS system is depicted in Figure 15, below, which indicates that the participants involved in this study believe that the adaptive advertising process can be effectively assisted by the AEADS system. The average for all the features of AEADS in terms of *usefulness* is 4.50. This shows a difference of 1.50 when compared with the neutral response (3). Moreover, for the usefulness of AEADS (the a-hypotheses, see Table 1 and Figure 15), the T-test rendered values of 39.99 (p= .0001<.05), pointing to a significantly greater average than the neutral response. This is further supported by the Mann-Whitney test (with Z-score 16.64, U-value 93.50, p=.0001< .05). The distribution is approximately normal because of the U-value. This result shows that, in terms of usefulness, the features of the AEADS system are appreciated by the businesses in the test sample, and that the positive difference, when compared to a neutral response of 3, is statistically significant.

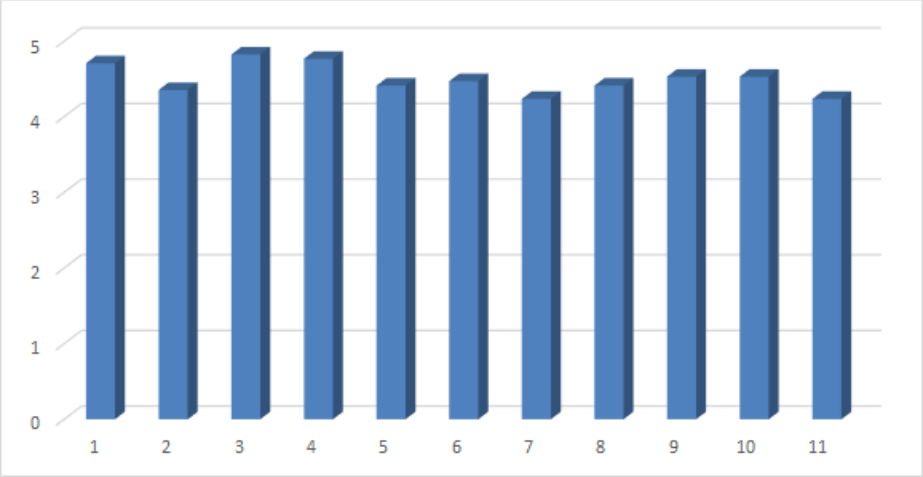

Figure 15: Usefulness (Ox axis detailed in Table 1)

The usability of the distinct features was separately evaluated, beside SUS, through targeted questionnaire questions, corresponding to the b-hypotheses, as explained above. Further delving into this data, the participants involved in testing the AEADS system felt that the system was satisfactory in terms of usability and accessibility. This suggestion is supported by the mean values of 4.29-4.88 and the standard deviation of .33-.50 (see Table 3). In addition, the Cronbach's Alpha score is $0.92 \in [\geq 0.9]$, meaning that the reliability of the psychometric test for usability is excellent [Cronbach, 1957]. In more details, for instance, 'The system applies the general rules easily' and 'The system applies plan recognition process easily' were highly rated by participants, which supports hypotheses **H6b and H8b.** Thus, business owners clearly like the fact that rules can be applied to individual advertisements and that multiple rules can be applied at the same time. Furthermore, they also like the general rules of the adaptation model, as, presumably, they can manage them relatively easily by using this tool. The second feature, the one applying the plan recognition process, was considered to be one of the best, possibly as they could link the relevant advertisements together easily, which supports Hypothesis **H8b** and **H9b**.

While some features received a slightly lower rating, the overall perceived level of usability remained high. For instance, a score of more than 4 was achieved with regards to the usability of the system's delivery process. This might have been since there is no additional effort required by it, as the delivery process only interprets the authoring process. Nevertheless, this was the lowest-rated system element - still with a score of more than 4 - which is just high enough to indicate good system usability, supporting hypothesis **H10b**.

The suggestion that the AEADS system and its functions would be usable for adaptive advertising, as proposed in hypothesis **H0b**, is visually supported by the graph of the results of this questionnaire section (see Figure 16).

Summarising, the average for all the AEADS features in term of ease of use is of 4.51. When compared with the neutral response (3), this shows a difference of 1.51. Moreover, overall, for the usability-related questions in the questionnaire (beside the SUS), the T-test rendered values of 41.29 ($p = .0001 < .05$). This shows a significant greater average than the neutral response. This is further supported by the Mann-Whitney test (with Z-score 16.73, U-value 0, $p = .0001 < .05$). The distribution is approximately normal because of the U-value. This result shows that the AEADS features are appreciated in terms of ease of use by the businesses in the test sample, and that the positive difference, when compared to a neutral response of 3, is statistically significant.

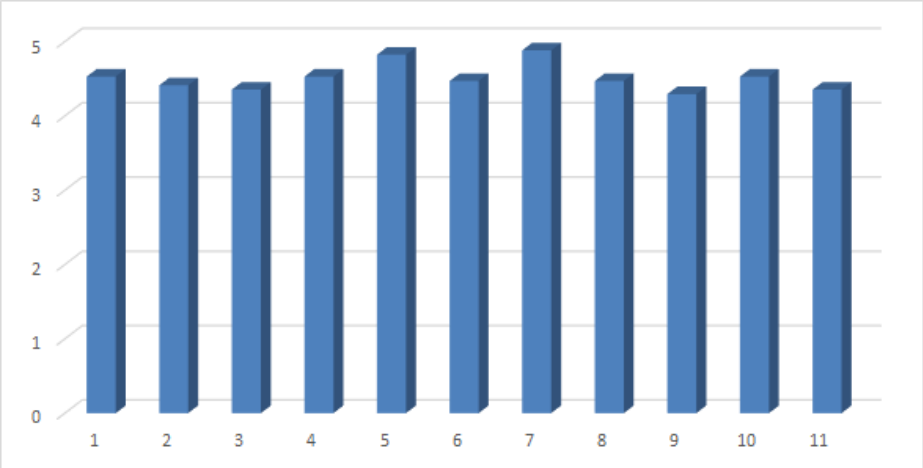

Figure 16: Usability (Ox axis detailed in Table 1)

8.4 Qualitative Answers and Discussion

As part of the businesses evaluation of the AEADS system within this study, a qualitative data collection was conducted with the same seventeen business owners, in order to gain a fuller understanding of the participants' thoughts regarding the system. This section provides the answers and suggestions given by participants during this stage of the data collection process, as well as discusses them, by triangulating also with the implications from the numerical data analysis.

Business owners answered that they believed that the AEADS system could be implemented effectively within actual companies, without the need for extensive system training. To this effect, they commented that the various functions of the system were easy to use and their staff does not need extensive training to use the system. It became thus clear, during the evaluation process, that the short presentation given to the business owners at the start of the evaluation offered enough training for them to be able to understand and use the system, organise advertisements and apply the adaptation rules. These findings from the open dialogue confirmed the results from the quantitative data analysis process, as in this process the AEADS system had achieved a high score regarding usability from most businesses that participated. For

instance, one participant stated that when they previously attempted to gain an understanding of Amazon advert recommendations, they were unable to do so; however, they were able to fully grasp and understand the workings of the AEADS system relatively rapidly. Consequently, this participant's satisfaction levels with the system were high.

However, it was also highlighted that the system should be able to provide further information, if it is to be useful and beneficial for specific businesses. For instance, one participant stated that it would be useful if they could obtain reports offering insight into factors such as clicked and unclicked advertisements and system users. Another participant supported this, as he asked "Can we get more information about users?". This finding is reflected by the analysis of the quantitative data, in which the user information acquisition by the system registration received one of the lowest scores (albeit still high) from the participants. Such a report is relatively easy to generate for AEADS (from its XML files), due to its modular, easily extensible structure, as prescribed by the LAAI model. However, the system implemented is intended to be a lightweight adaptive advertising system, which includes simple tools for businesses and Internet users. In addition, users' privacy was respected and the test results [Qaffas and Cristea, 2016] showed that users would be unwilling to disclose any more information at this stage. Thus, the data required for customising advertisements for individual users' obtained should only be used for this purpose. If businesses require more data, consent needs acquired from the users – especially with the new laws introduced by the GRDP[2] in Europe, for instance.

On the other hand, another related critique from one participant stated that the system currently contains an excessive number of XML files. Nevertheless, this was an isolated opinion, as, in the quantitative data analysis, the majority of respondents felt that the AEADS integration process was improved through the XML data store. It should be noted that the XML representation is there to allow the system to be easily integrated into any website, with only minor changes needing to be made to the database. This process has been exemplified by integrating the AEADS system with an online bookstore, for evaluation purposes as explained in [Qaffas and Cristea, 2016]. Moreover, these files can be used to generate reports, as requested by the other business owners. Potentially, however, the files themselves need masked from the business owners, to simplify the usage.

Additionally, during an initial qualitative data-gathering phase, not detailed elsewhere in this paper, it was suggested that the system could be improved by allowing somewhat richer (albeit still simple) adaptation behaviour rules (e.g., with different variables types, such as ranges, etc.). As a result, the initial general adaptation rules have been modified, allowing them to be more flexible, based on the customers' needs and the company views (the result of this is presented in Section 6, Adaptation Model, Figures 7-9). Additionally, most business owners agreed that the system applies the general rules easily.

Moreover, the process of manually linking one advertisement to another within the plan library was criticised by one participant, who stated "It is a long process to link advertisements together in the plan library and a time-consuming task". Still, this feature received a satisfaction score of more than 4; however, it represented the lowest score amongst all the system's components. Nevertheless, the plan library

[2] https://www.eugdpr.org/

feature was considered one of the best in terms of usability levels within the quantitative data analysis, as they could link the relevant advertisements together easily.

During this stage of the data collection phase, another participant raised the question of how many websites the AEADS system could manage at once. However, this scalability issue is not directly relevant, as all websites come from providers and the AEADS system is not supposed to run as a server, as it consists of lightweight tools and offers all that is needed to run directly on the server of the business.

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

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

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

8.5 Limitations

Here we discuss potential threats to the validity of the findings of this research. One is that the number of participants in this study is low. Nevertheless, this is alleviated by

their importance being high, as they can be considered *experts* of the field, as owners of their own business, so the actual number of participants is less important, compared to their feedback [Dworkin, 2012]. Furthermore, for evaluations with experts, 17 is a relatively high number [Dworkin, 2012], [Al Qudah, et al., 2015].

Moreover, statistical significance mentioned in the paper should be understood and interpreted only within the given number of participants. It shows, however, that these business owners from various fields had very similar opinions (hence the high significance, despite the small sample), and that their responses confirmed all our hypotheses. Additionally, statistical results are triangulated and backed up with qualitative data analysis.

It is also possible that the applicability of LAAI is different for different commercial domains. However, by interviewing business owners from different areas, and with varied sizes of business, we have tried to alleviate this issue.

Furthermore, on the data collection approach, especially with the advent of the new data protection law (GDPR, effective May 25th 2018 in the EU), the automatic collection of data process and the collection of data from social sites needs potentially reanalysed, in terms of, e.g., explicit permissions of users on their data usage.

9 Conclusions

A new adaptation model, called the *Layered Adaptive Advertising Integration (LAAI)*, for delivering adapted advertisements for users, is introduced in this paper. Based on this model, we have shown that an adaptive advertising system is perceived by businesses to be able to be implemented and integrated easily in any website, to adapt their advertisements. In addition, this model uses the concepts of social networks, to enhance and simplify the data retrieval process. It also uses interactive data about advertisements in the domain, to update the user model. The LAAI model is composed of four components, domain model (DM), adaptation model (AM), user model (UM), and delivery model (DM).

The domain model (DM) is organised in a format that was confirmed to enable easy creation, extension and adaptation of advertising content. The domain is conceptualised as a simple tree, and all advertisements are categorised within the tree, based on a business's marketing decisions. Each advertisement, represented as a leaf on the tree, can have many attributes, which are determined by any application that is built based on the LAAI model. This highlights the generalisability and flexibility of this model with respect to advertising adaptation.

The adaptation mechanism in the LAAI model separates the adaptation rules and strategies from their functionality, which resides in the inference engine in the delivery model. This allows applications to add adaptation rules and strategies in any format and implementing them in the inference engine. The adaptation model is represented as a storage area, containing adaptation rules and strategies that can be further extended or modified. It is also perceived as easy by interviewed business owners to assign these rules and strategies to domain items, simply by specifying that a particular rule or strategy should be applied to a group of advertisements in the domain.

The LAAI's user model (UM) adds two new creative components – *social networking data* and *future advertisements* – that enhance the adaptation process for advertising content. The social networking data component stores social networking data relating to similar advertisements found on social networking sites. 'Like' and 'stop' data are added, to support and extend the adaptation process. In addition, the 'future advertisements' component guarantees that targeted advertisements will not be neglected after logout.

The delivery component brings together all the functionality of the LAAI model. It modifies the user model, applies all adaptation rules, strategies and processes, and delivers appropriate advertisements to users. The modular design aims to support easy integration and portability for any application designed based on the LAAI model. Overall, the LAAI model targets supporting portability and integration in websites, by proposing a simple domain model structure, appropriate to the advertising adaptation process. In addition, it attempts to simplify the process of applying adaptation rules and strategies within a domain and delivers appropriate advertisements to users.

Finally, based on this model, a new adaptive system, the Adaptive E-Advertising Delivery System (AEADS), has been created, as described in [Qaffas and Cristea, 2014, Qaffas and Cristea, 2014, Qaffas and Cristea, 2015, Qaffas and Cristea, 2015] and evaluated. This system was to reveal the accuracy, effectiveness, and efficiency of the introduced LAAI model. Specifically, in this paper, the evaluation with *business owners* is presented. This is important, as this is often-overlooked in research, where evaluations with users are more frequent. Previously, we have also performed evaluations with internet users [Qaffas and Cristea, 2016]. The overall evaluation results from both business and user evaluations indicate that the LAAI model functionality and usability is promising. In this paper, the evaluation process covers various types and sizes of businesses. The evaluation results illustrate the perceived simplicity of the AEADS system, which can be used without training. In addition, most businesses agreed about the reliability and value of the AEADS system. Flexible location on the page and a flexible number of advertisements on each webpage are considered excellent features by businesses. Moreover, the advertisements' contents do not overlap with webpage contents (as happens, for instance, with other advertising systems, where ads pop and obscure the main content). Finally, the AEADS system was considered to introduce an easy and functional interface for the author.

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