eRaUI: An Adaptive Web Interface for e-Research Tools

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Abstract— **This paper presents the design and development of E-Research Adaptive User Interface (ERaUI) portable widget which uses case-based paradigm to learn web user profiles to enhance the usability and learnability of its host and adapt its content to that user profile. First, it uses click and mouse movement heat map techniques to track and record both user browsing behavior and the services provided by the host web site into text format which will be analysed by a text mining algorithm to form browsing patterns including changes in the web site content. Then, case-based reasoning paradigm and inductive learning algorithms analyse and index these browsing patterns into groups of web user profiles and store them into a case base memory from which most similar cases will be retrieved by ERaUI to identify and classify new users or discover new group of users. These web user profiles will be used by ERaUI to provide personalised services like content and collaborative search facilities useful for each web user profile, 'live help' box enabling the user to seek support and guidance from the admin feature of the host web site and display minimum content and a concise list of web site services that are most appropriate to individual web user profiles. This paper also discusses user evaluation of NaCTeM web site with and without ERaUI widget, and presents improvements identified through a series of usability tests.**

Keywords-Web User Modelling; Adaptive user interface; Learnability; Usability; Heat map; Widget

I. INTRODUCTION

Adaptation refers to the notion of changing something to meet some specific requirements or purposes [1]. Adaptive systems are described as tools that generate new information about how to do the task better by analysing past experience and relating it to performance criteria set by humans [2]. It is also stated that an adaptive system adapts its behaviour to individual users based on information about them which can be either explicitly gathered or implicitly obtained during user-system interaction, and the adaptive system performs the adaptation using some form of learning, inference or decision making [3].

While it is recognised that adaptive interfaces improve usability, users' experiences and learnability and that they bring potential gains and a cost-benefit trade-off for usability, critics argue that autonomous user interface adaptation may disorient users and reduce its usability. Most critics relate these limitations with the unpredictable nature of the adaptive user interfaces and lack of accuracy [4, 5, and 6]. Learnability here refers to the system's support of the user's efforts to learn how a system or an application has to be used

This paper looks at adaptive user interfaces from two viewpoints i.e. usability and learnability. The research considers two approaches in designing adaptive interfaces that address the above mentioned limitations: (i) those adaptive (static) user interfaces designed based on usability, learnability principles and methods, and user feedback are at the design level only and (ii) those adaptive (dynamic) user interfaces designed based on similar principles and methods but are different in that they keep on learning about users in dynamically adapting themselves to the needs of current and prospective users.

Case-based reasoning and inductive learning methods are used in profiling users and these user profiles are used in dynamically customising the web interface. The customisation comprises highlighting useful web page content and providing a list of selectable links to the content that is most appropriate to an individual user.

A number of methods have been used in the design of static adaptive user interfaces. For instance, analysis of the user interface using inspection methods such as heuristic evaluation, cognitive walkthroughs, GOMS (Goals, Operators, Methods, and Selection rules) analysis, and so on [7]. Also, empirical usability and learnability methods which involve user testing in a laboratory environment, could be either as formative or summative [8]. Formative studies are carried out during the product development process with the aim of fixing problems found during the product development process whereas summative studies are carried out after completion of the development and are used more as a basis for reflection and future work and base lining a product [9]. The activities undertaken include auto-recorded/measured user performed tasks, interviews, and analysis of experimental data.

However, dynamic adaptive user interfaces are enhanced with learning user profiles which could be either *Informative interfaces* that focus on filtering information the user finds interesting or useful, or *Generative interfaces* that generate some useful knowledge structures to support the user in their experience with the user interface [10].

In this paper, we present a dynamic e-Research adaptive user interface (ERaUI) widget. It is portable and is easy to add-on to any web site by adding a few lines of code to the header of the host web pages. It uses case-based reasoning paradigm and machine learning algorithms to learn from web user profiles that are generated whilst the users navigate through the website. ERaUI widget is an extension of a JISC project commissioned to develop an adaptive interface to improve usability and learnability of NaCTeM e-Research tool [29]. The main focus of the eRaUI project is to customize the content of the host web site and highlight appropriate resources (e.g., menu options) according to the user's profile.

The paper is divided into five sections. Section II focuses on previous work pertaining to static and dynamic adaptive user interfaces. Section III describes usability and learnability methods used in the design and development of ERaUI widget. Section IV evaluates the usability and learnability features of ERaUI, and finally Section V presents the research findings and future work.

II. Previous Work on Adapative Interfaces

Several recent projects have been sponsored by Joint Information Systems Committee (JISC) to develop usable and learnable user interfaces [30]. Most of these could be considered as static adaptive interfaces as usability and learnability are dealt with at the design level only. ALUIAR project [30] ranks the results of a user group feedback through interviews and "walk throughs" to improve the usability and learnability of the user interface of Synote [30], the open source web based video and audio annotation tool.

Rave in Context project [30] developed usable, accessible, learnable and adaptable W3C widget templates and widgets for MyExperiment, Simal and OpenDOAR web sites.

USeD project [30] developed a new user interface to improve the usability of Digimap data downloader, making it easier for a range of subscribers to use. It was designed by creating a number of stereotypical user Personas, which are based on the actual Digimap user requirements, their expectations of the service and their knowledge of spatial data.

ReScript Usability/Learnability Enhancement project [30] improved usability and learnability of the user interface of ReScript, a prototype of digital editing and research environment originally developed to support collaborative work on historical texts. Feedback compiled from a series of online surveys and interviews with editors and researchers was used to make changes to the ReScript interface to meet the needs of a variety of researchers working with very different texts, and with differing levels of expertise.

The Word Tree Corpuce Interface [30] had the goal of providing an alternative interactive user interface to traditional text-analytical tools like KeyWords In Context (KWICs). The website produced allows users to generate word trees for individual terms, starting from the searched term at the leftmost edge with branches of proceeding words extending to the right. To develop a usable and learnable user interface, the Word Tree Corpus team undertook a combination of quantitative and qualitative studies through surveys and video interviews of stakeholders. They also used Google analytics to analyse user behaviour and to further improve their new user interface to reflect the users' needs.

The literature review revealed a significant number of studies on dynamic adaptive interfaces. Pazzani and Billsus [11] reported the development of SySKILL & WEBERT adaptive web user interface, which recommends web pages on a given topic that the user is likely to find interesting. The user marks suggested pages as desirable and undesirable and the system uses naive Bayesian classifier [32] for this task, and demonstrates that it can incrementally learn profiles from user feedback on how interesting web sites are. Furthermore, the Bayesian classifier may easily be extended to revise user provided profiles.

Another web user interface, NEWSWEEDER system [12], recommends stories to the user using each word in the story to predict whether the user finds the story interesting or not.

P-TIMS [13] is a commercial financial management system and was revised to add an adaptive and adaptable interface using a simple user model and rule set. As the user spends more time using the system and uses more complex functions, the system reveals a more extensive interface. The user model is explicitly exposed by providing a "preferences" dialog box, which the user can adjust at any time.

AVANTI [14] is a hypermedia information system about a metropolitan area and uses an initial interview to create the initial primary assumptions (i.e., user profile), draws inferences to generate additional assumptions, and uses stereotypes for certain subgroups of users (e.g., tourists, blind users). It then customises the web pages presented to the user accordingly.

Interbook [15] is an adaptive system which derives much of its data for the user model from the user interface component, and which can track user actions and report them in detail to the application user model. Interbook addresses these problems by tracking what the users have seen, rather than what they have done, and using that to infer what the users know.

Most recently, Lee et al. [16] developed a user interface prototype for the Android smartphone, which recommends a number of applications to best match the user's context based on five variables; time, location, weather, emotion, and activities. The developed system derives the best three recommended applications based on a probabilistic learning and inference algorithm named "Spatiotemporal Structure Learning" [33], which extends Naive Bayesian Classifier [32].

It can be noticed that most of the above dynamic adaptive interfaces require explicit input from the user to be able to model web user profiles and adapt web user interfaces to satisfy individual user profiles. ERaUI which is also a dynamic adaptive web user interface implements an intelligent and portable widget, which provides both explicit and implicit input from the user to build web user profiles. In the implicit input, ERaUI uses automatic tracking mechanisms to track and record the user behaviour whilst browsing the web site on which ERaUI widget is hosted. It also uses inductive learning algorithms to identify or discover new web user profiles and enhances the host web site's usability and learnability capabilities. Furthermore, it detects changes in hosted web site content in terms of functionalities and resources while tracking the user browsing and reflecting that in the adaption of the web user interface and also the services presented to the user.

III. Development Process of *ERaUI* Adaptive User Interface

A. ERaUI Web User Interface Design

In ERaUI project, adaptive web user interface is seen as an interactive software system that improves its usability and learnability in its interaction with a user based on partial experience with that user. The formal definition of usability by the International Standards for HCI and Usability [31] is that usability is concerned with the “effectiveness, efficiency and satisfaction with which specified users achieve specified goals in particular environments.” Effectiveness means how accurately and completely users can achieve their goal. Efficiency means the effort required to achieve a goal. Satisfaction means the comfort and acceptability of using the system to achieve the goal. These definitions are in agreement with [7] who also stressed the importance of learnability as an important aspect of usability.

According to the Usability First glossary and reference [17] learnability is a measure of the degree to which a user interface design can be learned quickly and effectively. Learning time is the typical measure. User interfaces are usually easier to learn when they are familiar to the user and/or designed to be easy to use based on core psychological properties. Through literature reviews the learnability of a user interface design can be broken down into five types: Familiarity, Consistency, Generalizability, Predictability, and Simplicity. It is also stressed that although learnability could be part of usability, little is shown that an increase of ease of use (usability) can be realised without actually improving the user’s mental model (learnability) of adaptive systems.

Several methods have been used in the design of usable and learnable user interfaces. Analytical usability studies involve analysis of the system using inspection methods such as heuristic evaluation, cognitive walkthroughs, GOMS analysis, and so on [7]. Empirical usability involves people using test methods and traditionally conducted as either formative or summative studies [8]. Formative studies are carried out during the product development process with the aim of fixing problems found during the product development process whereas summative studies are carried out after completion of the development and are used more as a basis of deciding lessons learned and base lining a product [7]. The activities undertaken generally include recorded/measured usability evaluation, interviews, and laboratory-based experiments and so on. Nielsen and Phillips [18] research on “estimating the relative usability of two interfaces” concluded that the most reliable way of determining the relative performance was through the use of empirical usability studies rather than analytical usability studies although those empirical studies are more expensive to perform.

ERaUI was designed based on a methodology commonly found in usability studies and recommended by [7]. It uses personas and scenarios as a way of contextualising the what, where, how, when and why of the use of an application so that in essence it shows to the targeted users. Power of personas is that all stake holders involved in the design process are much more likely to engage with other people, real or fictional, than they are with statistical information [19].

We conducted an experiment within the university research community on the impact of usability methodology of personas and scenarios that led to the design of the ERaUI interface as an intelligent and portable widget that we deployed on the left hand side of NaCTeM web interface as shown in Figure 1.

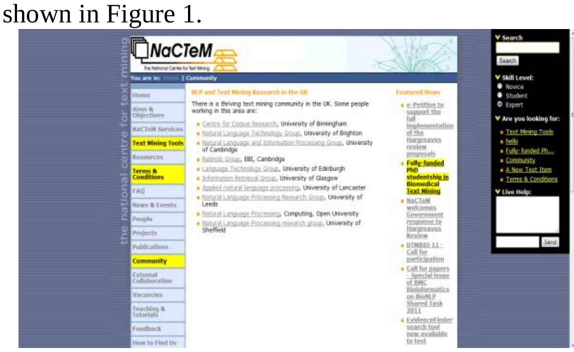

Figure 1. ERaUI Widget hosted by NaCTeM Web Site.

As shown in Figure 1, ERaUI can be hosted on any web site by adding few lines of code to the host website header files. The widget is comprised of a free-text / autocomplete search box which offers enhanced search capabilities for host websites. The learners can also specify explicitly their profile (e.g., skill level) for NaCTeM host web site, and can additionally choose from a variety of links which are recommended according to their user level. At the bottom of the widget, a ‘live help’ for users browsing the host website to communicate with the website administrator in real-time.

B. ERaUI Learning Web User Profile

ERaUI project uses case-based reasoning (CBR) paradigm [20, 21] to learn about the user’s profile and in developing the ERaUI adaptive web user interface. CBR uses machine algorithms to solve new problems by adapting solutions of previous similar problems following the cycle Retrieve, Reuse, Revise and Retain, as shown in Figure 2.

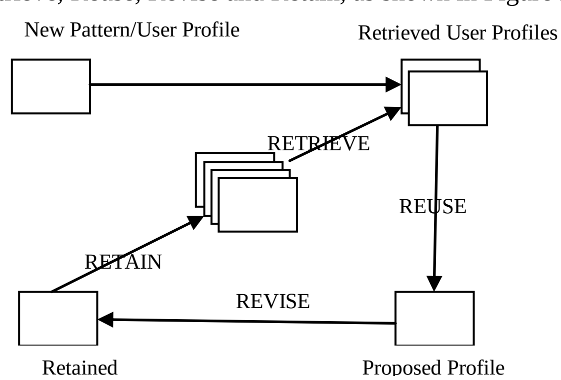

Figure 2. CBR Cycle [21]

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For example, CBR systems CLAVIER [22], which are developed as advisory systems to recommend loads and layout for aircraft parts to be cured in an autoclave, and CBRefurb [23], which retrieves previous similar refurbished buildings to estimate the cost of new refurbishment. Both use inductive learning algorithms within CBR to index and retrieve and revise/adapt most similar past cases from their case libraries.

1) *ERaUI Case Representation*

ERaUI case is represented by two data structures which will be initially set by the administrator of the host web site: a user categories structure in which the admin can set initial known categories of web user profiles like for instance Novice, Student and Expert category of users of NaCTeM e-Research tool. A second keyword structure of the host web site and links in which the admin can set keywords, web page links and external web sites and assign them to the categories already set. Once set, these two structures are automatically managed by ERaUI learning system. That means ERaUI case-based learning system can automatically make changes to the content of either structure by adding or removing categories of users in the category structures or adding or removing keywords in the keyword structures to reflect the changes in both the user behaviour and the changes in the content or functionalities in the host web site itself.

2) *ERaUI Case Indexing and Populating*

ERaUI use click / mouse movement heat maps techniques to tracks the user interaction with the host website as shown in Figure 3.

Figure 3. ERaUI Click & Mouse Movement Heat Map.

The results of click heat maps tracking are translated by ERaUI into text format and stored as a personal user record in ERaUI database as shown in Figure 4.

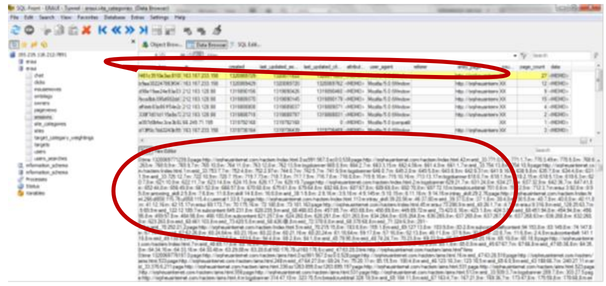

Figure 4. User Records and brpwsing patterns

The ERaUI text mining tool analyses the collected user text records to derive user patterns (clicked key words, functions, webs site links, etc.) which will be represented as new case (vector) of the current user updating the case base. This new case will be further analysed by the ERaUI case-based inductive algorithm to determine whether it is a new or an existing web user profile and therefore updating if necessary the content of the category structure

3) *ERaUI Machine Learning Algorithm*

Given a description of a problem, a retrieval algorithm, using the indices in the ERaUI case-memory, should retrieve the most similar cases to the current problem or situation. The retrieval algorithm relies on the indices and the organisation of the memory to direct the search to potentially useful cases.

The issue of choosing the best matching case has been addressed by research into analogy [24]. This approach involves using heuristics to constrain and direct the search.

Case-based reasoning will be ready for large scale problems only when retrieval algorithms are efficient at handling thousands of cases. Unlike database searches that target a specific value in a record, retrieval of cases from the case-base must be equipped with heuristics that perform partial matches, since in general there is no existing case that exactly matches the new case.

In order to retrieve or generate suggestions on the web user profile which are relevant to the given browsing pattern we had to consider amongst well-known methods for case retrieval like nearest neighbour, induction, knowledge guided induction and template retrieval. We found that the most effective algorithm to match users with results according for instance to their skill level in NaCTeM was Nearest Neighbour Algorithm (NNA) because it is more effective when the case base is not huge.

NNA involves the assessment of similarity between stored cases and the new input case, based on matching a weighted sum of features. A typical algorithm for calculating nearest neighbour matching is the one reported in [25] where ***w*** is the importance weighting of a feature (key word, web link, etc…), ***sim*** is the similarity function, and ***fI*** and ***fR*** are the values for feature ***i*** in the input and retrieved cases respectively.

$$\frac{\sum_{i=1}^{n} w_i \times sim\left(f_i^I, f_i^R\right)}{\sum_{i=1}^{n} w_i}$$

Figure 5. Nearest Neigbour Algorithm

Furthermore, Induction algorithms ID3 [26], which determine the dominant, are used to discriminate cases based on these features; they generate a decision tree type structure to organise and categorise ERaUI cases of web user profiles in memory.

IV. ERAUI USABILITY AND LEARNABILITY FEATURES

In addition to its design using an iterative design methodology that focuses on usability, learnability, participatory design suitable for service-based implementations, ERaUI widget uses case-based reasoning and inductive learning methods to learn about both the user profile and the host web user interfaces in deducing and displaying needful information for the user.

ERaUI has addressed most of the common issues reported in the literature that arise in developing adaptive or advisory interfaces including information filtering, supporting the user in his/her experience with the web site and also visual changes to the user interface itself.

1) *ERaUI Filtering Information*

ERaUI implements advanced filtering algorithm(s) for extracting digital content of the host web site like NaCTeM to match user needs. Content and collaborative based filtering methods [27, 23] have been used as the basis for selection and learning about the content of NaCTeM web site. Content methods suggest topics similar to the ones a user group with similar profile has liked in the past as shown in Figure 6:

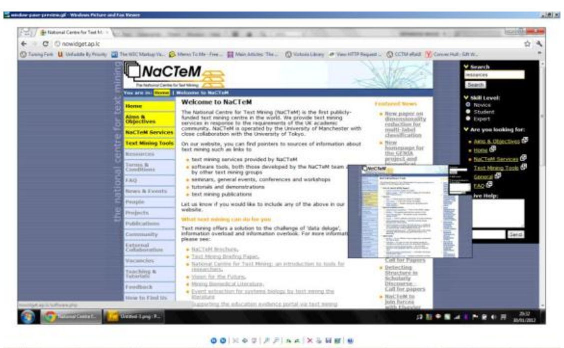

Figure 6. Results of content filtering method

However, as shown in Figure 7, collaborative filtering methods suggest items outside the user's normal area that the user will still find interesting, as the basis for selection and learning.

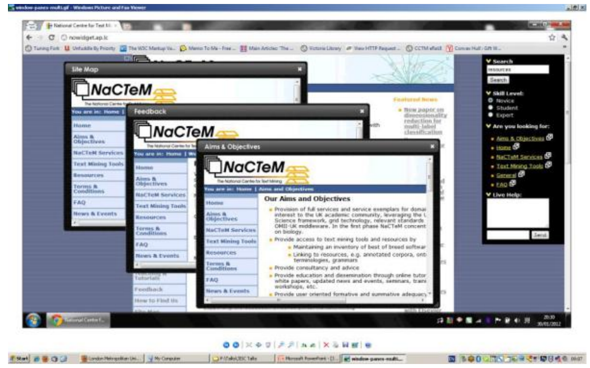

Figure 7. Panes of similar pages from collaborative filtering

2) *ERaUI Web User Interface Adaptation*

Also, based on the identified web user profile, ERaUI recommends choices on some aspects of the research processes as desirable or undesirable, rating them on a scale and giving some similar form of evaluation to help the user in his/her selection of retrieved information. An instance of ERaUI user interface adapting itself to a category of users is shown in Figure 8. This screenshot suggests to the user currently browsing the host web site a few links in yellow colour, normally used by users with similar web user profiles.

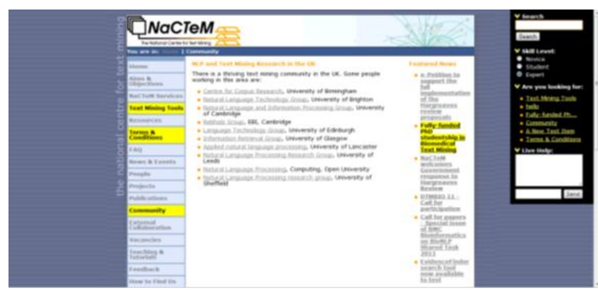

Figure 8. Suggesting useful links for a category of users

3) *ERaUI Live User Support*

As shown in Figure 9, ERaUI interface also provides live communication facilities through ‘live help' box enabling the user to seek support and guidance from the NaCTeM host web site administrator.

Figure 9. ERaUI live help box

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4) ERaUI Widget Evaluation

In a recent study, the investigation undertaken in Lazar et al. [28] found that users lose up to 40% of their time due to "frustrating experiences" with the application interfaces, with one of the most common causes of these frustrations being missing, hard to find, and unusable features of the software application.

In order to assess the frustration of the users and evaluate the ERaUI widget based on some usability and learnability criteria, we invited around fifty researchers and students with different skills to run NaCTeM web user interface with and without ERaUI widget. The users are divided into two groups. Each user has been given identical tasks to complete in a given time. The measure we used for evaluating ERaUI widget usability and learnability features were based on completion of tasks on time, accuracy in providing information to the user and also predictability of user interface.

They were asked to complete a series of simple tasks using the widget. Different researchers were asked to complete a series of tasks without the widget. We compared the results of the two groups to get an idea of how effective ERaUI is at enhancing the experience of users. We set the following tasks:

- Write down the postcode of the National Centre for Text Mining.
- Write down the name of one member of Core Staff working at NaCTeM
- Write down the name of the only listed Visiting Researcher at NaCTeM.
- Write down the closing date for applying for PhD studentship advertised on NaCTeM website (3 year studentship based at the School of Computer Science, University of Manchester).
- Post some simple feedback to NaCTeM. Write down the keyword which appears when you do this.

The results of this evaluation have shown that all users who used NaCTeM with ERaUI widget completed all the tasks on time compared to 80% when using NaCTeM without ERaUI widget.

Another evaluation carried out in this research is the accuracy of the actions predicted by the ERaUI widgets. For this, we conducted a second evaluation test with 45 researchers and students to assess predictability and accuracy of ERaUI through the following predictability and accuracy tests:

- Set you user profile (skills) in the ERaUI Interface for NaCTeM and check if the web links list in the widget and those highlighted in yellow in NaCTeM resources predict and match the profile you selected
- Browse through NaCTeM web site for five minutes without setting your user profile and check if ERaUI is predicting and highlighting in yellow colour a number of web page links and/or functionalities within NaCTeM web content which are useful to you
- Make a search using ERaUI Interface and another search using original NaCTeM and compare which one is more accurate and useful for the user,
- Check the accuracy of results by comparing the results of the same functions of the original NaCTeM (like search and browse through some of NaCTeM functionalities) with the same functions and searches provided by ERaUI

Results on predictability and accuracy test have shown that 75% reported that the ERaUI widget predicted what they are looking for and 85% reported that ERaUI provided accurate information they asked for. This is compared to around 15% predictability and 75% accuracy when using NaCTeM interface without ERaUI respectively.

V. Conclusion and Future Work

In this paper, we presented an initial design and development of an adaptive web user interface in the form of an intelligent and portable widget named ERaUI that could be hosted on top of any web site user interface to enhance its usability and learnability features.

The research proposed two approaches to the design and development of adaptive user interfaces. In both the cases the adaptive features are set either by using usability and learnability methods and elicitation of the users' needs at the design level only or by requiring explicit input from the user whilst browsing through the web site interface to be able to build user profiles and use it to adapt the web user interface.

ERaUI uses usability and learnability methods like persona and scenarios customising web user interface with or without explicit input from the user. This is achieved by learning user's profile through the following methods: (i) observe mouse click or mouse movement to track and collect user browsing behaviour, (ii) text mining to analyse the tracks and identify user browsing patterns/features, and (iii) case-based reasoning paradigm to index and store user profiles in case-based memory and nearest neighbour and ID3 inductive learning algorithm to retrieve or discover and also to classify web user profiles in the case-base memory. Each user profile will then be used to customise suitable web content.

ERaUI has used user profiles to implement some of the usability and learnability features like advanced search and filtering algorithms to provide useful information to user, adapting the content of the host web site to show only appropriate resources and functional features that meet the user profile and also support the user through communication tools.

One of the key approaches to assessing usability and learnability of a user interface will be via real users' evaluation and testing of the interface. For this, we conducted an initial evaluation and testing of ERaUI by inviting around fifty researchers and students to experiment with NaCTeM web site, with and without ERaUI widget. Although these evaluation tests are not comprehensive in that they do not include comprehensive usability and learnability measures, they have shown that there are significant improvements of the users' experience when using ERaUI widget based on testing usability and learnability measures like completing tasks on time, accuracy of returned information and prediction of users' expectations. Further work will be undertaken to experiment and improve the ERaUI widget.

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