TOWARDS THE SYSTEMATIC ASSESSMENT AND DESIGN OF ADAPTIVE USER INTERFACES

by

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Abstract

Adaptive user interfaces have been suggested as an alternative to help users deal with information overload and the complexity of software. However, experimental studies have questioned their effectiveness, while the introduction of adaptation techniques in commercial applications has had limited success. The negative past experience has caused skepticism among researchers in Human-Computer Interaction, as adaptive behaviour has been linked to poor designs, that have violated well-established usability principles. Several researchers have suggested that adaptable user interfaces, which are interfaces adapted by the user rather than the system itself, should be considered as a better alternative.

This dissertation explores the design space of adaptation techniques in a range of user interfaces, identifies tradeoffs between adaptive and adaptable user interfaces and makes recommendations about their design and evaluation. In particular, it examines three different types of interfaces: hypermedia systems, lists, and hierarchical drop-down menus. New adaptation techniques are proposed for each interface. We explore both techniques that assist navigation and visual search, and techniques that facilitate movement and selection. We address limitations of existing techniques by exploring designs that merge automation with

user control. The proposed designs are extensively evaluated. Specifically, the dissertation documents a total of seven user studies. Through our evaluation work, we explore the role of adaptation a*ccuracy* as a measure of the quality of automatic inference and decision-making, and evaluate its effect on the success of adaptation techniques. This allows us to investigate strengths and limitations of the techniques that we propose and come up with recommendations about the design and evaluation of adaptive user interfaces.

Overall, the dissertation has three major contributions: (1) the introduction of designs of hypermedia systems that combine automation and direct user manipulation; (2) the systematic treatment of accuracy as a way to assess the effectiveness of adaptation techniques; and (3) the systematic design and evaluation of *bubbling menus*, a new design of adaptive and adaptable menus.

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Table of Contents

List of Figures

Chapter 2

Introduction

The goal of this dissertation is to contribute to the systematic understanding of the design and evaluation of adaptive user interfaces. It explores new interface designs for hypermedia systems, menus, and lists and investigates tradeoffs between adaptive and adaptable user interfaces. In this chapter, we motivate our research, present its scope and goals, and give an overview of the document's structure.

2.1 Motivation

The complexity of computer applications has been growing rapidly, accommodating continuously emerging user needs. Users of desktop environments have to assess, manage and retrieve large amounts of information, switch between numerous tasks and often complete tedious and repetitive actions. Common tasks that users carry out on an everyday basis include searching and browsing for information on the Web, exchanging and archiving email messages, executing commands through menus, and exploring long file hierarchies. Power-

ful mechanisms such as history lists and shortcuts can reduce the cognitive and motor demands of such tasks, but their scope has been limited (Lane et al., 2005; Tauscher and Greenberg, 1997). A main limitation of traditional user interfaces acknowledged by previous work is their inability to fit first to the specialized needs of different users and second to the particular demands of different tasks. As McGrenere and Moore (2000) state, *"one-size-fits-all interfaces may not in fact fit all"*.

Several interface designs have attempted to relax the "one-size-fits-all" limitation by supporting manual personalization procedures that allow users to tailor a user interface to their own needs. For instance, Web browsers support the bookmarks utility that enables users to create personalized lists of frequently accessed Web pages. Similarly, several office applications support customizable toolbars and allow users to specify shortcut keys to accelerate command execution. However, customization mechanisms require users to consume additional effort and time to use them effectively; as a result, they have been highly underused (Abrams et al., 1998; Mackay, 1991; Weld et al., 2003).

In an attempt to relieve users of the burden of manually personalizing a user interface, automated personalization techniques have been suggested as a potential solution. Such user interfaces employ automated procedures and often borrow techniques from Artificial Intelligence (AI) to facilitate the tasks of users. The term *adaptive user interface* is commonly used to characterize the type of user interface that is automatically *personalized/adapted* according to the ongoing needs of a user. Adaptive user interfaces often perform adaptations based on predefined knowledge about a user's goals and preferences. Alternatively, they exploit information from past usage patterns to infer user needs and adapt the interface. For instance, based on the content of pages that a user visits during a Web browsing session, an intelligent mechanism could infer the information needs of the user and suggest other related pages. Similarly, an adaptive mechanism could personalize a menu so that frequently selected items would be accessed faster.

Evidence about the existence of usage patterns which adaptive mechanisms can be built upon has been revealed by previous research (McGrenere and Moore, 2000; Tauscher and Greenberg, 1997). Such evidence implies that the design of user interfaces could be possibly more effective if knowledge about usage patterns was taken into account. However, whether and how such knowledge could be effectively used is a matter of great debate within the community of Human-Computer Interaction (HCI). Several experimental studies have questioned the effectiveness of adaptive user interfaces, while their application in commercial environments has had very limited success. This negative past experience has caused skepticism among HCI researchers as adaptive behaviour has been linked to poor designs that have violated well-established principles of interaction design. Work on intelligent user interfaces has mainly been the product of the AI community. As a result, the value of such work has not been empirically evaluated through extensive user studies. Besides, the few usability studies (Findlater and McGrenere, 2004; Greenberg and Witten, 1985; Hook, 1997; Mitchell and Shneiderman, 1989) coming from the HCI community have focused on testing the general hypothesis of *whether* adaptive behaviour can be useful rather than answering the more valuable questions of *when* and *how* adaptive behaviour could help. Answering these questions requires that tradeoffs between costs and benefits associated with adaptive user interfaces are systematically investigated and that designs take such tradeoffs into account. This dissertation attempts to explore these issues and propose novel forms of interaction that take advantage of automation, respecting, at the same time, well-established usability principles.

2.2 Scope

The term *adaptive* has been used to characterize various different types of assistive behaviour, such as information filtering, recommendation, task auto-completion, notification, spell checking, and personalization of user interface widgets. Our work does not touch all these

types of adaptation. Its scope is limited to techniques for desktop applications that facilitate exploration and selection in common information structures. In particular, it explores adaptation techniques for hypermedia documents, longs lists, and cascading menus. All the techniques studied in this dissertation apply various types of filtering to personalize an interface, promoting a small number of interface elements, such as frequently selected menu items or paragraphs on a Web page that closely relate to the information needs of the user. We examine the effect of adaptation on user performance for both tasks where difficulty resides in visual search and tasks where difficulty resides in movement and selection. For instance, we explore navigation in hypermedia environments, in which part of users' task is to locate and gather information. We also explore selection in menus, where motor performance and visual search are equally important. Applying filtering to promote specific items in a user interface can enhance both visual search and motor performance. On the other hand, different types of tasks require different adaptation techniques. This is an issue that this dissertation tries to clarify.

2.3 Research Goals

Overall, the work presented by this dissertation has been driven by three goals:

1. To design new adaptation techniques for a range of user interfaces.
2. To explore tradeoffs between adaptive user interfaces and adaptable user interfaces. In particular, a main objective of this dissertation has been to explore designs that effectively combine automation with user control.
3. To investigate approaches for the systematic evaluation of adaptation techniques.

2.4 Methodology

The research presented by this dissertation can be split into three parts. The first part explores adaptation techniques for hypermedia systems. It focuses on the notion of controlla-

bility and proposes new designs that merge automation with direct user manipulation. Also, it presents two small user studies that evaluate the proposed designs.

The second part investigates the evaluation of adaptation techniques in a more systematic way. It identifies the role of adaptation accuracy in the success of adaptive user interfaces. Then it empirically tests its effect on the performance of two adaptation techniques for long lists. Based on the results, we make recommendations about the design and evaluation of adaptive user interfaces.

The third part of the research presents the development process for the design of an adaptation technique for cascading drop-down menus. This process includes two design iterations and four user studies. Within the context of menu selection, we identify and explore cognitive costs associated with uncertainty when adaptation is user-initiated. We evaluate the effect of such costs on the success of the new technique, taking into consideration the effect of adaptation accuracy. The results of this process allow us to assess the strengths and limitations of the proposed technique and make recommendations about its use.

2.5 Overview

The dissertation is organized as follows. Chapter 2 reviews related work. It summarizes previous approaches on adaptive and adaptable user interfaces and discusses their main strengths and limitations. It focuses on usability problems associated with automatic adaptation. It reviews the methodology and results of relevant user studies and identifies their shortcomings. Chapter 3 investigates how the combination of automation and direct user manipulation can address shortcomings of adaptive behaviour. Adaptation and user control are studied in the context of adaptive hypermedia systems through two Web-based prototypes. Chapter 4 concentrates on the evaluation of adaptation techniques. It presents an experimental study, which evaluates two adaptation techniques applied to long lists. The study explores the effect of adaptation accuracy on user performance and results in recommenda-

tions for the design and evaluation of adaptation techniques. Chapter 5 presents the third part of our research. It describes a complete user-centered design process, conducted to develop *bubbling menus,* a new adaptation technique for hierarchical drop-down menus. Chapter 6 summarizes the findings and contributions of this dissertation. Finally, it suggests directions for future work.

Chapter 3

Related Work

In this chapter, we present related work within the area of adaptive, adaptable and customizable user interfaces. We start by putting this work into context and clarifying relevant terminology. We continue by discussing problems that have motivated research on adaptive user interfaces and describe adaptation techniques that have been used in the past. Then we identify problems associated with adaptive behaviour and discuss how previous work has tried to deal with them. Finally, we discuss previous evaluations and identify their main problems and limitations.

3.1 Personalization, Customization, and Adaptation

The terms *customization*, *personalization* and *adaptation* are all used to describe alterations or adjustments made to a software system based on user characteristics, preferences, goals and ongoing needs. Such alterations and adjustments may concern: (1) the functionality provided by the software, e.g., different sets of functions for different users; (2) the content that is communicated through the system, e.g., language and style; and (3) elements of the user

interface, e.g., the structure and layout of visualized widgets, the presentation of the content, metaphors used, and interaction styles.

The term *personalization* better describes variations in software that reflect individual characteristics, preferences and needs of users. Some aspects of such variations may be determined at *design time*, while other aspects may be determined at *use time* (Fischer, 2001). For instance, after eliciting user needs, the designers of a new system may decide to accommodate the needs of multiple groups of users by providing multiple views of the same user interface. In this case, user groups and their associated views are determined at design time. However, the actual classification of a user to a specific user group is decided at use time. When applied at use time, personalization can be decided by the system, by the actual user or often by someone else on behalf of the user, such as the system administrator. As McGrenere (2002) explains, customization usually refers to changes applied manually by the user himself/herself or the system administrator rather than changes automatically decided by the system. Customization usually involves long-term or medium-term changes to a user interface and is often a time-consuming task; it requires users to interrupt their regular tasks, make decision about changes in their working space, and sometimes use knowledge about advanced features. In older Unix user interfaces, for instance, several customizations were performed by editing files with specialized syntaxes. Mackay (1991) reports that "customization involves a tradeoff for users, who must choose between activities that accomplish work directly and activities that may increase future satisfaction or productivity". According to her study, participants reported "lack of time" and "lack of knowledge" as the main barriers to customization. Modern applications have tried to reduce the burden of customization actions by coupling them with more intuitive, direct-manipulation interactions. For instance, office applications allow users to customize their workspace by simply manipulating toolbars. Similarly, Google allows users to customize their search page by selecting and dragging floating boxes that contain RSS feeds or other Web-based tools.

As opposed to customization, adaptation normally involves personalization that is fully or partially decided and executed by the system using automated mechanisms. Such mechanisms often employ techniques coming from research in Machine Learning, User Modeling and Information Retrieval. Changes due to adaptation are less radical and normally short-term compared to changes due to customization. Ideally, an adaptive mechanism can anticipate the evolving needs and goals of a user and reflect them in the user interface. An adaptive user interface may allow for limited or extensive user control. When adaptation is primarily determined by the user, the term *adaptable* is used instead of the term *adaptive* (Findlater and McGrenere, 2004; McGrenere, 2002). The distinction between customizable and adaptable user interfaces is not always clear. Both terms are often used interchangeably to describe the same interface. Customization usually refers to long-term changes applied to an interface by a user, whereas the term "adaptability" is more appropriate for more dynamic forms of personalization.

Another term that is used to characterize user interfaces that provide automated assistance is *intelligent*. The stress, now, is given to the intelligent component of the mechanism that adapts a user interface. McGrenere (2002) regards intelligent user interfaces as a broader set of interfaces that are not necessarily adaptive. Intelligent agents provide an example of such interfaces. Intelligent agents can carry out tasks on behalf of a user (e.g., automatically download a software update) without providing any kind of interface personalization.

3.2 Is There any Real Need for Adapting a User Interface?

Before we examine existing approaches on adaptive user interfaces, we attempt to give an answer to a fundamental question: is there real evidence that automatic personalization can be useful? A lot of evidence is anecdotal, but there has also been research demonstrating the need for user interfaces that can adapt to the particular user needs and tasks. For presentation

reasons, we divide this research into research that has studied navigation in Web environments and research that has studied user interaction in office applications.

3.2.1 Web Environments

Information overload has been commonly cited as one of the most important problems of today's Web. Every day, users have to navigate through numerous Web pages and evaluate their content. A relatively old study on Web usage by Catledge and Pitkow (1995) showed that users visited approximately 14 different pages per day. A later study by McKenzie and Cockburn (2001) found that users working in a Computer Science department visited approximately 42 different pages per day. The number of Web visits is expected to have grown considerably within the last six years, following the huge growth of the Web since then, the improvement of network speed, and the spread of new Web-based services and forms of online communication such as online banking, news feeds, collaborative online encyclopedias, Weblogging, social networking and online dating. Early work on hypertext systems has shown that navigation, even in small hypertexts, is subject to cognitive overheads and disorientation problems (Conklin, 1987; Nielsen, 1990). The overwhelming amount of information in the Web and the fact that the Web is used by millions of users with a wide range in information needs and expertise make the need for dealing with such problems crucial.

Search engines and navigation tools such as history lists and bookmarks help users access information in the Web more effectively. Their scope has been limited though. According to Marchionini (1995), information seeking in electronic environments involves both *analytical* and *browsing* strategies. Analytical strategies depend on careful planning, iterative query formulations and evaluation of searching results. On the other hand, browsing strategies are heuristic and interactive, depend on recognizing relevant information and demand smaller cognitive load. Search engines, bookmarks and history lists can support analytical strategies by facilitating searching and re-visitation of Web documents, but they can-

not assist browsing strategies. In addition, history lists and bookmarks bear several usability problems, which have been long reported by previous research. History lists have been shown to be rarely used (Catledge and Pitkow, 1995; Tauscher and Greenberg, 1997), and despite the fact that various history mechanisms have been proposed (Cockburn and Greenberg, 1999; Cockburn et al., 1999), the history utility in commercial browsers has little evolved. Bookmarks have been proved more successful, but they are not free of problems. According to Abrams et al. (1998), 37% of respondents to their survey never organized bookmarks, as they considered bookmark maintenance to be a laborious and time-consuming task. The same study found that bookmark lists can grow too fast and eventually become unmanageable. Also, McKenzie and Cockburn (2001) report that bookmarks often contain duplicates and a large number of bookmarked items become invalid after some time. Abrams et al. (1998) suggest that systems should provide automated mechanisms to help users organize their bookmarks effectively and access frequently selected items faster.

3.2.2 Email and Office Applications

Information overload is not only a problem of Web environments. Everyday, users have to scan through a continuously increasing number of email messages, frequently search for their documents within deep hierarchical file structures and interact with overloaded menus and toolbars. At the same time, they have to process and classify information, filter out information that does not satisfy their needs and, finally, organize their working space so that they can use it effectively in the future. Whittaker and Sidner (1996) report that maintaining email inboxes requires a lot of effort, and users often experience problems when managing email folders. Whittaker and Sidner (1996) suggest that information retrieval techniques should be used to automatically cluster email documents and reduce the clutter of inboxes.

A related problem is coping with the increasing complexity of computer applications. Modern software includes a large number of features, a phenomenon characterized as soft-

ware "bloat" (McGrenere and Moore, 2000). In order to understand how users deal with the complexity of software, McGrenere and Moore (2000) conducted a user study with 53 participants selected from the general population. The study examined participants' experience with Microsoft Word 97. Each participant answered a questionnaire and was engaged in two interviews. The goal of the first interview was to collect quantitative data about each participant's familiarity with the functionality of Microsoft Word. The goal of the second interview was to collect qualitative in-depth data about their experiences with word-processing applications. According to the results of the study, 15.8% of the 265 first-level functions of Microsoft Word were not used at all, and only 21.5% were used by more than half of the participants. Finally, only 3.3% of the functions were used regularly by more than three quarters of the participants. Answers given by participants to the questionnaire and the second interview showed that there was no general consensus about how unused functionality should be handled. Only 24% of participants agreed that they would want only the functions that they used, but 45.3% of participants stated that they would prefer to have unused functions "tucked away". These results agree with results reported by other studies. Linton et al. (1999) recorded data from 16 users of Microsoft Word 6.0 over a period ranging from 3 to 11 months per user. They found that out of a total of 642 commands available, each user used only 56 commands (8.7%) on average during the study period and only 25 commands (3.9%) in an average month. Furthermore, the top 10 commands accounted for 80% of use and the top 20 commands accounted for 90% of use. Real data reported by Findlater and McGrenere (2004) also show that only a small percentage of menu items are frequently selected. According to Greenberg and Witten (1985) and Cockburn et al. (2007), the frequency of command use in desktop environments, and similarly the frequency of menu selection, follows a *Zipfian* distribution. A Zipfian distribution has the form $P_n \sim 1/n^a$, where P_n is the frequency of the n^{th} ranked command or menu option and a is a constant whose value is close to 1.

Hotkeys help users to access frequently selected items faster but require them to remember several key sequences. According to Lane et al. (2005), even experienced users may fail to use hotkeys effectively. Besides, hotkeys cannot be used to access dynamically evolving components such as mailboxes or bookmark lists.

3.3 Adaptation Techniques

Existing evidence seems to suggest that adaptive user interfaces could possibly improve user interaction with desktop environments. However, how a user interface needs to be adapted is an open question. In this section, we review various adaptation techniques, aimed at facilitating common tasks, such as information exploration and selection in hypertexts, lists, file managers, menus and toolbars. We split our presentation into two parts. First, we discuss adaptation techniques in the context of hypermedia and Web environments. Second, we review adaptation techniques for common user interface widgets in desktop environments.

3.3.1 Adapting Hypermedia Environments

Hypermedia systems with adaptive features are known as *Adaptive Hypermedia (AH)* systems (Brusilovsky, 1996, 2001). Adaptation in AH systems can serve a variety of different goals:

1. Facilitate navigation and reduce disorientation problems
2. Reduce cognitive overheads by helping users make decisions about what information to read or which link to follow
3. Reduce information overload by filtering out noise and content that is not needed by the user
4. Accelerate access to information that is relevant to the user's needs
5. Adapt content based on level of user expertise, skills, and preferences
6. Recommend pages

7. Adapt the layout and presentation style of pages based on the hardware and network capabilities of the client machine or based on individual user preferences

Adaptation techniques used in AH systems are commonly classified based on a taxonomy proposed by Brusilovsky (1996). According to Brusilovsky's taxonomy, adaptation techniques are divided into two main categories: (1) adaptive presentation, and (2) adaptive navigation support.

Adaptive Presentation

The primary goal of adaptive presentation is to reduce information overload within hypertext pages, eliminate scrolling and subsequently, reduce cognitive overhead. A popular method of content adaptation is hiding content that is not relevant to the information needs of a user. The main weakness of this approach is the fact that hiding information can prevent users from accessing information that is possibly valuable. A technique that relaxes this problem is *stretchtext*. Stretchtext is a form of hypertext, in which text can be collapsed or expanded by clicking on *hot words*. The role of hot words in stretchtexts is similar to the role of hyperlinks in common hypertexts, with the difference that clicking on a hot word does not result in jumping to a new page. MetaDoc (Boyle and Encarnacion, 1994) was the first AH system to apply stretchtext to adapt the presentation of content. In MetaDoc, experts were provided with fewer details than novice users. However, experts could still view the hidden details of content by clicking on hot words in the text. Similarly, novice users could collapse detailed text and reduce the size of pages. PUSH (Hook, 1997) also employed stretchtext to adapt the presentation of learning material.

In contrast to the above techniques, *sorting* or *dimming fragments* can help users identify useful information without hiding content. Sorting fragments can minimize the scrolling effect as the most relevant page fragments are presented at the top of a page. The main drawback of this approach is that reordering fragments on a page can disturb the natural flow

of content. Dimming was introduced by Hothi et al. (2000). It is the simplest and least intrusive adaptation technique. According to dimming, document fragments that are not relevant to a user's goals are shaded. Dimming does not reduce the size of the adapted pages and, as a result, it does not cope with the scrolling problem. Besides, shaded information can easily gain the attention of users and distract them from their task.

Adaptive Navigation Support

Brusilovsky's (1996) taxonomy specifies six main types of adaptive navigation support: *direct guidance*, *adaptive link sorting*, *adaptive link hiding*, *adaptive link annotation*, *adaptive link generation*, and *map adaptation*. Different combinations of these techniques have been integrated into AH systems to facilitate navigation and help users discover interesting information. For instance, WebWatcher (Joachims et al., 1997) and Personal WebWatcher (Mladenic, 1996) provide direct guidance by highlighting a small number of links. Syskill & Webert (Pazzani et al., 1996) annotates links with descriptive icons, where each icon represents a different likelihood of relevance. Finally, HYPADAPTER (Hohl et al., 1996) uses different font sizes and link sorting to adapt the presentation of links.

Link generation techniques enhance pages with supplementary hyperlinks. There are two types of link generation: (1) generation of lists of recommended hyperlinks, and (2) link augmentation. Several systems (Hirashima et al., 1998; Kaplan et al., 1993) combine link recommendation with link sorting so that the most relevant links appear first. Other approaches (Budzik et al., 2001) cluster recommendations and present them under different categories. In addition to recommendation, Letizia (Lieberman, 1995) provides explanations about why each link is recommended. Link augmentation involves direct insertions of hyperlinks into the body of a document (Bailey et al., 2001; El-Beltagy et al., 2001; Faaborg and Lieberman, 2006); words or phrases in the document's text are selected as link anchors.

Map adaptation refers to the adaptation of global or local hypermedia maps presented to the user. Several visualization techniques such as tree-maps (Johnson and Shneiderman, 1991), fisheye views (Furnas, 1986; Noik, 1993), and hyperbolic trees (Lamping et al., 1995) can be used to provide personalized maps of hypermedia structures.

Some systems such as MONTAGE (Anderson and Horvitz, 2002) use a combination of different adaptation techniques. MONTAGE automatically generates personalized Web portals that aggregate hyperlinks and summaries of Web content. In such portals, links and content are classified into topics that appear in separate panes. Finally, a few approaches have tried to add adaptive features to navigational tools, for example, bookmark lists. PowerBookmarks (Li et al., 1999), for instance, supports the automatic collection of bookmarks by analyzing the frequency of page visits and hyperlink connections between visited pages. It also provides facilities for sophisticated searching in bookmarks.

3.3.2 Adapting User Interface Widgets

As with adaptive hypermedia, highlighting, hiding, restructuring items and making recommendations have been used to adapt menus, toolbars, lists and file hierarchies. Such adaptation techniques have been aimed at (1) reducing cognitive overhead by decreasing the number of the available choices in an interface, (2) accelerating the selection of frequently selected items, (3) helping users easily identify relevant information and useful functionality, and (4) relaxing the physical strain caused by repetitive actions.

A variety of adaptation techniques have been used by the Microsoft Windows operating system. For instance, in the Start menu of Windows XP, newly installed applications are highlighted to help users learn where a new application has been placed. A more famous design is the version of adaptive menus, namely Adaptive Menus, introduced by Microsoft Office 2000. The goal of Adaptive Menus was to reduce the bloat in menus by hiding infrequently used options. As shown in Figure 3.1, users could expand an adapted menu to its

regular form by clicking on an arrow-like button at the bottom of the menu or by waiting for a few seconds. This design has not been very successful and has been criticized by previous research (McGrenere, 2002). It has been noted that hiding can prevent users from gaining awareness about menu items not previously selected. Hiding can also create uncertainty about the location of items and hurt performance. For instance, a user who does not remember the position of a menu item will need to scan through multiple menu categories and spend significant time expanding menus in order to discover it.

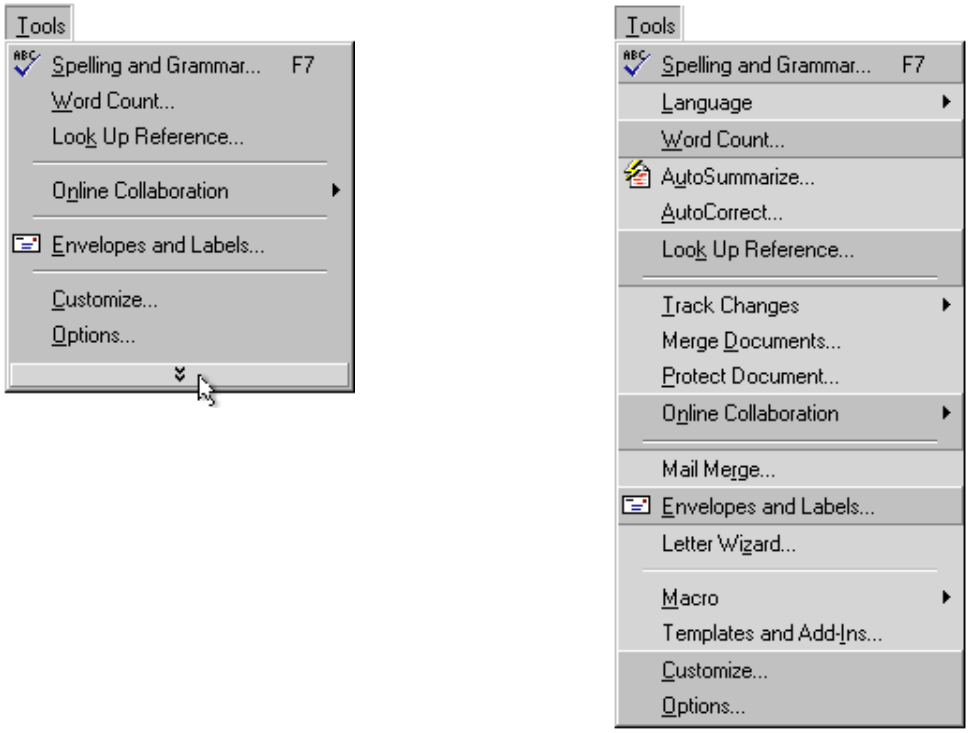


Figure 3.1. Adaptive Menus in Microsoft Office 2000. Some options in the adapted menu have been hidden. The user can expand the menu to its regular view by clicking on a button with an arrow icon at the bottom of the menu. In the expanded form of Adaptive Menus, shading is used to show which items have been expanded.

An alternative design is sorting menu items by placing frequently selected items higher in the menu. Sorting has not been shown to be effective (Mitchell and Shneiderman, 1989; Sears and Shneiderman, 1994) as continuously restructuring a menu prevents users from learning the position of items when they reuse the menu. Split menus (Sears and Shneider-

man, 1994) partially solve this problem by splitting menus into two sections: (1) a top personalized section, and (2) a bottom static section. The top section contains a small number of the most frequently selected items (e.g., four items). The bottom section contains the rest of the items in their original order. Note that attempting to locate a frequently selected item at its original position will fail if using this version of split menus. Gajos et al. (2005) observe that this issue can be addressed by copying instead of moving items to the split section. This approach has been adopted by newer versions of Microsoft Word (e.g., Microsoft Word 2004 for Mac) to personalize the list of font styles in the formatting toolbar.

SUPPLE (Gajos et al., 2005), a toolkit that automatically creates personalized user interfaces, generalizes the split design to other user interface components, such as dialog boxes and configuration windows. Such user interfaces are called *split interfaces*. Their components are split into static sections, which respect the original structure of widgets, and dynamic sections, which are dynamically adapted to better accommodate the ongoing user tasks. An example of a split interface applied to toolbars was tested by Gajos et al. (2006). In this interface, an additional toolbar was added, containing the most frequently (or more recently) selected tools. Items in the new adaptive toolbar were copied rather than moved from the original toolbars. Users could still access items from their regular location; on the other hand, additional screen space was consumed, which might be a problem in small screens.

An approach different than highlighting, sorting or splitting was adopted by Janecek and Pu (2002). This approach uses *scaling* in the context of distortion-based fisheye views (Furnas, 1986) to deemphasize non-relevant information in tabular data. Distortion is applied by varying the font size of tabular content with respect to a continuous function that evaluates the degree of user interest for each cell in a table. McGuffin et al. (2004), on the other hand, introduced *expand-ahead*, an adaptation technique aimed at helping users drill down paths in tree browsers faster. Expand-ahead automatically expands folders, e.g., frequently expanded folders, to fill available screen space. Expansion is only performed when there is

free space for the visualization of an expanded folder, and thus, disturbance due to adaptation is minimal. However, as McGuffin et al. (2004) admit, expand-ahead increases clutter and can hinder visual search.

Finally, software assistants such as spelling checkers and word predictors (Hui and Boutilier, 2006), notification systems (Horvitz and Apacible, 2003), and anthropomorphic agents (Horvitz, 1999; Koda and Maes, 1996) constitute a separate class of adaptation techniques not examined here.

3.4 User Modeling

User models are essential components of adaptive user interfaces. A user model is a representation of a user that a system maintains. A user model may capture any information about a user such as preferences, skills, expertise, disabilities, cognitive styles, goals, interests, usage patterns, and information needs. User models are typically application-dependent. Different systems have used a wide range of representation schemes for user models. In their simplest form, user models are static *stereotypes* of users, such as novices and experts. There exist, however, sophisticated modeling techniques that capture rich information about a user, for example, histories of previous actions, summaries of information that the user has accessed in the past, and probability distributions over alternative user goals.

A common approach to capturing and modeling information about users is to observe past usage patterns such as the frequency or recency of certain user actions. For example, Adaptive Menus in Microsoft Office 2000 were adapted based on an algorithm that combined frequency and recency of menu selections (Findlater and McGrenere, 2004). More generic approaches (Horvitz et al., 1998; Hui and Boutilier, 2006) have used Bayesian modeling to capture uncertainties about user goals and needs. Such models are inferred through various observations of user actions and can be rather complex as Figure 3.2 illustrates.

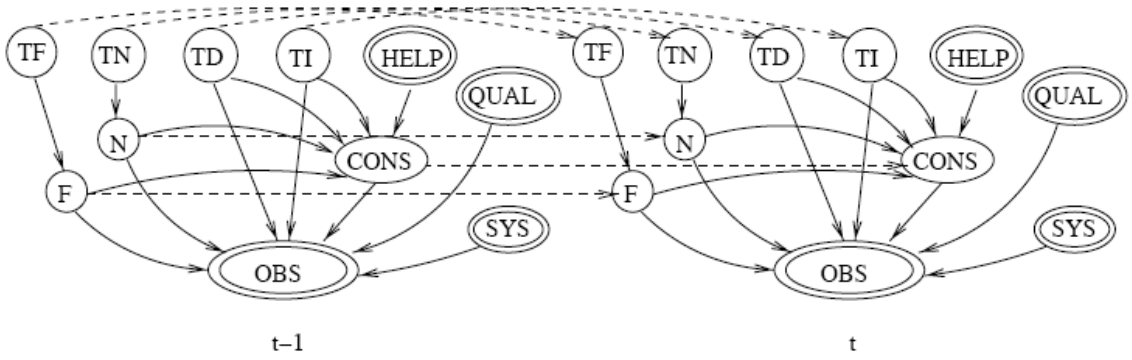


Figure 3.2. An example of a complex, probabilistic user model (Hui and Boutilier, 2006). In this example, a Dynamic Bayesian network captures temporal probabilistic dependencies among observations (double-line ovals) and variables (single-line ovals) representing user types, abilities and attitudes.

In systems that support the exploration of large information spaces such as hypertexts, observing repetitive patterns of user actions is not an effective strategy for inferring user goals. In this case, navigation involves the visit of semantically similar or relevant pieces of information rather than repetitive visits of the same object. Semantic similarity has been used by content-based user modeling techniques (Joachims et al., 1997; Pazzani et al., 1996). Content-based techniques use vectors of terms, also called *feature vectors*, to represent both the content of visited pages and the user model (Salton, 1991). In content-based user modeling, the construction of a user model can be based on keywords explicitly specified by users (Joachims et al., 1997) or, alternatively, keywords extracted from the content of a collection of pages, visited by the user in the past (Mladenic, 1996). Other approaches (Bauer and Leake, 2001; Hirashima et al., 1998) have tried to capture the evolving context of navigation by analyzing the content of the recent browsing history of a user. Models that capture multiple parallel navigation contexts have also been proposed (El-Beltagy et al., 2001). In the absence of information about the history of a user's navigation patterns, collaborative techniques (Konstan et al., 1997) are more appropriate than content-based approaches. Collaborative techniques assume that users with similar characteristics (e.g., same age) will exhibit

similar interests. Given this assumption, they assist users based on the interests of other users with similar characteristics. E-commerce sites such as Amazon.com have extensively adopted this approach to personalize recommendation.

3.4.1 Evaluation Measures

Presumably, the effectiveness of a user modeling technique could be measured based on how *accurately* a user model captures the real goals, preferences or needs of users. However, a user model is, by definition, an incomplete and simplified representation of a user. As a result, establishing objective evaluation measures of user models is not always feasible. Brusilovsky et al. (2004) report that user models can be subjectively tested by having experts monitor users as they work and evaluate the conclusions of the system stored in the user model. Alternatively, the actual users themselves can evaluate whether a user model reflects their needs.

In some cases, objective measures can be established by analyzing data from the interaction of users and then matching this data with the system's assumptions, maintained as part of the user model. Consider, for instance, the following scenario. An adaptive user interface is aimed at improving visual search in toolbars. As part of its evaluation, a number of users are observed while they interact with the user interface. Data about the history of toolbar selections are collected. This data is then analyzed to test how accurately the observed user selections reflect the user model under consideration.

When the role of user modeling is to classify documents or elements of a user interface into a finite set of classes, e.g., tools in a toolbar are classified as either "relevant" of " irrelevant" or a hyperlink is classified as "interesting" or "uninteresting", then information-retrieval measures as *accuracy*, *precision* and *recall* (Sebastiani, 2002) can be used. For instance, *accuracy* could be defined as the mean probability that an element in the user interface is classified into the correct class.

3.5 Problems Associated with Adaptive Behaviour

We can identify three major problems of adaptive user interfaces:

1. They depend on the construction of user models that are incomplete and often erroneous.
2. They result in complex conceptual models that cannot be well understood by users.
3. They often make it difficult for users to control the system's actions.

Although research in the areas of User Modeling and Machine Learning tries to address the first problem by applying new user modeling techniques and new learning algorithms, it is commonly acknowledged that no user model can accurately describe a user. It is also hard to believe that future intelligent systems will be able to precisely predict what users want as even human experts may fail to do so. The second problem derives from the fact that the way that adaptive user interfaces behave is often determined by complex decision-making that users may not be aware of. User models are usually hidden from the user, and the response of an adaptive user interface can seem inconsistent and unpredictable. The third problem becomes crucial when the system cannot accurately infer user goals and needs. User intentions often change rapidly. Unfortunately, in absence of evidence about changes, automatic learning is not feasible. In such situations, and unless the user can provide direct feedback to the system, adaptation will fail to capture the changing user intentions. According to Shneiderman, who has been a passionate critic of adaptive user interfaces in the past (Shneiderman and Maes, 1997), adaptive user interfaces violate basic usability principles that have been established in the context of *directly manipulated* user interfaces. Direct manipulation involves continuous representation of objects, rapid, reversible and incremental actions, and feedback (Shneiderman, 1983). Adaptive behaviour usually lacks such properties.

Besides the above problems, adaptation can affect *landmarks* on which users base their navigational and reading tasks. In general, landmarks are distinctive environmental features functioning as reference points (Vinson, 1999). In a user interface, examples of elements that act as landmarks are images, graphics, fonts, and structural forms of laying out information or widgets. Users depend on the presence of landmarks when they interact with a desktop environment, so disturbing these landmarks may disrupt their *mental models* and result in disorientation. In the rest of Section 3.5, we survey how existing approaches have tried to address such problems and identify their main limitations.

3.5.1 Predictability, User Trust, and Transparency of Adaptive Behaviour

Mental models are dynamic representations of the real world, constructed by users to predict and explain the operation of a target system. D. A. Norman (1986) states that mental models are incomplete, unstable, unscientific and parsimonious, while humans' abilities to run them are limited. He also distinguishes between mental models and *conceptual models*, which are models invented by teachers, designers, scientists and engineers. Conceptual models are intended to be accurate, complete and consistent representations of the target system. Making a system transparent can help users to build adequate mental models that closely match a system's conceptual model.

An adaptive system's behaviour can vary according to the details of the user model and its inference mechanism, which are usually not transparent to the user. As a result, there is a danger that the user will not understand the actions of the adaptive system. Unpredictable behaviour, particularly when it fails to satisfy user needs, can lead to user frustration and poor use of the system. Parasuraman (1997) distinguishes between two deficient uses of automation, which occur when the operation and capabilities of automation are not correctly anticipated by users: (1) *misuse,* which refers to the over-reliance on automation caused when the user has overestimated the system's intelligence; and (2) *disuse*, which refers to the

underutilization of automation when the user has underestimated the system's ability to provide assistance. Misuse and disuse closely relate to user *trust*, which can be defined as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Lee and See, 2004). User trust and willingness to use automation have been shown to decrease as automation becomes incompetent (Muir and Moray, 1996). Eliminating the problems of misuse and disuse is known as *trust calibration* (Lewis, 1998), which can be achieved by making automation predictable. According to Lewis (1998), automation can be made predictable by (1) consistently pairing simple observable actions with inputs, (2) making the causes and rules governing an agent's behaviour transparent, or (3) making the purpose, capability, and reliability of the agent available to the user.

As a solution to this problem, researchers (Cook and Kay, 1994; Kuhme, 1993) have suggested that user models should be *inspectable* or simply viewable. As user models can be complex and involve several parameters, the main challenge of this approach is how to represent the user model in a form that the user can easily understand. In their system, Cook and Kay (1994) provided visualizations of user models, the components of which were organized as interactive hierarchical structures. Different shapes were used to indicate the type of each node in the hierarchy, e.g., crosses represented user characteristics and diamonds represented user beliefs. The user could click on the nodes to unfold them and uncover their details. Such views of user models can be rather complex and hard to understand. Furthermore, they are decoupled from the main user interface and are not directly associated with the interaction model of the application. Consequently, although the details of such user models are viewable, the process of their construction is not fully transparent.

Hook (2000) observes that depending on the application domain and the individual user's experience, it can be difficult to provide comprehensible views of user models. In this case, it would be more appropriate to hide complex inference mechanisms from the user and

show, instead, simplified views of the user model that provide a sense of predictability. Several learning systems have used *skillometers* to give an indication of a student model (Kay, 2001). Skillometers enable learners to see how the system models their progress. Other approaches (Andre and Rist, 2002; Horvitz, 1999; Koda and Maes, 1996) have suggested the use of anthropomorphic agents that imitate human-human communication. Such agents are gifted with facial expressions that provide an indication of transparency of what the agent believes about a user's goals. The main argument against anthropomorphic agents is that they give false expectations about their intelligence and their ability to communicate with the user (Shneiderman and Maes, 1997).

3.5.2 Controllability

As mentioned earlier, researchers often distinguish between adaptive and adaptable user interfaces (Fischer, 2001). In contrast to adaptive user interfaces, personalization in adaptable user interfaces is mostly determined by the user and less by the system itself. The main advantage of adaptable systems over adaptive user interfaces is that they give users control over adaptive behaviour and minimize the likelihood of incorrect system decisions.

The distinction between adaptability and adaptivity is usually theoretical, as an adaptive user interface can incorporate adaptable characteristics and allow for some level of user control. User control can have different forms and affect different levels of the interface's adaptive behaviour. An empirical study conducted by Jameson and Schwarzkopf (2002) indicated that some users may like to have control over the system's actions, while others may prefer automatic assistance. On the other hand, some users may be willing to switch between more or less controllable versions of an interface depending on how their task evolves over time. Kuhme et al. (1992) identify four stages in an adaptation process: (1) the *initiative* for adapting the user interface, (2) a *proposal* of alternative adaptations, (3) a *decision* about

which alternative to choose, and (4) the *execution* of chosen adaptation. A user could be in control of any of these four stages.

In Figure 3.3, we provide a different analysis of how user control can be manifested with respect to which part of the system is controlled. We identify three main forms of controllability in adaptive or adaptable user interfaces:

1. Users customize the interface by selecting the view that best satisfies their needs or select which functionality appears in the interface. The system does not provide any automatic assistance to support this task.
2. Users do not have direct control over the actual interface but they rather control the user model on which the system bases its adaptive behaviour.
3. Users control the level of the system's intrusiveness or the adaptation method.

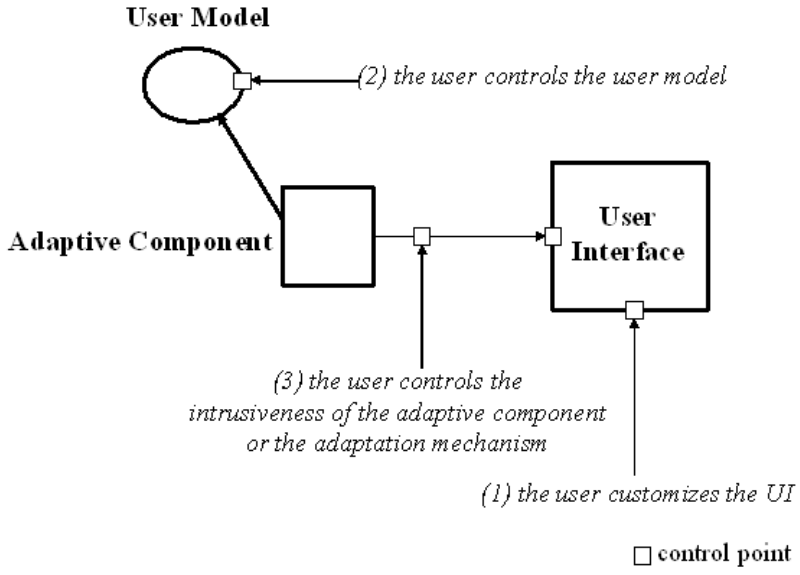


Figure 3.3. Forms of user control in adaptive/adaptable user interfaces

In Section 3.1, we mentioned that customization can be a laborious and time-consuming task. On the other hand, customization gives the user full control and eliminates the problem of unpredictability. McGrenere et al. (2002) designed a version of Microsoft Word that supported two different interfaces, between which users could deliberately switch.

A full interface contained all the functionality of the software, whereas a personal interface was customizable, containing only functionality that users explicitly determined. The results of a field study showed that the majority of participants preferred this customizable *multiple interface* over the adaptive interface of menus, as appeared in Microsoft Windows 2000. Besides, participants generally made extensive use of customization.

The fact that several users are willing to customize does not necessarily imply that customization is always beneficial. Users employ a variety of different customization strategies, and some of these strategies could be more effective than others. The effectiveness of different customization strategies in the multiple interface, as introduced by McGrenere et al. (2002), was explored by Bunt et al. (2004). In particular, this work tried to give answers to two questions:

1. When to customize? Up front or later, when functionality is actually used?
2. What to customize? Everything that is being used or only the most frequent functions?

Following a model-based evaluation approach, Bunt et al. (2004) found that customizing up front and only the most frequent functions is the most effective strategy in terms of performance benefits. Benefits coming from customization were greater for novice users. On the other hand, the performance of novice users was found to be more sensitive to ineffective customization strategies than the performance of experts. Unfortunately, novice users are normally not in the position to predict their future usage patterns. This means that novices are prone to follow suboptimal customization strategies. Bunt et al. (2004) hypothesized that enhancing customization with automated assistance would help users customize a user interface more effectively. More recently, Bunt et al. (2007) extended the multiple interface and modified the customization mechanism to combine automation with customization. According to this approach, the initiative for customizing the user interface is taken by the user, but

the system assists the customization task by making suggestions about which functionality to be included in the personal interface. Users can view the rationale that directs the suggestions and either approve the suggestions or apply their own customization. These control mechanisms make automation transparent, thus dealing with the problem of unpredictability. On the other hand, they add additional complexity to the user interface. A main drawback of the multiple interface is the fact that users are required to switch from the personal interface to the full interface to find functionality not included in the former one. The cognitive overhead of switching interfaces has not been yet clearly assessed as Bunt et al. (2004) admit. Such a cost could reinforce the adherence to a minimal set of functions and, in the long run, discourage novice users from learning how to use new functionality.

The second form of controllability shown in Figure 3.3 does not support direct control over the elements of the user interface. Customization is performed indirectly as the user controls the parameters of the user model. Controllability of user models has been mainly investigated in the context of intelligent tutoring systems. Kay (2001) states that, as opposed to early tutoring systems that viewed users as *students*, the term *learner* has been favoured in later systems. This implies that the role of the users is not passive; they are responsible for their own learning, participating in the construction of their model and selection of teaching strategies. Kay has also introduced the notion of *scrutable* adaptive systems. Scrutable adaptive systems enable the user to investigate and review the way that the system has been adapted. Tutor (Czarkowski and Kay, 2003) is a scrutable AH system developed within this framework. At the beginning of each session, Tutor constructs a student model based on the answers of the student to a small set of profile questions. Based on the constructed model, pages are adapted by excluding parts of the content. Furthermore, at the bottom of each adapted page, there is a link to an explanation section. The explanation section explains how adaptation is performed and what content has been excluded from a page. Users can revise their answers to profile questions by clicking on an icon on the top of an adapted page. Tutor

does not distinguish between user feedback, which is received by the system in order to build the user model, and user control over the system's adaptive behaviour. Both types of interaction are performed by the user by answering a small set of predefined questions. Therefore, this approach cannot be applied to systems in which the construction of user models depends on extensive and implicit user feedback.

Adaptable systems that belong to the third form of controllability let the user control the adaptation method or the intrusiveness of adaptation. As an example, research by Microsoft has tried to tackle the problem of balancing between automated assistance and intrusiveness and investigate how intelligence could be incorporated into directly manipulated interfaces. Horvitz (1999) refers to the type of interfaces in which users and intelligent agents collaborate to achieve the user goals as *mixed-initiative* user interfaces. Although, in such systems, beliefs about the goals of a user are based primarily on implicit user input, users are allowed to explicitly specify utilities and threshold probabilities that affect the system's intrusiveness and adaptation strategy (Horvitz, 1999).

3.6 Evaluation of Adaptive User Interfaces

Because of the problems discussed above, adaptive user interfaces have been criticized for being more a hindrance rather than help (Shneiderman and Maes, 1997). Part of this criticism can be explained by the lack of clear evaluation results that could show advantages of adaptive user interfaces over static user interfaces. After reviewing articles on user modeling and user-adapted systems prior to 2001, Chin (2001) found that only about one third of the articles on user models and user-adapted systems included any type of evaluation. As several evaluations were just pilot or informal studies, only a quarter of the articles reported statistically significant results. Besides, a large volume of work within the communities of artificial intelligence and user modeling has assumed that adaptive behaviour is beneficial as long as effective intelligent algorithms can be developed, disregarding the effect of adaptive

behaviour on real users. On the other hand, results from evaluations with real users have been non-conclusive and contradictory or were limited in scope.

3.6.1 Evaluation Strategies and Frameworks

Based on Chin's (2001) analysis, we can distinguish between two different types of evaluations: (1) evaluations that only test the effectiveness of the underlying learning algorithm and user modeling approach; and (2) evaluations that test the overall success of a particular system. Evaluations that belong to the first category make use of evaluation measures like the ones discussed in Section 3.4.1. For instance, Joachims et al. (1997) measured the performance of WebWatcher in terms of accuracy. Accuracy was defined as the percentage of cases in which users followed the advice given by the system. In a different experiment, WebWatcher's performance was compared against the performance of eight human experts as well as the performance of random suggestions. Unfortunately, such approaches cannot test the overall success of the system and the usability of the techniques used to adapt a user interface.

Evaluations that belong to the second category evaluate the overall utility and usability of a particular system through studies with real users. A common approach of such studies is to compare the adaptive system against its non-adaptive version with respect to measures of user performance, such as task-completion time, number of errors, quality of user answers to comprehension questions as well as measures that capture user satisfaction. Hook (1997) notes that this evaluation approach can often be problematic, if the non-adaptive version of the user interface has not been optimally designed for a given task. If adaptivity is a natural part of the system, the evaluation could be biased against its non-adaptive version if the latter has not been carefully designed. In addition, an evaluation will be biased if the selection of the tasks that participants complete stresses the strengths of the adaptive system and the

weaknesses of the non-adaptive one. Selecting a set of representative tasks that capture both the strengths and weakness of an approach is a tricky procedure.

Brusilovsky et al. (2004) observe that evaluating an adaptive system as a whole is not always useful, as it cannot lead to safe conclusions about which parts of a system are successful. If the system fails to satisfy the user or proves to hinder his/her tasks, such an evaluation cannot clearly show which aspect of the system did not work well. Should the failure be attributed to limitations of the user modeling approach or is it the adaptation technique that is used to personalize the user interface that fails? As a solution to this problem, Brusilovsky et al. (2004) propose a layered evaluation process. They suggest that the evaluation of adaptive systems should be conducted at two distinct layers: (1) user modeling and (2) decision-making. We have already discussed how user models can be evaluated, so we skip the first layer here. The question, according to Brusilovsky et al. (2004), that an evaluation at the second layer should address can be stated as "are the adaptation decisions valid and meaningful, for the given state of the user model?" For instance, given the scenario that the user model "thinks" that the user will insert a new table using a menu, is highlighting the corresponding menu option the correct adaptive decision to be made? Would hiding the other options in the same menu be a better approach? The layered evaluation process, as proposed by Brusilovsky et al. (2004), allows for testing and comparing different adaptation techniques independently of the implementation of the user-modeling and learning component. On the other hand, it disregards the fact that the appropriateness of a particular adaptation technique highly depends on the ability of the user model to correctly capture the user needs. Hiding menu options might be the best decision given a user model that was always accurate, but highlighting might be more appropriate if the user model contained errors. Since user models are usually incomplete and erroneous, studying adaptation decision-making independently can result in misleading conclusions.

Similar layered evaluation frameworks but with a greater degree of granularity have been proposed by Paramythis et al. (2001) and Weibelzahl (2002). Weibelzahl (2002) identifies four rather than two evaluation steps: (1) the evaluation of the reliability and validity of the data collected from a user to built a user model; (2) the evaluation of the inference mechanism and the accuracy of user properties; (3) the evaluation of adaptation decisions; and (4) the evaluation of the overall interaction with respect to system behaviour, user behaviour and usability. On the other hand, Paramythis et al. (2001) identify seven modules that together comprise the various stages of adaptation, and for each module, they propose different evaluation approaches. The seven modules capture all the different aspects of a system that performs adaptations including user modeling, learning, decision-making, user interaction, feedback, and transparency of adaptation. The approaches that Paramythis et al. (2001) and Weibelzahl (2002) suggest for the evaluation of adaptation decisions and adaptation techniques are very similar to the approach suggested by Brusilovsky et al. (2004) and bear similar limitations. Overall, their scope has been the extensive evaluation of particular systems rather than the assessment of designs independently of the system in which they are used.

3.6.2 Evaluating the Viability of Adaptive User Interfaces

Several user studies have tested the effectiveness of particular designs of adaptive user interfaces. Some studies have shown that adaptation is beneficial while others have shown the opposite. In this section, we review the most thorough, according to our opinion, studies. We also attempt to explain their results and identify their limitations.

Overview of Studies Assessing Adaptive User Interfaces

An early experiment on the viability of adaptive user interfaces was conducted by Greenberg and Witten (1985). The experiment compared two hierarchical menu interfaces: (1) a regular menu interface that did not use any information about usage patterns; and (2) an adaptive

version of the menu interface that organized nodes based on popularity patterns. The results showed that the adaptive design was significantly more effective in terms of both task-completion time and error rates. A later experiment conducted by Mitchell and Shneiderman (1989) on adaptive menus showed that adaptive user interfaces may hurt rather than improve performance. The experiment compared static versus dynamic menus. Dynamic menus were continuously reordered so that frequently selected items appeared closer to the top of the menu. The results showed that dynamic menus did not improve menu selection speed. Moreover, an 81% of the 73 students that participated in the study favoured the static menus.

More than a decade later, McGrenere et al. (2002) conducted a field study to evaluate their multiple interface design applied to Microsoft Word 2000 and compare it against the normal interface of this software, both with and without Adaptive Menus (see Figure 3.1) enabled. The researchers classified participants into two different user types: *feature-shy* users, i.e., users who generally prefer interfaces with few features; and *feature-keen* users, i.e., users who generally prefer up-to-date versions of software with many features. The majority of participants (13 out of 20) ranked the multiple interface design as the most favoured one. Preferences over the static and the adaptive version of the user interface were split among participants. Feature-shy participants seemed to favour the static interface while feature-keen participants favoured the adaptive one.

More recently, Findlater and McGrenere (2004) compared a design of static menus against a design of adaptive menus and a design of adaptable menus. All the three designs were implemented as split menus. Adaptive split menus were automatically organized based on both selection frequencies and selection recency. Adaptable split menus were manually customized by users. In their original design (Sears and Shneiderman, 1994), split menus were assumed to be pre-organized at design time rather than being adapted at use time. Tested on rather long menus (28- item long), frequency-based split menus were shown to be faster than alphabetic menus (Sears and Shneiderman, 1994). However, prior to the study of

Findlater and McGrenere (2004), there was no evidence about whether automatically reorganized split menus could be effective. The latter study showed that static split menus performed better than adaptive split menus.

Benefits of adaptive behaviour have been identified by early experimental work on adaptive hypermedia systems. Boyle and Encarnacion (1994) compared three different versions of a hypertext-based documentation system: (1) traditional hypertext; (2) stretchtext-like hypertext; and (3) adaptive stretchtext-like hypertext. The results showed significant performance benefits of stretchtext over traditional hypertext. In addition, compared to the static version of stretchtext, adaptive stretchtext improved some performance measures such as the time spent by participants to answer comprehension questions. Hook (1997) also evaluated adaptive stretchtext, but she focused on measures of user satisfaction rather than measures of user performance. The results showed that participants generally preferred the adaptive version to the static version of stretchtext.

Discussion

The above results indicate that the success of an adaptive user interface depends on several parameters. Clearly, we cannot reach general conclusions about the effectiveness of adaptive user interfaces without having first identified these parameters and understood their impact. The findings of Greenberg and Witten (1985) are different than the findings of Mitchell and Shneiderman (1989) and the findings of Findlater and McGrenere (2004) despite the fact that they all tested adaptation in menus and used similar heuristics to adapt menus, such as frequency and recency of use. Yet, these variations are reasonable if we consider that each study tested different techniques under very different conditions. For instance, Greenberg and Witten (1985) tested adaptation on hierarchical rather than flat menus. It is possible that personalization is more valuable when applied to hierarchical menus, as it reduces the need for accessing items in high depths, which is a time consuming task. Besides, Greenberg and Witten (1985) tested their adaptive interface after selection frequencies had been stabilized.

Without having access to the actual data and the adaptation algorithm used in their experiment, it is not possible to know how frequently the structure of the adaptive menus changed. We can expect, though, that changes were not as rapid as they would be if learning had not yet occurred. In addition, both the adaptive and static menus tested by Greenberg and Witten (1985) were alphabetically sorted. As a result, the danger that a user would search for an item in the wrong submenu was minimal. It is very likely that that the cost of disturbance due to automatic restructuring of menus would be greater if menus were not alphabetically sorted.

In contrast to the above study, the study conducted by Mitchell and Shneiderman (1989) evaluated an adaptive interface that bore the worst attributes of adaptation. First, learning was performed while participants interacted with the system. As participants had to complete only 12 menu selection tasks per user interface, we can expect that any benefits coming from adaptation would be minor. Besides, Mitchell and Shneiderman (1989) do not report any information about the tested frequency patterns. Therefore, it is unclear whether and to what extend frequency-based adaptation, which was tested by their study, was justified.

Similarly, the outcome of the study conducted by Findlater and McGrenere (2004) can be better understood if we examine their experimental design in more detail. More specifically, the static menus tested by the study were optimally organized based on previous knowledge of selection frequencies. According to the reported data, the items that appeared in the top partition of the static split menus accounted for 720 out of 788 selections, i.e., approximately 91% of the time the static split menu provided correct suggestions. As adaptive menus did not use any prior knowledge about selection frequencies and learning was involved, this accuracy could have been lower than the accuracy of suggestions made by the static menu. In other words, the static version could have been equally or even more “intelligent” than the adaptive version of menus.

The benefits of adaptive behaviour shown by Boyle and Encarnacion (1994) and Hook (1997) are also non-conclusive. Boyle and Encarnacion (1994) do not provide any details about the tasks given to participants. They also do not report on how accurately adaptation had supported the given tasks. If tasks were carefully selected to promote the utility of adaptation, no safe conclusions can be made about the success of adaptive stretchtext in more general contexts. Similarly, Hook (1997) explains that her study was designed so that "usually, the system adapted correctly to what the subjects were up to". It is not known how the adaptive system would perform if adaptive actions were less accurate.

3.6.3 Comparing Adaptation Techniques

Gajos et al. (2006) distanced themselves from previous approaches by comparing different adaptation techniques applied to the same system rather than testing the viability of a particular adaptive user interface. More specifically, they conducted two experimental studies to evaluate three adaptive interfaces applied to the toolbars of Microsoft Word: (1) a split interface that added an additional toolbar, in which "hot", e.g., frequently used, buttons were copied from other toolbars; (2) a moving interface in which hot buttons within hidden popup panes were moved up to the main toolbar; and (3) a highlighting interface in which hot buttons were coloured in magenta. The above work addressed several methodological problems found in previous studies discussed earlier. First, it controlled various factors that could impact the effectiveness of an adaptation technique, such as the accuracy of adaptation. Second, it attempted to quantify both costs and benefits of the tested adaptation techniques and examined the impact of these costs and benefits on the overall acceptance of the evaluated techniques.

The work documented in this dissertation has progressed in a similar direction. Gajos et al. (2006) cite our published research (Tsandilas and schraefel, 2005) to justify their evaluation approach.

Chapter 4

Combining Automation with User Control

This chapter explores adaptation techniques for adaptive hypermedia (AH) systems. Special attention is given on the issue of user control. In particular, we introduce two Web-based prototypes, through which we examine techniques that merge automation with direct manipulation. The first prototype makes use of information retrieval techniques to filter hyperlinks on Web documents. Interaction is enhanced with techniques that allow users to directly control the display of hyperlinks on a page and receive incremental feedback about the outcome of their actions. The second prototype allows users to adapt the presentation of Web content rather than the display of links. The prototype incorporates a new adaptation technique, which has been influenced by fisheye views (Furnas, 1986). The new technique allows for incremental adjustments in the adapted view of a page and integrates several powerful control mechanisms. Two evaluation studies demonstrate strengths and limitations of this approach. They also reveal challenges concerning the evaluation of adaptation techniques, an issue explored in more detail in the next chapter.

The research presented in this chapter has been published in the 14th ACM Conference of Hypertext and Hypermedia (Tsandilas and m. c. schraefel, 2003a), the AH2003 Workshop on Adaptive Hypermedia and Adaptive Web-based Systems (Tsandilas and m.c. schraefel, 2003b), and the New Review of Hypermedia and Multimedia (Tsandilas and schraefel, 2004).

4.1 Motivation

As discussed in Chapter 2, in several AH systems (Cook and Kay, 1994; Czarkowski and Kay, 2003), adaptation is based on direct user input rather than implicit feedback gathered through the user's interaction with the system. The scope of these systems has been limited, since the parameters of adaptation that form the basis of user control have to be predefined by the authors of the hypermedia system; not by the actual users with respect to their own needs. For the same reason, the above approaches cannot easily generalize to regular Web documents, as Web developers do not design Web sites with adaptation in mind.

To better understand the problem, consider the following three scenarios.

Scenario 1: *"Alice, a new graduate student at the University of Toronto, looks for information about housing, courses, and teaching assistantships in the university's Web site. Although the site contains a large number of links with relevant information, these links are spread in different places and under a variety of different categories. Unfortunately, these categories do not match closely her navigation goals. Information about housing can be found under Colleges and Residences, Prospective Students, Student Services, and City Information. Information about courses and teaching assistantships can be found under Prospective Students, Programs, and so forth. Alice wants to be able to easily identify which links are relevant to the topics of her interests. She also wants to be able to easily switch between these topics while she explores the Web site."*

Scenario 2: *"Stephan frequently visits a Web site that contains a large list of recipes. Stephan usually searches the site having in mind specific combinations of ingredients. He would like to be able to easily recognize which recipes are vegetarian and which recipes contain nuts, to which he is allergic. Unfortunately, recipes are organized either alphabetically or by country, and Stephan normally has to visit several links before finding an appropriate recipe."*

Scenario 3: *"Mary visits several Web sites to find information about cultural events in Toronto. Mary is primarily interested in music events that are appropriate for kids. In the majority of the sites that she visits, events are posted in long pages and are organized by date. As a result, finding entries that relate to her interests is time-consuming."*

Someone could argue that studying user needs before designing Web sites would eliminate such problems. Unfortunately, this is a not a common practice; the majority of Web sites have been designed without a prior careful examination of user needs. Further, coming up with a design that satisfies all the users of a Web site can be difficult. Search tools can help users complete tasks as the ones described in the above scenarios, but their scope has been limited. They require users to solely depend on the success of their query formulations, and search results are isolated from the global context of information. WebWatcher (Joachims et al., 1997), on the other hand, allows users to give explicit input to a hypertext system by entering keywords that represent their information needs. Then the system automatically adapts pages, based on the occurrence of such keywords in the text of the pages. Unfortunately, user information needs can change frequently as navigation evolves over time, and in WebWatcher, switching between different personalization goals is a cumbersome process. It requires the user to start a new session and reformulate his or her goals by entering a new set of keywords; no reuse is supported.

Motivated by these problems, our work focused on the design of tools that combine the strengths of both searching and browsing. Our goal was to allow users to formulate queries,

as they normally do with search tools, but as in WebWatcher, queries would be used to support adaptation rather than searching. Furthermore, we considered as a high priority the design of interaction mechanisms that do not interrupt the browsing task of users and allow them to quickly refine their interests. We also aimed at adaptation techniques that do not disturb the original structure of information. In order to reach these goals, we developed two Web prototypes, presented in the following sections.

4.2 First Prototype

The first prototype addressed the problem of representation and reuse of user interests, in a way that users can directly control adaptation. Our efforts concentrated on the representation of reusable user interests with easy-to-use interface controllers like sliders. Sliders have been traditionally used to filter well-structured data such information about movies stored in a database (Ahlberg and Shneiderman, 1994). Our challenge was to generalize their use to hypermedia environments, where information is generally unstructured. Similarly to previous work by Joachims et al. (1997), our work focused on adaptive link annotation. Specifically, we examined how sliders could be used to incrementally control the annotation of links on hypermedia pages with respect to reusable topics of user interest.

Figure 4.1 illustrates the user interface of the prototype. As shown in the figure, a separate browser window is used to enhance interaction with a set of sliders. Each slider represents a weighted topic of user interest. Users can dynamically add sliders by entering sets of keywords and reuse them in future browsing sessions. As users interact with the sliders, visual properties of the links on the visited pages are incrementally updated. In other words, users are given direct feedback about the effect of their manipulations.

In the prototype shown in Figure 4.1, colour annotation is used: links pointing to pages whose content is relevant to the current user interests become red, while links pointing to pages whose content is not relevant to the user interests become blue. Hue variations be-

tween blue and red represent intermediate levels of relevance. Links shown in grey point to documents whose content cannot be analyzed, such as images and PDF files.

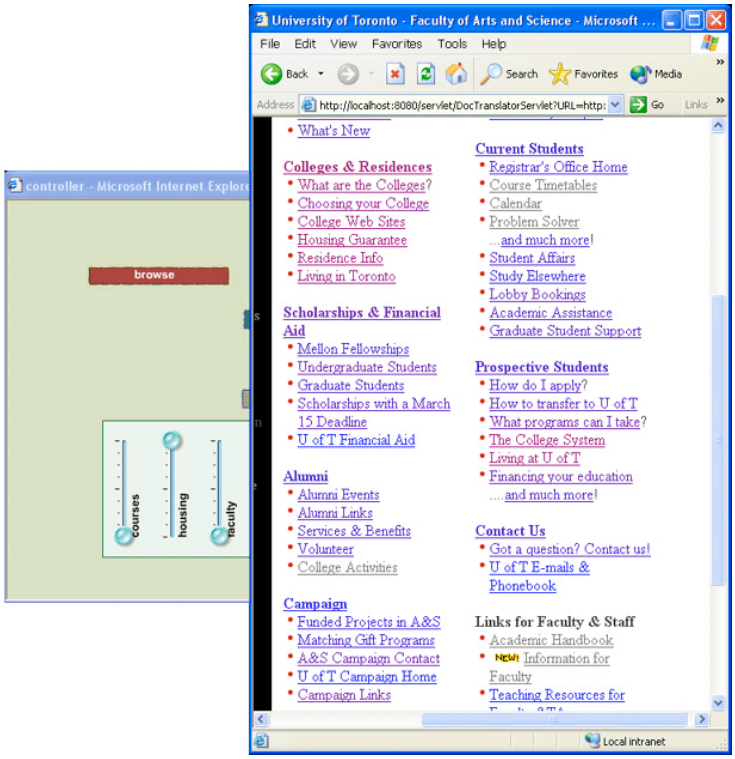


Figure 4.1 Using sliders to control the display of hyperlinks on a Web page. Here, the user is interested in information about housing. Relevant links are shown with a red or reddish colour.

In the following paragraphs, we describe the prototype in more detail. We also show how the same interaction mechanism has been extended to assist the revisitation of Web pages.

4.2.1 System Architecture

Our decision to use sliders to control how links were displayed required that pages were dynamically adapted, without having to be reloaded. We examined three alternatives of Web-based architectures that satisfied this requirement:

1. Extending Web browsers with additional functionality, e.g., by developing a new plug-in that would enable users to directly control the visualization of Web pages.
2. Using a Web server to transform Web pages to adaptable pages that could be directly controlled by users.
3. Using a proxy server as an intermediate component between clients and Web servers to transform pages to adaptable pages.

The first approach is possibly the most elegant and most effective in terms of stability and performance. Yet, it would require us to stick to a particular browser such as Mozilla Firefox. Moreover, when we started this project in late 2002, there was only limited documentation and poor development tools for user interface extension languages like the XML User-Interface Language (XUL) , which is commonly used today to extend the capabilities of Firefox. The second and third alternatives are similar in concept. We opted for the second one, because it is simpler in terms of implementation.

According to the selected alternative, the role of the server application is to analyze the content of requested Web pages and transform them to adaptable pages. Adaptable pages are pages whose HTML code has been enhanced with JavaScript code. The user interface through which users control such adaptable pages was implemented in Macromedia Flash MX and ActionScript. Finally, we decided to use the Java Servlet API (Sun) for server-side programming, as it allows for platform-independent and easily extensible server applications.

Figure 4.2 illustrates how the different components of the system communicate. The servlet resides at the server side and is responsible for handling page requests made by the client, i.e., the Web browser. The servlet first extracts the URL of all the links in the requested page. Then it retrieves the content of the destination page pointed to by each link. This content is analyzed and compared with descriptions of user interests. The servlet also

maintains a cache of pages whose content has been already extracted and analyzed. The main goal of this cache is to improve the performance and response time of the servlet.

Descriptions of user interests are sent to the servlet by the Flash interface every time the user specifies a new topic of interest. Content analysis results in values that express relevance between topics of user interest and links within the requested page. The final adaptable page sent to the browser is constructed by inserting JavaScript code into the original HTML of the requested page. This JavaScript code specifies the values of relevance between the linked pages and the topics of user interest. Finally, the JavaScript code assigns object identifiers to link anchors. These identifiers allow the sliders in the Flash user interface to control the style of the link anchors on the rendered page.

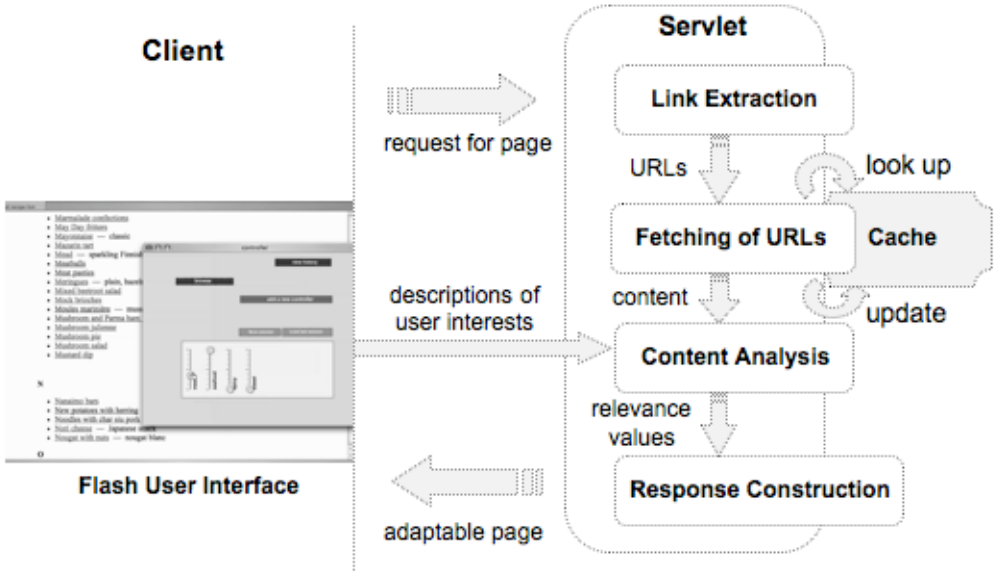


Figure 4.2. System architecture

4.2.2 Representing User Interests and Content

We represent both user interests and documents, i.e., the content of Web pages, as vectors of terms, usually referred to as *features* in Information Retrieval. Each feature in a vector is the

stem of a single word and is assigned a real value. This value is calculated by means of the widely used *TF·IDF (Term Frequency – Invert Term Frequency)* heuristic (Salton, 1991):

$$TF \cdot IDF(w,d) = TF(w,d) \cdot \log(\frac{n}{DF(w)}) \quad (4.1)$$

where *TF(w,d)* is the frequency of the feature *w* in document *d*, and *DF(w)* is the number of documents that contain *w* in a total of *n* documents.

The generation of large feature vectors is prevented by eliminating stop-words and omitting features with very small TF·IDF values. We use the cosine similarity metric (Salton, 1991) to measure relevance between topics of user interest and documents. Based on this approach, the relevance between the i^{th} topic and a document *d* is expressed as the cosine of the angle ω_i between their vectors:

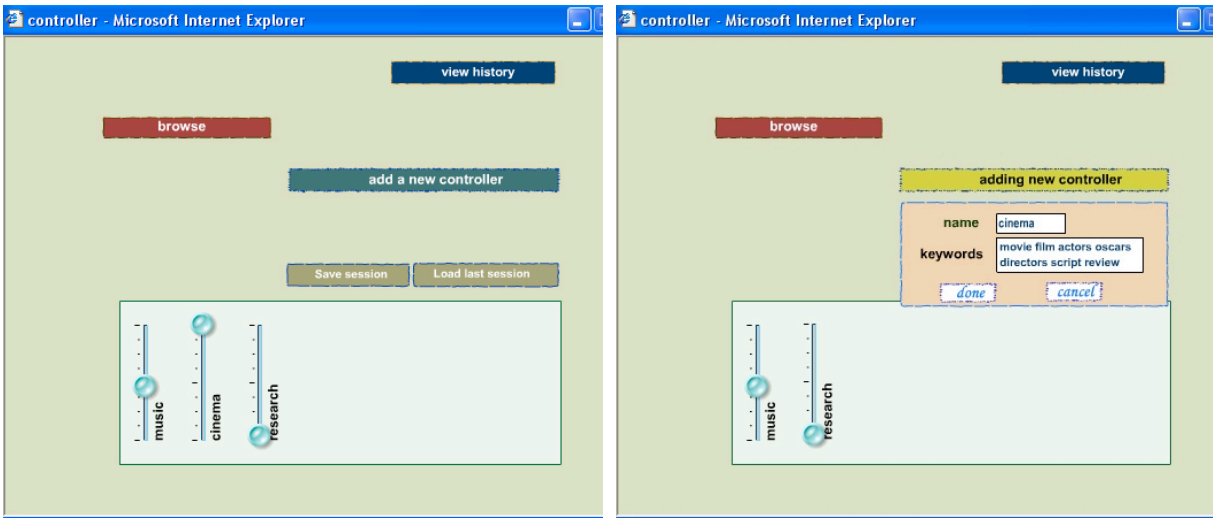
$$\cos(\omega_i) = \frac{\vec{v_i} \cdot \vec{d}}{\| \vec{v_i} \| \cdot \| \vec{d} \|} \quad (4.2)$$

where $\vec{v_i}$ is the vector representation of the topic, $\vec{d}$ is the vector representation of the document, and $\| \ \|$ stands for the Euclidean norm.

Each topic of user interest is controlled by a different slider. Nevertheless, user interests can extend to more than one topic. To combine different topics, we use an "or" interpretation, which assumes that the user looks for documents that relate to any of the highly weighted topics of interest, independently of each other. As a result, the relevance between a document $\vec{d}$ and a set of weighted topics *I* is expressed as the summation of the weighted values of relevance between the document and the individual topics:

$$relevance(I,\vec{d}) = \sum_{i=1}^{|I|} w_i \cos(\omega_i) \quad (4.3)$$

We denote by w_i the weight of the i^{th} topic of user interest that is derived by normalizing the weight of the corresponding slider so that $\sum_{i=1}^{|I|} w_i = 1$.



(a) (b)

Figure 4.3 The Flash user interface used to control the parameters of page adaptation. (a) Main view of the interface. (b) The user inserts a new topic by typing its name and a set of keywords.

4.2.3 User Interface

Figure 4.3 shows the Flash user interface. The window of the component contains a panel of sliders, which correspond to the topics of user interest. By moving a slider up and down, the user can specify whether and to what degree the corresponding topic describes the current browsing process. Five buttons provide some basic functionality. The first button ("view history") enables the visualization of browsing histories, allowing the user to see an overview of pages that have appeared in the past. This function is discussed in more detail in Section 4.2.4. The second button ("browse") activates a new panel, which lets the user request the display of new pages. The third button ("add a new controller") displays a panel for defining new topics of user interest. When a new topic is defined, a new slider is added. As shown in Figure 4.3(b), the user is asked to enter a name for the new topic and a set of keywords to

define it. New sliders can be added dynamically during a browsing session. The last two buttons ("Save session" and "Load last session") can be used to save the current session and load the last saved session, respectively. Saving concerns both the browsing history and the definitions of user interests. As mentioned in Section 4.2.1, the Flash interface can directly communicate with the servlet. This communication allows the servlet to receive information about the defined topics of user interest.

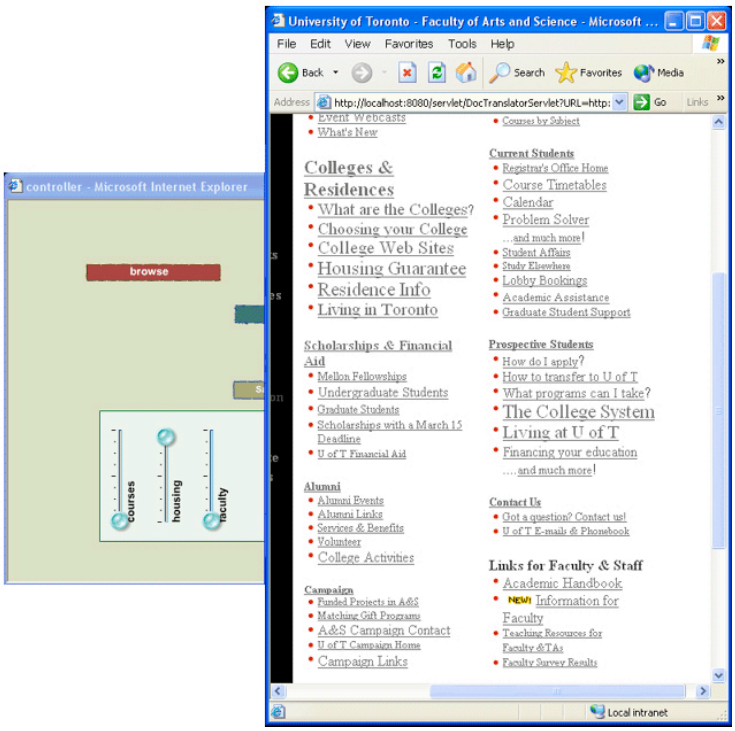


Figure 4.4 Filtering hyperlinks by adapting the size of fonts

As we have already discussed, the sliders in the Flash user interface allow users to filter the links on a Web page shown in the main window of the browser. We have experimented with several techniques to visualize degrees of relevance between links and user interests represented by sliders. In Figure 4.1, we illustrated how visualizing relevance was achieved by continuously adjusting the colour hue between red and blue. The use of colour to annotate hyperlinks is not free of problems: it changes the original colouring scheme of the page, which can have an important role in helping users process information. Figure 4.4

illustrates an alternative approach. The most relevant links are presented with larger fonts, whereas irrelevant links are presented with smaller fonts. In order to map relevance values, as calculated by Equation (3.3), to distributions of font sizes or colour ranges that are close to uniform, we use logarithmic functions:

$$DOI \propto \log(relevance) \tag{4.4}$$

where *Degree of Interest (DOI)* determines the colour or the font size of the linked text.

The main advantage of our approach is that changes in user interests activated through slider manipulations are immediately reflected on the adapted Web pages. Visual feedback is direct and incremental. Users can use sliders to filter links in a fashion similar to how sliders were used in Film Finder (Ahlberg and Shneiderman, 1994). Notice that automation has a significant role in the prototype's architecture; matching between user interests and links is automatically performed by the system. On the other hand, users have full control of how pages are adapted, since their interests are explicitly defined by themselves rather than automatically inferred by the system.

4.2.4 Visualizations of Browsing Histories

The system architecture presented in Section 4.2.1 allows for the extraction of rich information about the content of previously visited pages and their links. Making use of this information, the first prototype allows users to filter visualizations of browsing histories in addition to filtering links on Web pages. In the following paragraphs, we first give some background to put this functionality into context and then describe it in detail.

Background

History lists and bookmarks are common utilities supported by existing browsers. Nevertheless, as discussed in Chapter 2, these utilities have been underused due to the effort that their maintenance requires (Abrams et al., 1998). Previous research (Cockburn et al., 1999) has

stressed the need for techniques that automatically capture information about visited pages, so that the user is relieved of the burden of bookmark maintenance. The title and the URL of the page, its access time and sometimes a thumbnail (Cockburn et al., 1999) form page descriptors that existing history tools capture and use to organize browsing histories. Hochheiser and Shneiderman (1999) have shown how such descriptors can be used to visualize and filter browsing histories. Using simple page descriptors such as the page URL, the page domain and the time of access, they have demonstrated a variety of starfield visualizations, appropriate for the analysis of trends and patterns in past page visits. Other visualization approaches (Hascoet, 2001) have been based on the same set of descriptors.

Visualizations and Controllers

Our system captures rich page descriptions in the form of feature vectors. This enables the use of more sophisticated history organizations and filtering mechanisms than the ones used by previous work. According to our approach, pages are automatically associated with multiple topics based on their content, as the content of the pages has been extracted and analyzed by the servlet.

Figure 4.5 present a starfield history visualization supported by the Flash interface. The visualization appears when the user clicks on the “view history” button and shows previously visited pages as blue star nodes. Nodes are organized by time, following a clockwise spiral layout, where recently visited nodes are shown closer to the center, whereas older nodes are spread close to the boundaries of the visualization. This layout allows for the display of a relatively large number of nodes. It minimizes cluttering by spreading nodes fairly uniformly in the two-dimensional space. Furthermore, it provides quick visual feedback about the relative recency of page visits. Note that spiral layouts can be used to display periodic patterns in temporal data (Carlis and Konstan, 1998). We have not examined this possibility, but it is worth being considered in future work.

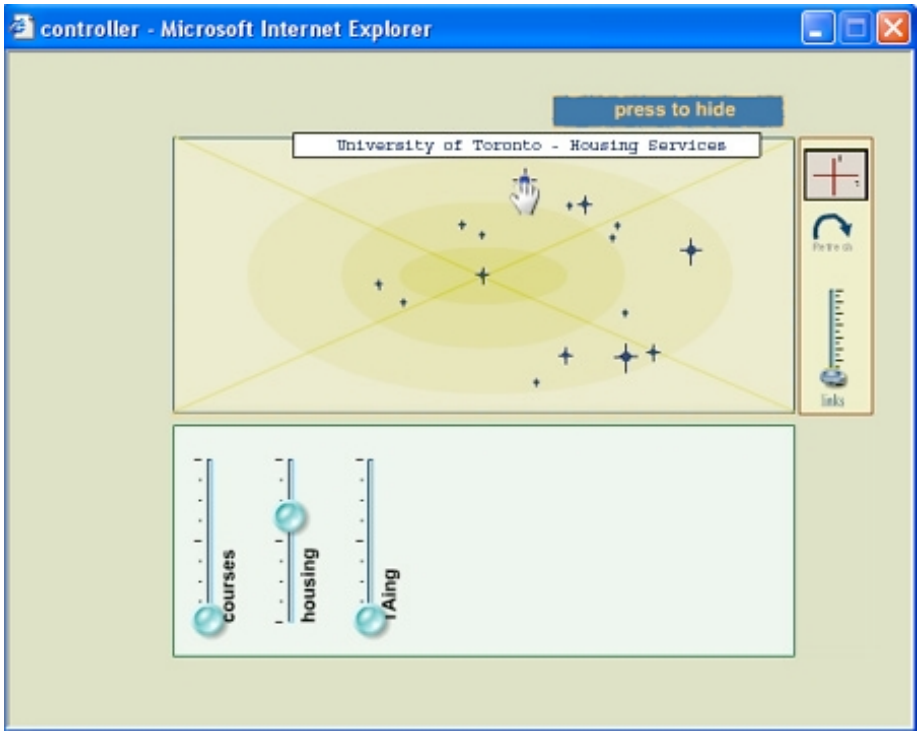


Figure 4.5. Starfield visualization of a browsing history. The user hovers the mouse over a node to reveal information about the Web page that the node represents.

As shown in Figure 4.5, some nodes are shown larger than others. Larger nodes are the ones whose content matches the user interests specified by the sliders. Nodes that are not relevant to these interests are hidden. In order to get information about a node shown in the visualization, the user must hover the mouse over it. By clicking on the node, the corresponding Web page is displayed on the browser.

In addition to previously visited pages, the history visualization can display their links. The rationale behind this approach is that interesting pages are usually surrounded by other interesting pages. Therefore, following a link from a page is often succeeded by returning to the same page and following a neighbouring link. Also, the significance of a page highly depends on the significance of its links. In particular, a page that is not interesting, but contains many interesting links, could be more useful than an interesting page with no interesting links. Providing information about the links that reside in a page can help a user decide about the significance of the page. In our prototype, the display of links can be controlled by mov-

ing the slider included in a control panel at the right of the visualization. Low slider values allow only the most relevant links to be shown. As Figure 4.6 illustrates, links are represented by red dots around the star nodes. As with star nodes, their size is analogous to their relevance to the specified user interests.

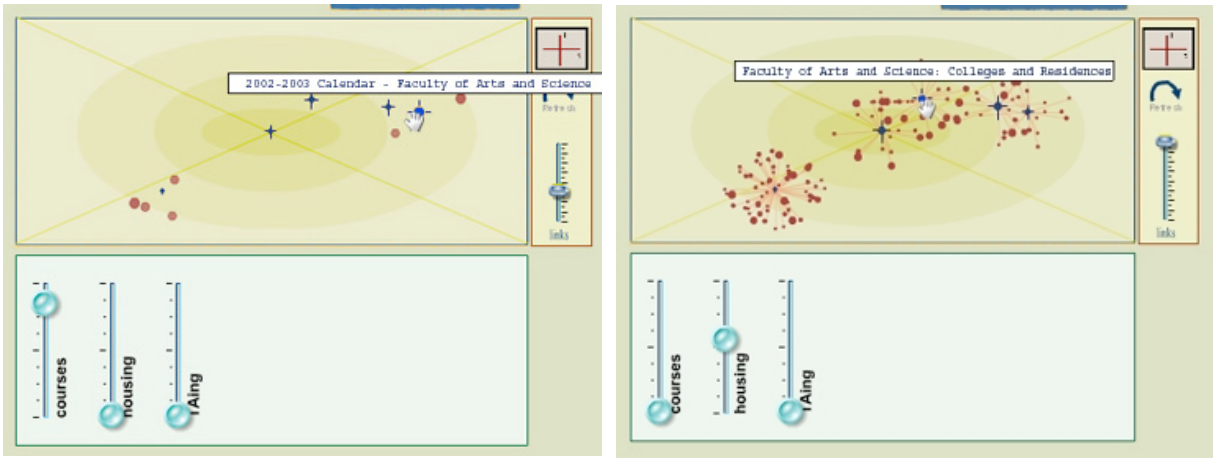


Figure 4.6. Showing links of pages in the history

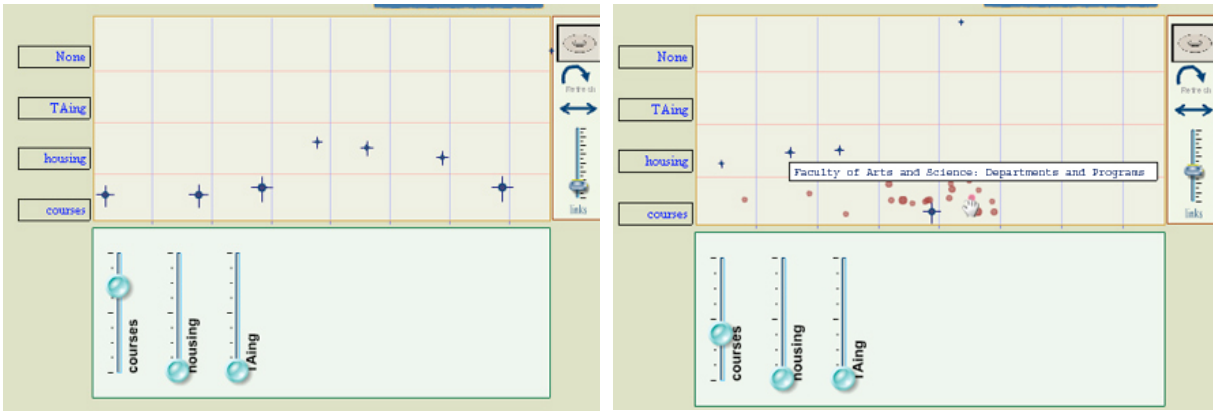


Figure 4.7. Alternative view organizing nodes by topic and time

Figure 4.7 demonstrates an alternative view, which organizes previously visited pages and their links in two dimensions: (1) the time the page was last visited, and (2) the topic that is most relevant to the page. Each column in the visualization area corresponds to a single visit of a page. Columns at the left part of the visualization correspond to the most recent visits. Each row corresponds to a different topic of user interest. There is an additional row

for pages or links that do not relate to any of the available topics. The distribution of visualized nodes over different topics allows a user to draw conclusions about the content of previously visited pages and their relevance to various topics.

In the alternative view of the history visualization, only a small part of the history can be displayed at the same time. Moving back or forward in time is performed by clicking the arrows in the control panel at the right of the visualization area. All the functionality supported by this panel is summarized in Figure 4.8. In addition to the functionality mentioned above, the control panel allows users to switch between the two visualization layouts and refresh the history, fetching updated information from the cache that is kept by the servlet.

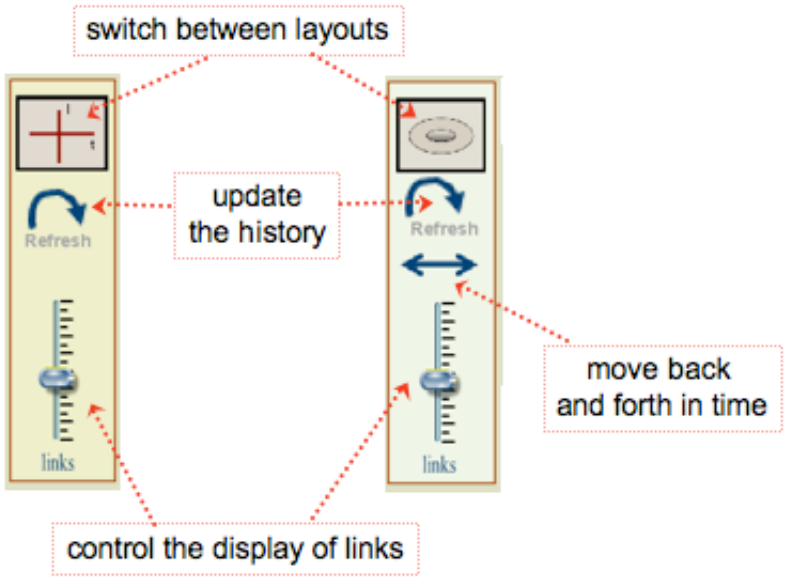


Figure 4.8. Panel to control the history visualizations

4.3 Second Prototype

Web browsing involves tasks other than following hyperlinks. Users regularly have to explore long pages, such as Web blogs, and skim through many paragraphs before being able to find something interesting. Our second prototype extends the approach presented in Section 4.2 to the personalization of Web content. The prototype introduces a new content adap-

tation technique. The new technique filters in/out Web information by adjusting the scale of its visual properties. The technique is aimed at helping users *focus* on information that supports their current information needs, while preserving *context* about surrounding information. The prototype integrates mechanisms that allow users to fluidly switch between different views of a Web page.

As we wanted to concentrate on interaction issues and avoid dealing with information retrieval and classification problems, we simplified the system architecture by assuming that topics of user interest have been predefined. However, the addition of a mechanism through which user could specify topics of user interest is possible, simply based on the system architecture described in Section 4.2. We do further discuss this issue here.

4.3.1 Focus, Context and Fisheye Views

Supporting context and focus has been the goal of several techniques in HCI research. Most of these techniques are based on fisheye views (Furnas, 1986). Fisheye views provide both local detail and global context in a single display. They have been applied to visualize information in several domains.

Furnas (1986) applied fisheye views to program code, tree structures and calendars. Fisheye techniques were used by Sarkar and Brown (1992) to support viewing and browsing graphs. Bederson (2000) applied fisheye zooming to pull-down menus with the goal to reduce the cognitive load caused by long lists of choices. Greenberg et al. (1996) introduced fisheye views to support group awareness when multiple people work on the same document. Fisheye views were used by Janecek and Pu (2002) to visualize semantic relationships within tabular data. Fisheye views have also been applied to hypertext applications. For instance, Noik (1993) introduced fisheye-like visualizations of large hypertext networks. Bederson et al. (1998) introduced the *Multi-Scale Markup Language (MSML)*, a markup

language implemented using the HTML <Meta> tag, to enable multiple levels of scaling within Web pages. Finally, Holmquist (1997) developed fisheye views of page collections.

Fisheye-view techniques define a *Degree of Interest (DOI)* function that specifies how the elements of the visualized information are presented. The actual definition of the DOI function is application dependent. Different approaches use different techniques to visualize information with respect to a DOI function. Noik (1993) classifies fisheye-view approaches into two main categories: *filtering* and *distorting* fisheye views. Approaches that belong to the first category use thresholds to constrain the display of information to relevant or interesting elements. Approaches that belong to the second category apply geometrical distortion to the visualization. Distortion is usually performed by altering the position and size of the visualized elements. Fisheye-view techniques assume that there is a focal point, and the value of the DOI function decreases with distance to this point. Several fisheye approaches (Greenberg et al., 1996; Sarkar and Brown, 1992) support multiple focal points at the same time.

4.3.2 Fisheye-Like Content Adaptation

Here, we explain how fisheye views can be used for content adaptation. Limiting our attention to information exploration tasks, we assume that a user model captures the current interests of the user. In this context, the DOI function can be expressed as the relevance between the user interests and the individual pieces of information on visited hypermedia pages. Each page is assumed to be segmented into smaller fragments such as sections or paragraphs. Under this assumption, the DOI value for a fragment *f*, given that *I* is the set of the current user interests, is as follows:

$$DOI(f \mid I) = relevance(f, I) \tag{4.5}$$

where *relevance(f, I)* is a function measuring similarity between *I* and *f*. If *f* and *I* are represented by feature vectors, the DOI function can be expressed as the cosine similarity between the two vectors, as we have previously shown in Equation 3.2.

According to this definition, the value of DOI for a particular fragment of a page grows as user interests become relevant to the content of the fragment. This definition differs from the original conception of fisheye views: proximity is measured in terms of semantic distance rather than geometrical distance. Furthermore, the focal point is determined by the focus of user interests rather than the focus of the user's attention. Since multiple fragments on a page can be relevant to the current interests of the user, multiple focal points are supported.

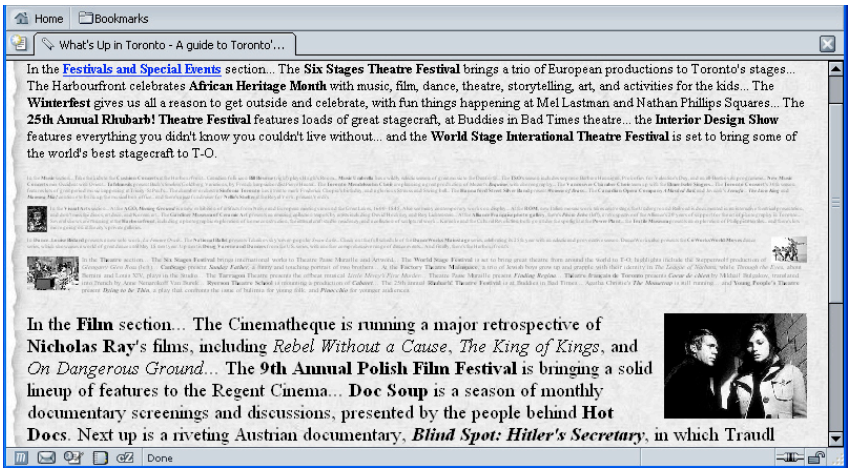


Figure 4.9. Fisheye view of a Web page

Figure 4.9 illustrates a distorted version of a Web page, where the DOI function determines the size of the visible elements of each paragraph. According to the scenario presented by the figure, the user is interested in music events. Therefore, paragraphs that relate to music are shown with larger fonts, whereas irrelevant paragraphs have been minimized. Image sizes have also been adapted, in the same way as the paragraphs that contain them. In general, given a user's current interests *I*, if $s_{e,max}$ and $s_{e,min}$ are the maximum and minimum

size, respectively, of a visual element *e* within a fragment *f*, adaptation is performed by setting the element's size $s_e(I)$ as follows:

$$s_e(I) = \max(s_{e,\max} \cdot DOI(f \mid I), s_{e,\min}) \tag{4.6}$$

where the range of values of the DOI function have been normalized between 0 and 1.

An advantage of distortion-based fisheye views over other visualization techniques is the fact that they preserve landmarks of information, appearing as context. Distinct structural elements of the page such as pictures, layout, and number of paragraphs are maintained, although they are distorted. According to two experimental studies conducted by Skopik and Gutwin (2003) on distortion-based fisheye views, distortion did not disturb the spatial memory of users as long as users could identify and trust landmarks such as distinctive nodes in the visualized space.

Figure 4.10. Use of glosses to give feedback about the content of minimized fragments

4.3.3 Interactions

Although the fisheye-like adaptation technique preserves information about fragments that are out of the focus of user interests, the actual content of minimized fragments becomes illegible. To give users access to the content of minimized paragraphs, we enhanced the technique with a set of interaction mechanisms that increase user control over the adapted views of a page. Figure 4.10 presents a simple mechanism that we used, the use of popup glosses. Glosses are text boxes that provide hints about the content of a paragraph when the user hovers the mouse over its boundaries. In addition to the use of glosses, we allowed for fluid transitions of individual paragraphs between context and focus. The mechanism that we developed to enable such transitions resembles Fluid Links (Zellweger et al., 1998). It works as follows. By double-clicking on a paragraph that is out of focus, the user zooms in the text of this paragraph together with its images. Animation is used to smoothly change the scale of the paragraph. If the user double-clicks again, the paragraph is zoomed out to its initial size. Notice that this mechanism activates a local rather than a global shift in focus. The global adaptation of the page is not affected when a paragraph is double-clicked. In other words, temporary changes in the user's attention are not translated into switches of his/her interests.

The left portion of the page shown in Figure 4.10 contains widgets that give the user additional control over adaptation. More specifically, it contains a menu with icons and titles that represent stereotypes of user interests. The menu illustrates the current focus of navigation on which adaptation at the right part of the page is based. It also lets the user change the current focus by selecting a different icon. The left part of the page also contains a slider, which adjusts the level of context by setting the minimum size $s_{e,min}$ of the visual elements. When the value of the slider is zero, adaptation has no effect on the appearance of the pages. When the value of the slider is maximum, non-relevant fragments are hidden, which means that no context is provided. In other words, the slider allows users to zoom in (or zoom out) to more (or less) adaptive versions of a page.

4.3.4 Making the User Model Transparent

Representing User Interests

As discussed earlier, user interests can be represented as feature vectors, where each element in a vector is weighted according to its relevance to the interests of the user. Here, we assume that a vector of user interests can be expressed as a linear combination of a set of stereotyped user interests. Given *n* stereotypes, the vector $\vec{u}_t$ of user interests at time t is calculated as follows:

$$\vec{u}_t = \sum_{i=1}^{n} w_{i,t} \vec{v}_i \tag{4.7}$$

where $\vec{v}_i$ is the vector of the i^{th} stereotype, and $w_{i,t}$ is a weight that shows how relevant to the current user interests this stereotype is. The weights are normalized so that:

$$\sum_{i=1}^{n} w_{i,t} = 1 \tag{4.8}$$

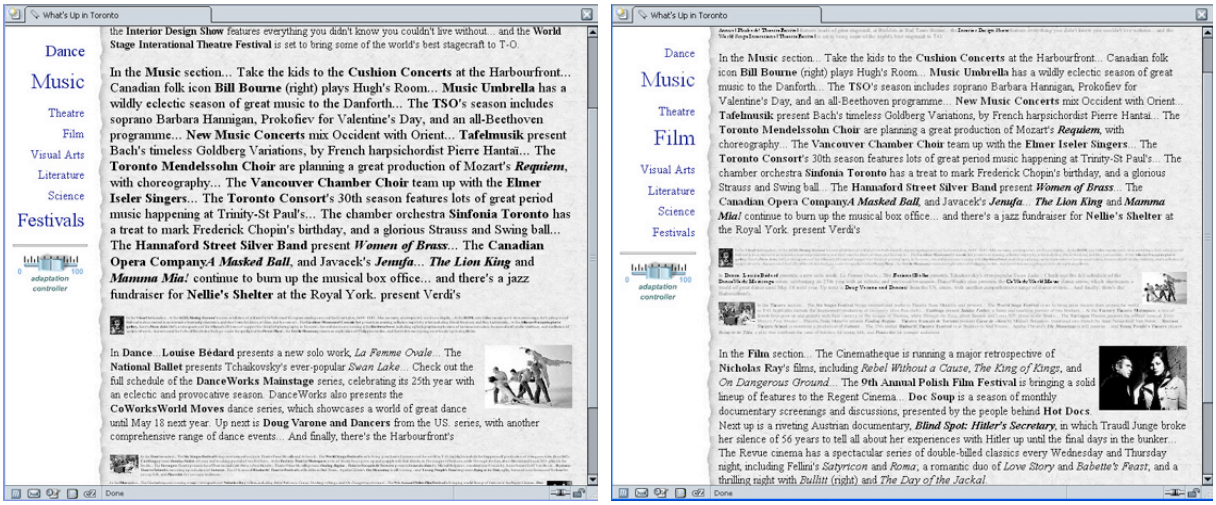
The above representation allows for the decomposition of a user model into elements that can be easily visualized, comprehended, and controlled by users.

Visualizing User Interests

The behaviour of an adaptive hypermedia system can be the outcome of several user actions, and the way that these actions can be interpreted by the system is not always unique. Therefore, if the system does not provide enough feedback to its users about how their actions are interpreted, eventually, users will fail to understand the response of the system.

To investigate this problem, we assumed that pages could be adapted automatically while users interacted with our second prototype. Given this assumption, we implemented a solution that is based on our representation of user interests, as presented earlier. More specifically, we enhanced pages with simple visual representations of the vectors of the stereo-

typed user interests. Figure 4.11 illustrates this solution. It presents two different views of the same page. Each view corresponds to a different instance of the user model. The user model is displayed at the left side of the page. As shown in the figure, the user model is visually represented by a small set of scalable labels. Each label describes a different stereotype of user interests. The font size of each label varies between a minimum and a maximum value, which is proportional to the weight of the corresponding vector in the user model. For instance, the user model that defines the first view of the page shown in Figure 4.11 has weights 0.5 for music, 0.3 for festivals, and 0.2 for dance. The other weights are 0. Similarly, the user model that corresponds to the second view has weights 0.5 for music and 0.5 for film.



(a) (b)

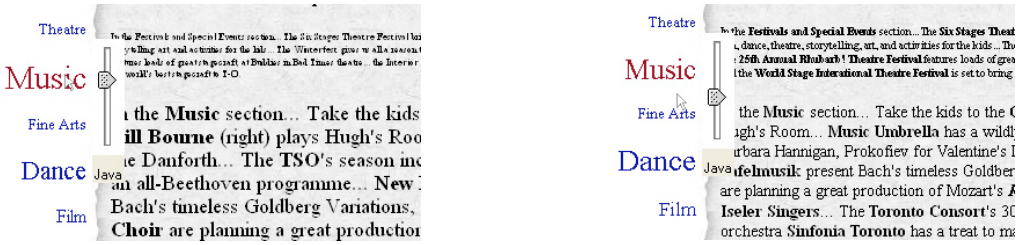
Figure 4.11 The same page under two different instances of the user model. (a) The user interested in music, festivals, and dance. (b) The user is interested in music and films.

Our design ensures that any change in the user model is immediately reflected to the size of the labels on the left frame of the page. We also make use of animation to smooth changes in the size of labels. Overall, our design approach tries to help users understand how the user model is constructed even if the actual details of how the system translates their ac-

tions are not completely transparent. At every moment, users are aware of the system's state, since the user model is visible. Also, users receive direct feedback about the effect of their interactions. Therefore, as long as the inference and adaptation mechanisms are reasonable, i.e., paragraphs are associated with semantically related stereotypes of user interests, users can foresee the outcome of their actions.

4.3.5 User Control

In Section 4.2, we demonstrated how link adaptation could be directly manipulated by users through sliders. Here, we describe a similar approach to adapting the content of Web pages. Fisheye-like content adaptation supports continuous transitions between different views of a page. Therefore, incrementally changing a weight in the user model results in incremental changes in the adapted view of a page.



(a) (b)

Figure 4.12 Refining user interests with a popup slider. (a) When the user clicks on a label, a slider pops up. (b) The user moves the slider by dragging the mouse upwards or downwards.

Figure 4.12 demonstrates how, in our prototype, a user can adjust the weights of individual vectors in the representation of a user model. The user can press on any label in the page section that visualizes the user model. A mouse press causes a slider to pop up, allowing the user to adjust the weight of the corresponding vector. The user can move the slider by dragging the mouse. The slider disappears after the mouse is released. This interaction model improves the approach described in Section 4.2; users do not have to shift their attention, for example, to a different window.

This type of slider has been influenced by FaST Sliders (McGuffin et al., 2002). FaST Sliders are sliders that pop up when the user performs a quick gesture over a visual object. They have been used to control continuous parameters of visual objects. The use of popup sliders eliminates the need of preserving continuously visible controllers, whose presence is redundant in a regular interaction mode. The activation of a popup slider is quick and requires minimal screen space.

As the value of a slider changes, the size of the labels also changes to reflect the updated user model. Since the weights in Equation 3.7 are normalized, moving a slider affects the weight of all the vectors. The benefit of this approach is that users can easily change the view of a page by moving a single slider. In more detail, when the weight $w_{k,t}$ of the k^{th} vector controlled by a slider changes to $w_{k,t+1} = w_{k,t} + \Delta w$, then the rest of the weights are updated as follows:

$$w_{i,t+1} = \begin{cases} w_{i,t} - \Delta w \cdot \dfrac{w_{i,t}}{1 - w_{k,t}} & w_{k,t} < 1 \\ \dfrac{-\Delta w}{n-1} & w_{k,t} = 1 \end{cases} \qquad \text{for } i = 1..n,\ i \neq k \qquad (4.9)$$

The top condition in Equation 3.9 holds when the weight of the slider changes from a value that is lower than one. In this case, the other weights change proportionally to their current value. The bottom condition holds when the weight of the slider changes from one, which means that all the other weights are zero. In this case, the increment Δw is equally distributed among these weights.

When a slider moves, the size of the paragraphs on the page also changes to reflect the new weights in the user model. In this way, users receive continuous feedback about how the content of a page is associated with the stereotypes of user interests.

4.3.6 Evaluation of Fisheye-Like Adaptation

In order to get feedback about the effectiveness of fisheye-like adaptation, we conducted a preliminary experiment that compared our approach against stretchtext adaptation (Boyle and Encarnacion, 1994; Hook et al., 1996). Stretchtext can be viewed as a filtering fisheye-like technique: content is hidden as long as its DOI is below a certain threshold. Compared to our approach, stretchtext has some limitations: (a) it does not provide any feedback about the quantity and layout of the hidden content; (b) support of context depends on the selection of a representative hot word for each fragment in a page, which is a manual task; and (c) for each fragment, it can visualize only two states of adaptation, i.e., fragments are either fully visible or hidden. On the other hand, stretchtext results in more concise page views.

Tested Techniques

We tried to simplify the evaluation procedure and avoid biased conclusions in favour of one technique against the other. Therefore, we focused on a single variation of the two techniques, which is the way that paragraphs are visualized. For our approach, we used a single scale to present paragraphs that were out of focus. Fonts were selected to be legible. The stretchtext version was based on the same implementation. The font size of out-of-focus paragraphs was set to zero, but each paragraph had a representative title or introductory sentence (hot word) whose font size was constant. The interaction model was identical for both techniques. Users could double-click on the body of the minimized paragraph or the paragraph's hot word to zoom in or expand, respectively, the paragraph. In a similar fashion, users could minimize or collapse the paragraph. Animation was applied in both cases to smooth these transitions. Figure 4.13 shows two versions of the same page, corresponding to the two techniques that we tested.

Apparatus

The study was conducted on an 18-inch flat monitor with 1280×1024 pixels resolution. Internet Explorer was used as the browser. Text font was set to Times New Roman, 18px for normal text, and 10px for minimized text. User actions were captured using JavaScript; a JavaScript program posted the captured user actions together with time stamps to a servlet running locally, and the servlet saved the data into a log file.

(a) (b)

Figure 4.13. A page adapted by the two tested techniques: (a) scaling paragraphs, and (b) stretchtext.

Design and Procedure

Two female and four male volunteers, all graduate students in Computer Science, participated in the study. Each participant completed six information-locating tasks and six information-gathering tasks for each technique, on three different Web pages. The content of the pages was taken from "What's up in Toronto", a Web site that presents cultural events in Toronto. The first page (P1) contained six paragraphs; the second page (P2) contained eight paragraphs, while the third page (P3) was considerably longer, containing approximately seventy paragraphs. The first two pages included images in addition to text. Links were removed, i.e., only navigation within pages was allowed.

Tasks were grouped into two sets of six tasks. The goal of the first set of tasks was to compare the ability of each technique in helping users locate information within pages. Each of these six tasks had two parts. First, participants were asked to locate a piece of information contained in a paragraph that was in focus. Then participants were asked to locate one piece of information that could be in any paragraph, either hidden/minimized or not. The goal of the second set of tasks was to test the ability of each technique in supporting information-gathering tasks. For each task, participants were asked to find three pieces of information within P1-P2 or five pieces of information within P3 that satisfied a particular condition, e.g., they advertised a cultural event for kids. In the first case, two out of the three pieces of information were in paragraphs displayed in focus, while one piece of information was in a paragraph that was out of focus. In the second case, three out of the five pieces of information were in paragraphs displayed in focus, while two pieces were in paragraphs that were out of focus. Participants completed each task by first selecting the relevant piece of information with the mouse and then clicking on the "select" button in the left frame of the browser's window. They were asked to give answers as precisely as possible without using the search facility of the browser.

We eliminated learning effects by dividing participants into two equally sized groups. The tasks to which the two techniques were applied were switched between the two groups, but all the participants were exposed to both techniques in similar tasks. The actual sequence of tasks was different for each participant in a group. Before the beginning of their sessions, participants were trained to locate and gather information using the two techniques on a different page. The time spent for training was about 10 minutes, while the time spent for the main session ranged from 30 to 40 minutes. At the end, participants were asked to fill in a questionnaire, rating the two techniques and giving us additional feedback.

Results

Although the small number of participants and tasks did not allow us to conduct tests for statistical significance, the study helped us collect valuable feedback about strengths and weaknesses of the two techniques. Results did not show any clear advantage of either of the two tested techniques in terms of task-completion times. The scaling technique outperformed the stretchtext technique in the case of the two smaller pages (P1 and P2). On the other hand, stretchtext performed better in the case of the large page (P3). This outcome can be explained by the fact that stretchtext pages were considerably shorter than pages adapted by scaling. Therefore, stretchtext required less scrolling. It seems that this issue becomes more apparent when adapted documents are large.

As a participant observed, the text of the hot words in the stretchtext pages provided concise summarization of the hidden content. Consequently, users did not always have to read the actual text of each paragraph in order to decide on its relevance to their task. On the other hand, four out of the six participants ranked the scaling approach higher than stretchtext, as they felt that it provided richer information about the content of out-of-focus paragraphs. When using the technique, participants could scan the content of minimized paragraphs without having to zoom in. As a result, zooming led to a smaller number of double-clicks compared to hiding: 122 versus 99 for locating-information tasks, and 166 versus 104 for information-gathering tasks. However, we acknowledge that scanning the content of minimized paragraphs could have delayed the reading process. The experiment did not measure costs associated with reading small font sizes. Some participants stated that reading small fonts required additional effort since, sometimes, they had to move closer to the monitor to read the text.

4.3.7 Evaluation of Control Mechanisms

A second study was conducted to evaluate the interactions and control mechanisms supported by the second prototype. Two females and four males participated in the study. All six participants used the Web on a daily basis.

The evaluation procedure was as follows. Each user was shown several versions of the prototype. Different versions included different combinations of navigational aids, i.e., popup glosses, visualizations of the user model, and popup sliders. In order to encourage participants to interact with the prototype, we asked them to freely navigate within pages or complete tasks that required them to locate specific information. Examples of specific instructions were "locate a reference to a Jazz event" or "find events that you would like to attend". While performing the tasks, each participant was asked to explain the system's reactions and justify the adaptation result. Adaptation was based on simple heuristics, such as the assumption that the user was interested in music every time he or she clicked on paragraphs that described music events. The tester did not give any details about why and how adaptation was performed.

Each participant spent about 20-30 minutes interacting with the different versions of the prototype. At the end of their session, participants were asked to complete a questionnaire (see Appendix B.1), evaluating the use of glosses, the visualization of the user model, the popup sliders, and the animation mechanism.

Observations

All the participants exhibited difficulty in trying to describe the adaptation mechanism when both the glosses and the visualization of the user model were disabled. They seemed to understand that paragraphs followed a semantic relationship and that the zooming behaviour somehow respected this relationship. However, most participants failed to clearly describe these relationships and explain the system's reactions. On the other hand, the existence of

the zooming labels in the visualization of the user model helped participants explain relationships among paragraphs on the given pages. Furthermore, participants were able to roughly describe the meaning of the changing label sizes and characterize the current view of a page. Two participants, though, felt that even when the zooming labels were displayed, they could not completely understand how adaptation worked. The main reason is that some paragraphs seemed to be irrelevant to the categories suggested by the zooming labels, although a more careful reading of the text could reveal that the paragraphs were actually relevant.

When available, the popup sliders were heavily used by five out of the six participants. These participants preferred using the sliders to uncover hidden information rather than double-clicking the minimized paragraphs. The sixth participant followed a different strategy: he interacted directly with the paragraphs and did not use the sliders. Some participants found the sliders unintuitive and kept clicking on the labels rather than dragging them. This was not surprising as participants were not familiar with this type of interaction.

User Answers and Comments

All the participants agreed that glosses were useful and facilitated their tasks. Five participants answered that both zooming labels and sliders were valuable and helped them understand the system's behaviour. The same group of participants evaluated the complete version of the system, i.e., the version that included all the navigational aids, with the highest mark. As mentioned above, one participant interacted with the content of the pages directly, without using popup sliders. This participant reported that zooming labels and sliders did not add any value to the user interface. He explained that having to observe the left frame of the page distracted him from his main task. He suggested that the state of interaction should be shown closer to the area of the user's focus of attention. Another participant suggested that information displayed by glosses and zooming labels should be always visible above each paragraph.

Half of the participants reported that popup sliders were easy to use, whereas the other half reported the opposite. These negative answers were consistent with our observations mentioned earlier. In addition, two participants suggested that the values of the sliders and the size of the corresponding labels should change independently rather than being normalized. Consider, however, that participants were not given the opportunity to test this alternative design. Normalized sliders suggest a more complex conceptual model but minimize the number of actions required to change the weights in a user model.

Finally, all the participants liked the animation used to smooth the transitions between the views of the adaptive pages. They all agreed that animation helped them understand these transitions.

4.4 Summary and Discussion

The two prototypes presented in this chapter combine automation and direct user control for the personalization of Web applications. In the designs that we have described, several decisions about how adaptation is performed are made automatically. For example, links are automatically classified into topics of user interest. On the other hand, adaptation is user-initiated and user-controlled. Note that users do not directly customize the elements of the user interface. They rather adjust visualized parameters of the user model. Such adjustments are tightly coupled with the adapted pages, i.e., any change in the parameters of the user model is instantly reflected on the pages. This interaction model has been a major contribution of our work.

Each of the two prototypes has focused on a different aspect of adaptation. Through the first prototype, we have demonstrated a system architecture that allows users to define their own categorization schemes and use these schemes to personalize, first, the display of links within a page and, second, visualizations of a browsing history. The second prototype has served as a basis for exploring techniques that adapt content within Web pages. Again,

page adaptation has been defined over a set of classification parameters that represent stereotypes of user interests. As discussed in Section 4.3, although we assumed that such stereotypes were defined at design time, adopting the architecture of the first prototype would allow for the support of user-defined stereotypes.

The second prototype has been based on a new content adaptation technique, which could be considered as a distortion-based fisheye-view technique. It has also introduced several techniques that enable users to control adaptation. The new designs were evaluated by two user studies. The first study has shown that the new technique has several advantages over stretchtext adaptation. Compared to stretchtext, it preserves the overall layout of the adapted pages and provides richer feedback about their original form and content. Results also suggest that it can reduce the number of user actions required to locate or gather information. On the other hand, the new technique results in longer pages.

We acknowledge that we did not consider several factors that could affect the success of the evaluated techniques, such as the size of minimized paragraphs, the number of paragraphs appearing in focus, and the ability of the decision-making mechanism to correctly infer user needs. Given these limitations, making general statements about which technique is better would not be appropriate. In the more general context of adaptive user interfaces, how adaptation techniques should be evaluated and compared is an issue that needs special consideration. Chapter 5 explores this problem more systematically.

Through the second study, six users gave their feedback on the usefulness and usability of the techniques implemented in the second prototype. The study showed that the presence of visual representations of the user model can help users better comprehend automatic adaptation. The user-control techniques were found to be particularly helpful. Nevertheless, they added complexity to the user interface. For instance, some users felt that the activation of popup sliders was not intuitive. Future work needs to evaluate the techniques with more users, more pages, and in more realistic environments.

Chapter 5

Assessing Adaptation Techniques

This chapter focuses on the evaluation of adaptive user interfaces. Issues raised through the first steps of our research, presented in Chapter 3, gave motivation for the work documented here. How should adaptation techniques be compared? How should we decide about which adaptation technique is more appropriate for a given user interface? What is the role of the quality of inference when making such decisions? These are the main questions that we try to answer in this chapter. In particular, we focus on the effect of the accuracy of inference and come up with recommendations about how accuracy should be manipulated in experimental designs. To explore the effect of accuracy, we present the design and results of an experiment with 12 participants. The experiment compares two different adaptation techniques applied to long lists.

The research described in this chapter has appeared in the Extended Abstracts of the CHI 2005 ACM Conference on Human Factors in Computing Systems (Tsandilas and schraefel, 2005).

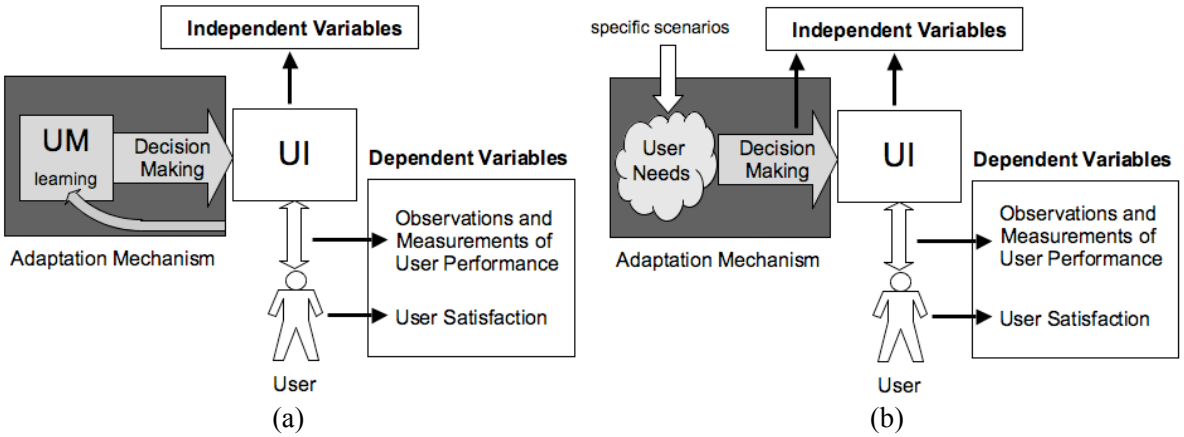


Figure 5.1. Schematic demonstration of approaches towards the evaluation of adaptive user interfaces. (a) Common approach: the system is evaluated as a whole. There is no separation between the user model (UM) and the user interface (UI). (b) Approach suggested by Brusilovsky et al. (2004) and Weibelzahl (2002): user needs are defined as part of specific scenarios of use and are considered to be fully known.

5.1 An Evaluation Approach for Assessing Adaptation Techniques

As discussed in Chapter 2, existing evaluations of adaptive user interfaces can be divided into (1) studies that tested user modeling and inference techniques without considering the effect of adaptation on real users, and (2) studies that evaluated a particular adaptive system as a whole, usually by comparing it against its non-adaptive version. As stated by Brusilovsky et al. (2004), none of these two approaches allow for testing the role of adaptation techniques on the success of a system. Trying to overcome this limitation, Brusilovsky et al. (2004) proposed a two-layer evaluation process. The first layer concerns the first type of evaluations listed above and might not involve real users. As studying new user modeling techniques and improving inference algorithms are beyond the scope of this thesis, we do not discuss this type of evaluation further. The second layer is essentially identical to the third evaluation step proposed by Weibelzahl (2002) and focuses on the evaluation of the decision-making and adaptation components of an adaptive user interface, independently of the

user model. In Figure 5.1, we schematically illustrate the differences between (1) the traditional evaluation model, which evaluates a system as a whole, and (2) the evaluation model proposed by Brusilovsky et al. (2004) as part of the second layer or alternatively, the third evaluation step proposed by Weibelzahl (2002).

In both models, evaluation is based on observations and measurements of user performance as well as measurements of user satisfaction, normally obtained through interviews and questionnaires. However, the two models bear several differences in the way independent variables and covariates are controlled. According to the traditional approach, inference is part of the evaluated system, and therefore, it determines the overall success of the system. According to the second model, no inference is involved and the user model is abstracted. The goal of this type of evaluation is to test the appropriateness and effectiveness of different adaptation techniques under the assumption that user needs are known. Specifically, instances of the user model are created according to predefined scenarios of use. They are also assumed to accurately capture the user needs communicated through these scenarios. In addition, according to the traditional evaluation approach, decision-making is part of the evaluated adaptive user interface and is not tested independently. In contrast, the second model suggests that parameters of the decision-making process should be handled as independent variables.

The evaluation approach proposed by Brusilovsky et al. (2004) and Weibelzahl (2002) has some advantages over the traditional approach. It allows for the evaluation of adaptation techniques independently of the system to which they are applied. User interface designers can concentrate on the design of new techniques before or in parallel with the actual implementation of the user modeling and learning components. Nevertheless, the scope of the approach is limited as it is based on the assumption that the effectiveness of adaptation techniques is independent of the quality of inference. As a result, in situations in which user

modeling and inference are not perfect, possible limitations of an examined adaptation technique cannot be assessed.

In Figure 5.2, we propose a different approach. According to this approach, the adaptation mechanism is considered as a black box and is clearly separated from the evaluated user interface. Variable parameters in the adaptation mechanism with a possibly significant impact on the dependent variables are controlled or handled as independent variables. Our work has focused on the role of the quality of inference, but other parameters of an adaptation mechanism could have an equally important role. For instance, the frequency of changes applied to a user interface and the visibility of the user model could have a great effect on how an adaptation technique behaves. Here, we do not explore the effect of such parameters, but we rather try to handle them as control variables. Like Brusilovsky et al. (2004), we constrain user interaction to specific interaction scenarios. On the other hand, such scenarios do not assume that user needs are perfectly known. On the contrary, uncertainty about user needs is taken into account and its effects on user performance can be measured through the dependent variables.

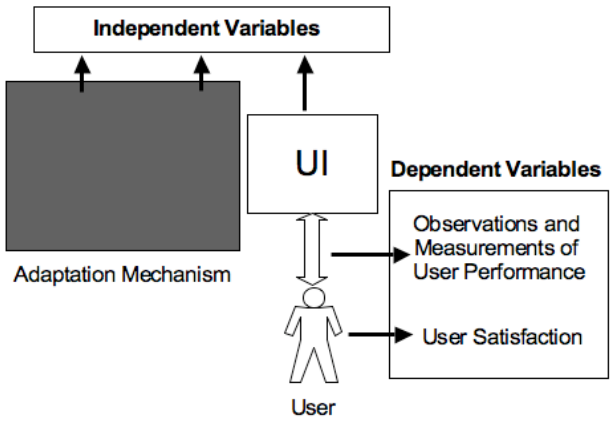


Figure 5.2. Our suggested evaluation approach. The adaptation mechanism is considered as a black box, and its behaviour is fully controlled. Parameters of the user model and the decision-making process that determine the quality of automation are handled as independent variables.

Clearly, the above model of evaluation can only be used for the design of strictly controlled experiments. We acknowledge that controlled experiments cannot capture the context of real user behaviour. Field studies have a complementary role and researchers should employ them to verify the results of experimental studies in real environments. In the case of field studies, we recommend that researchers should measure and report the values of observed parameters, such as the accuracy of inference, so that comparisons with the results of other studies are possible.

5.2 Experiment

We have hypothesized that the accuracy of inference has an impact on the effectiveness of a user interface. We have also hypothesized that this impact can be different for different adaptation techniques. But how valid is this hypothesis? Is it really important to consider the quality of inference before assessing an adaptation technique? The introduction of additional independent variables can complicate evaluation designs. Is the additional complexity justified? To answer these questions, we conducted an experimental study. The study compared two simple adaptation techniques applied to long lists.

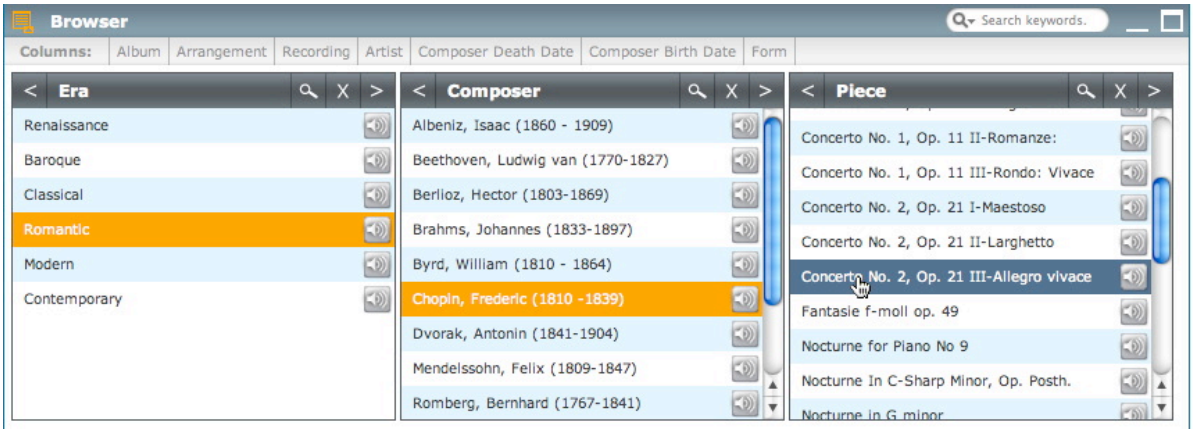


Figure 5.3. The mSpace browser (schraefel et al., 2005), used here to explore classical music. The interface consists of multiple lists, which can be browsed from left to right.

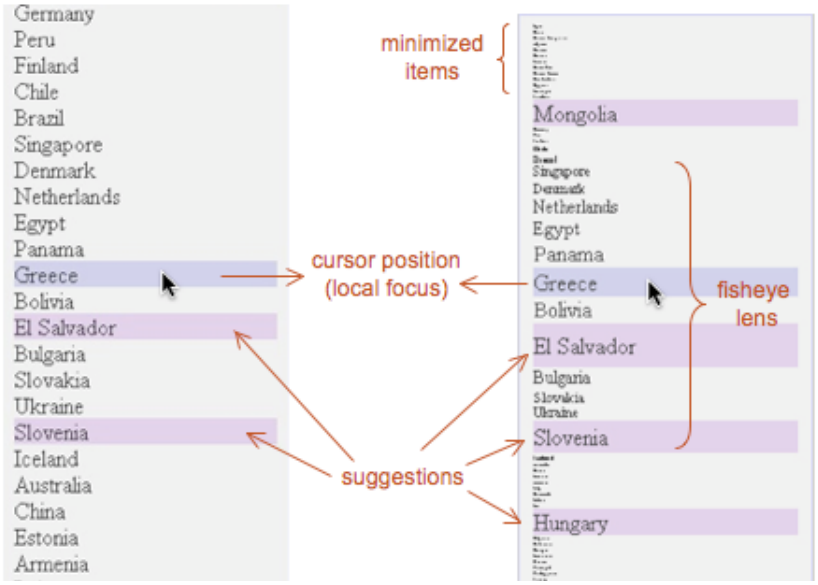
Lists constitute a common interface for presenting and browsing information. Our work on lists has been motivated by research on the mSpace project (schraefel et al., 2005). The main goal of the mSpace project is to help users, in particular users who are not familiar with a domain, explore information and gain domain expertise. As illustrated in Figure 5.3, the mSpace interface includes multiple lists that represent various dimensions, through which users can explore information. Such lists can contain dozens or even hundreds of items. Unfortunately, when lists become large, exploration can become problematic. Although lists in the mSpace interface are sorted, e.g., alphabetically, order is not always effective in helping users locate information. Domain-naïve users often depend on cues other than order, since they do not have a good knowledge of the language that describes information. As an example, consider the scenario illustrated in Figure 5.3. A user who is looking for a particular Allegro piece by Chopin but does not remember its exact title will not be able to take advantage of the alphabetical order supported by the interface. Our goal was to explore adaptation in such scenarios, where lists are relatively large and exploration does not depend on order.

The techniques that we tested were designed to facilitate visual search, given that user goals were predictable. The experiment evaluated the techniques under various levels of prediction accuracy. Rather than testing the techniques on top of a real adaptation mechanism, adaptation was predefined with respect to the levels of accuracy that we tested.

5.2.1 Evaluated Techniques

The experiment tested two adaptation techniques. The first technique was based on the use of colour to *suggest* items in a list. The reason for suggesting items by colour was to help users identify list items and locate them faster. In addition to highlighting items with a colour, the second technique shrunk (zoomed-out) non-suggested items. The reason for shrink-

ing items in a list was to reduce the space occupied by the list, reduce mouse movements, and minimize information overload.



(a) (b)

Figure 5.4. Evaluated techniques: (a) highlighting suggestions (NORMAL), and (b) shrinking non-suggested items in addition to highlighting (SHRINK)

The two techniques are illustrated in Figure 5.4. For simplicity, the first technique is denoted as NORMAL (Figure 5.4(a)), and the second technique is denoted as SHRINK (Figure 5.4(b)). As shown in the figure, the SHRINK technique is enhanced by a fisheye lens that allows users to explore minimized items, reducing the cost of incorrect system suggestions. Influenced by fisheye menus (Bederson, 2000), the fisheye lens affects both the font size of the items as well as the height of their visualization. In the experiment, the fisheye lens contained 17 items in total. Their height ranged between 18 pixels, which was the normal height used by the NORMAL technique, and 3 pixels, which was the height of minimized items. The whole lists of items were visualized, i.e., no scrolling was used. Clearly, the SHRINK technique required significantly less space to visualize the same number of items. Depending on the number of suggested items, the height of a shrunk list was 51-57% shorter than the height of a normal list. On the other hand, as exploration was more con-

strained, locating non-suggested items in a shrunk list was presumably harder.

Items were randomly sorted in the lists tested by the experiment. This allowed us to examine adaptation in situations in which either ordering does not obey a clear semantic relationship, or a particular order does not help the user.

5.2.2 Independent Variables

Following the evaluation model presented in Figure 5.2, we examined three independent variables that capture the variable properties of the user interface, the decision-making process, and the user model. The first independent variable was *Technique* (NORMAL, SHRINK), which captured the main tested variation of the user interface. The second independent variable was *Suggestions* (4 suggestions, 8 suggestions), which represented the number of suggested items in a list and captured a secondary variation of the user interface. The third independent variable examined by the study was *Accuracy* (100%, 80%, 60%), which captured a variation coming from both the user model and the decision-making process. Accuracy was defined as the mean probability that, if a user sought an item in the list, this item had been included in the system's suggestions.

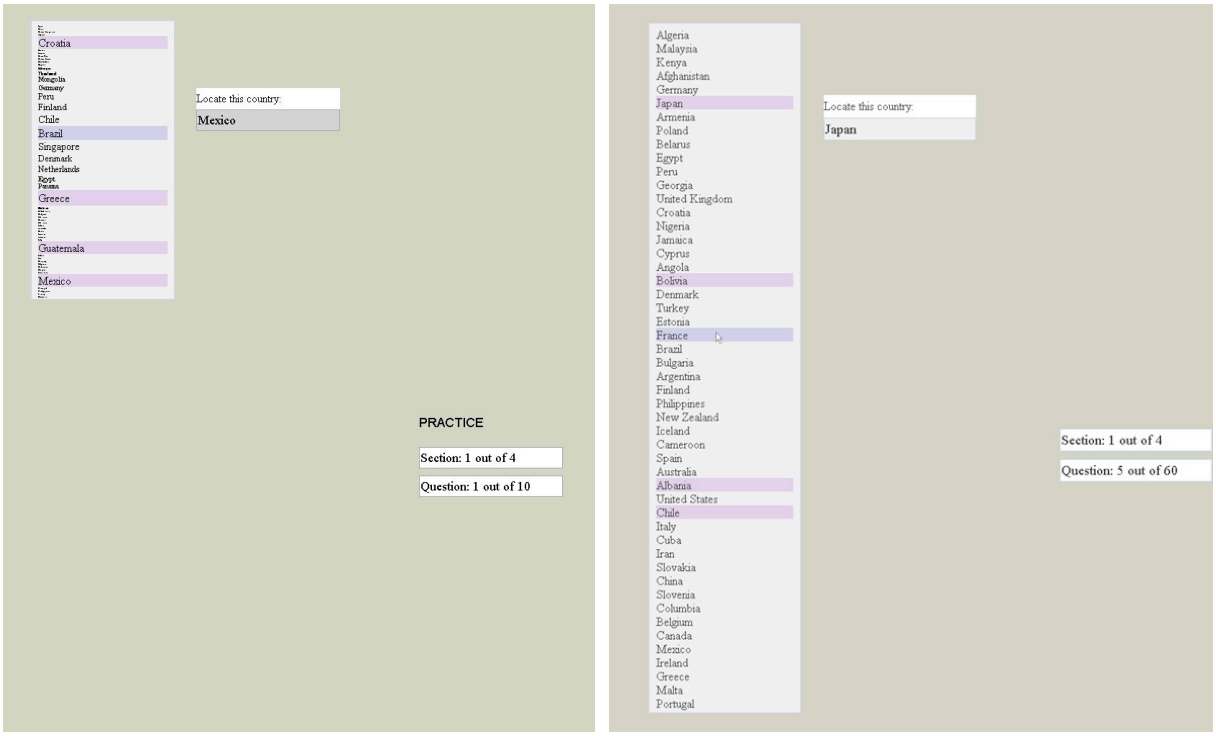
As discussed earlier, the experiment examined adaptation techniques separately from the adaptation mechanism. The adaptation mechanism was considered as a black box that "somehow" highlighted items with respect to a given accuracy level. Participants could not predict the result of adaptation, as adaptation did not follow any logical pattern.

5.2.3 Participants

Six female and six male volunteers, 24-40 years old, participated in the experiment. All the participants were graduate students in various departments and had previous experience using a mouse device. All the 12 participants used the right hand to interact with the mouse. As shown in Section 5.2.6, the number of participants was selected with respect to the number of independent variables and the number of their nesting levels.

5.2.4 Apparatus

The experiment was conducted in full-screen mode on a 2GHz P4 PC with 512 MB RAM running Windows XP. An 18-inch flat monitor was used at a resolution 1280 by 1024 pixels. The experimental software was coded in Java 2 and run using Java Runtime Environment 1.4.1. The implementation of the lists was based on Java Swing's JList class. A mouse was used as input device. Performance data were captured and stored in the local file system. The experimental software is illustrated in Figure 5.5.



(a) SHRINK technique (b) NORMAL technique

Figure 5.5. Experimental software

5.2.5 Task

Participants had to complete a series of selection tasks. For each task, participants were presented the name of a country (*goal item*) and were asked to locate it and select it from a list of country names. Each list contained 50 items randomly selected from a pool of 80 country names. Four or eight items were highlighted in the list by using either the NORMAL or the

SHRINK technique. The goal item was either included or not included in the set of highlighted items with respect to which adaptation accuracy was tested. Accuracy was measured as the percentage of tasks for which the goal item was highlighted. Immediately after the user selected the correct country name, a new task started and the experimental system requested the user to select a different country name. The set of highlighted items was constantly updated when a new task started. In the case of the SHRINK technique, a subtle animation effect was used to smooth the transition between such updates.

Tasks were grouped into blocks of five tasks. For each block, in 5 out of 5 (100% accuracy), 4 out of 5 (80% accuracy), or 3 out of 5 (60% accuracy) tasks, participants were asked to select an item that had been suggested by the system.

5.2.6 Design

A full factorial design with repeated measures was used. The three independent variables were nested according to the order *Accuracy, Technique,* and *Suggestions*. Each participant was exposed to all the 12 conditions, i.e., different combinations of the independent variables. A Latin square was used to balance the order in which participants tried the three accuracy levels. The order in which the instances of *Technique* and *Suggestions* were presented to participants was also balanced.

For each condition, participants completed 12 blocks of selection tasks. In addition to these blocks, participants completed two practice blocks for each condition. All the participants completed the same blocks in the same order for all the 12 different conditions. Following the methodology of Findlater and McGrenere (2004), learning effects between different conditions were minimized by masking the adaptive list with a different set of country names for each condition. A pilot study indicated that long and well-known country names were usually located faster than short or less known country names. In order to balance this effect among the 12 participants, we used 12 configurations of country names, which were

assigned to the 12 conditions using a Latin square. This means that each configuration was applied to every condition exactly once, and no participant was exposed to the same configuration more than once. The selection of goal items was pseudorandom and followed an approximately uniform distribution along the length of the list. The selection of suggested items was also randomly and uniformly distributed along the list.

In summary, the experiment was designed as follows:

12 participants

× 3 levels of adaptation accuracy (100%, 80%, 60%)

× 2 adaptation techniques (NORMAL, SHRINK)

× 2 levels of suggestions (4 suggestions, 8 suggestions)

× 12 blocks

× 5 locating tasks per block

= 8640 locating tasks in total

5.2.7 Procedure

The experiment was designed to fit in a single session, which was approximately 60-80 minutes long. First, participants were presented with the two techniques, in a practice session that lasted approximately three minutes. They were also asked to locate a series of items using both techniques. The purpose of this session was to help participants become familiar with the experimental setting and test the fisheye lens employed by the SHRINK technique.

After the end of the practice session, participants were asked to complete the experimental tasks as quickly as possible, avoiding errors. Participants were not aware of any type of separation between blocks. This design prevented participants from developing strategies to predict the system's adaptive behaviour. Nevertheless, there was a brief pause after every four blocks (20 tasks). A short one-minute break was also taken after the end of each condi-

tion. A longer three-minute break was taken after the end of all the conditions corresponding to a particular accuracy level.

With the exception of the 100% accuracy level, participants were not informed about the exact level of accuracy used in the experiment. The terms “low prediction accuracy”, “high prediction accuracy”, and “perfect prediction accuracy” were used every time a participant was introduced to an accuracy condition. Labeling the accuracy conditions was necessary so that we could later refer back to these conditions when surveying the participants. After the end of their session, participants were asked to give estimates of the accuracy levels that they had experienced. They were also asked to rank the two adaptation techniques with respect to accuracy. We did not expect that the language that we used to describe the accuracy levels would have any impact on the strategy that participants would follow to select items in the lists. As we mentioned earlier, participants had to complete two practice blocks before each condition. As a result, they could develop a strategy based on their own experience.

5.2.8 Measures

We examined three main dependent variables: (1) *BlockTime*, which was the time to complete a single block, (2) *SuggestedTime*, which was the time to complete a task when the goal item had been correctly suggested, and (3) *NonSuggestedTime*, which was the time to complete a task when the goal item had not been suggested.

Since the number of successfully assisted tasks varied among accuracy levels, *SuggestedTime* was only measured for the subset of tasks in which adaptation was correct for all the experimental conditions. Likewise, *NonSuggestedTime* was only measured for the subset of tasks in which adaptation was incorrect for all the experimental conditions. Clearly, *NonSuggestedTime* was only measured for the 60% and 80% accuracy levels. In summary, there was one measurement per block for the first dependent variable (*BlockTime*), three meas-

urements per block for the second dependent variable (*SuggestedTime*), and zero (100% accuracy) or one (60 and 80% accuracy) measurement per block for the third dependent variable (*NonSuggestedTime*). Errors made during the selection tasks were also recorded.

5.3 Hypotheses

Our hypotheses were as follows.

Hypothesis 4.1. *BlockTime* will increase as accuracy decreases.

Hypothesis 4.2. The SHRINK technique will be faster than the NORMAL technique for the selection of suggested items. In other words, *SuggestedTime* will decrease when the SHRINK technique is used.

Hypothesis 4.3. The SHRINK technique will be slower than the NORMAL technique for the selection of non-suggested items. In other words, *NonSuggestedTime* will increase when the SHRINK technique is used.

Hypothesis 4.4. As accuracy decreases, *BlockTime* will deteriorate faster for the SHRINK technique than the NORMAL technique. This hypothesis is a direct outcome of Hypotheses 4.2 and 4.3.

5.4 Results

This section provides information about the collected data, documents the analyses that we conducted, and discusses their results.

5.4.1 Data

Data for a total of 8640 locating tasks were collected. Before starting the analysis of the data, we eliminated problems in the data that could hurt the reliability of the statistical instruments. These problems and their treatment are discussed in the following paragraphs.

Normality Assumption and Transformations

Several data distributions did not follow a normal distribution, which is an assumption of ANOVA significance tests. The existence of positively skewed distributions was the main problem that we identified. To address this problem and ensure the reliability of our tests, we transformed data before performing any significance tests. This is a well-documented approach (Ferketich and Verran, 1994). Transformations resulted in distributions that were close to normal. They also eliminated most violations of the sphericity assumption (Girden, 1992). All the three main dependent variables *BlockTime*, *SuggestedTime* and *NonSuggestedTime* were transformed using a natural logarithmic function as shown below:

$$lnBlockTime = ln(BlockTime)$$

$$lnSuggestedTime = ln(SuggestedTime)$$

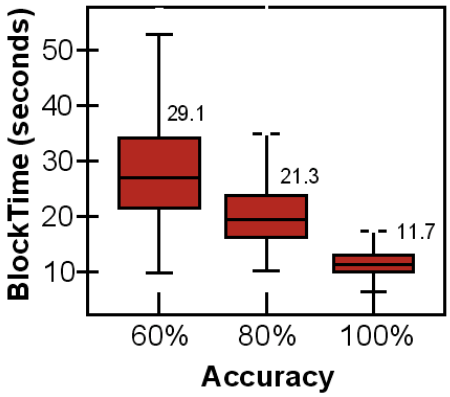
$$lnNonSuggestedTime = ln(NonSuggestedTime)$$

Outliers

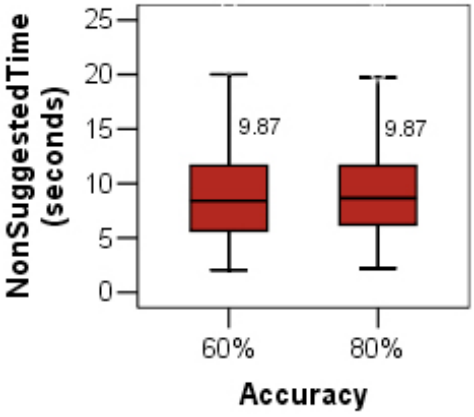
An adaptation technique can be vulnerable to the generation of outliers, which is something that needs to be taken into account when comparing the techniques. Outliers, therefore, were not omitted from the analysis, as they could give valuable information about the effect of the tested factors. Specifically, we did not remove any outlier in the case of the dependent variables *BlockTime* and *NonSuggestedTime*. Nevertheless, the impact of outliers on the effectiveness of the statistical tests was reduced after data were transformed.

In the case of *SuggestedTime*, we followed a different approach. As several participants reported after the end of their session, they frequently failed to identify a goal item within the set of suggested items. This situation caused large delays as participants realized their mistake later, after failing to locate the goal item in the set of non-highlighted items. We decided to isolate outliers generated by such situations and analyze them independently from the rest of the data. We used 8 seconds as the cut-off value for such outliers, rather than

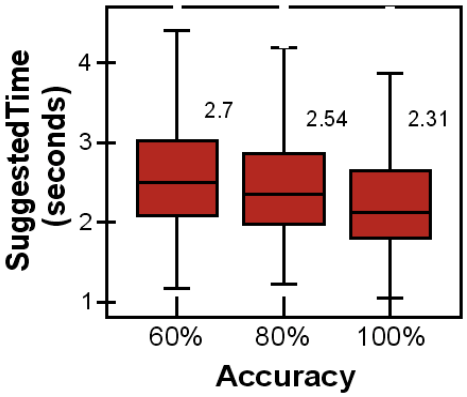
characterizing outliers based on their distance in terms of standard deviations from the mean. This decision was based on the fact that the distribution of *SuggestedTime* was discontinuous at this value for all the experimental conditions, i.e., the time 8 seconds clearly partitioned the data into two different sets. A total of 114 outliers were identified, which accounted for the 2.2% of the total number of measurements for *SuggestedTime*.



(a) Results for *BlockTime*



(b) Results for *NonSuggestedTime*



(c) Results for *SuggestedTime*

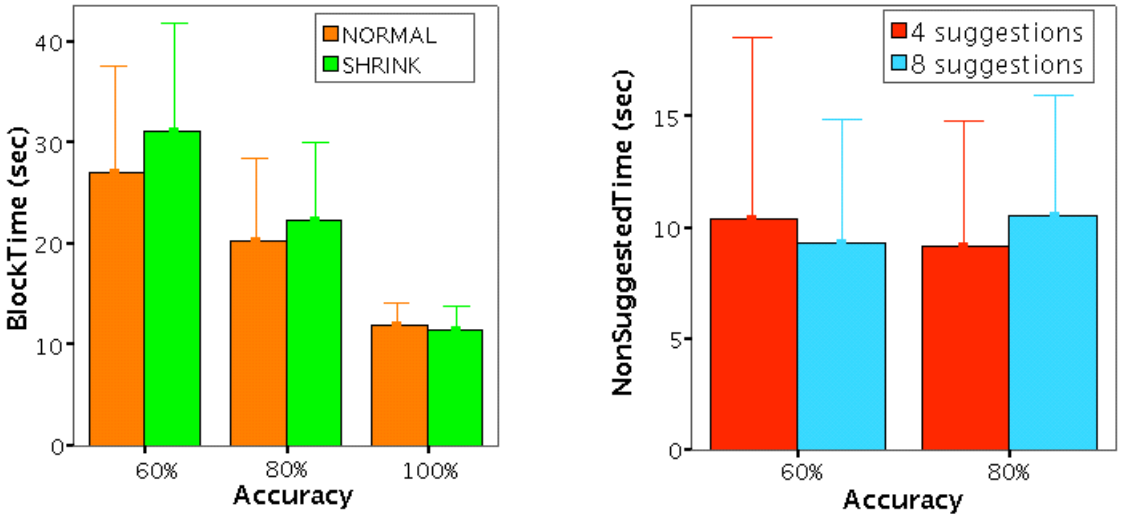
Figure 5.6. Boxplots[1] showing the effect of *Accuracy*. The numbers above the boxes show mean times.

[1] The box in a boxplot (Tukey, 1977) contains the middle 50% of the data, ranging from the 25th to the 75th percentile of the data set. The line within a box represents the median while the vertical lines show the range of values within two box lengths from the center of the box.

5.4.2 Time Measures

Hypothesis 4.1 was confirmed: user performance degraded as accuracy became low (see Figure 5.6). The main effect of *Accuracy* on *lnBlockTime* was found to be significant ($F_{2,22}$= 526.296, p<.0001). Pairwise comparisons revealed significant differences for all the pairs of means (p< .0001).

Hypotheses 4.2-4.4 were also confirmed. More precisely, the effect of the interaction *Accuracy* × *Technique* on *lnBlockTime* was shown to be significant ($F_{2,22}$ = 20.890, p<.0001). The performance of SHRINK degraded faster than the performance of the NORMAL technique as accuracy decreased, which confirms Hypothesis 4.4. As Figure 5.7(a) demonstrates, the SHRINK technique was slightly faster when accuracy was 100% ($p \leq .002$, using Bonferroni's adjustment), since participants had shorter mouse movements to perform. This result confirms Hypothesis 4.2. Hypothesis 4.3 was also confirmed, as SHIRNK was significantly slower than NORMAL in selecting items that were not suggested by the system ($F_{1,11}$= 103.734, p <.0001).



(a) (b)

Figure 5.7. Graphs showing the interactions (a) *Accuracy* × *Technique* on *BlockTime*, and (b) *Accuracy* × *Suggestions* on *NonSuggestedTime*. Standard deviations are shown.

We have explored additional effects of accuracy on user performance. Interestingly, *Accuracy* had a significant effect on *lnSuggestedTime* ($F_{2,22}$= 29.052, p<.0001). This result implies that low accuracy levels may have affected participants' trust on suggestions. It seems that as accuracy declined, participants tended to spend more time "thinking" before following a suggestion. The same effect was observed in the distribution of outliers, as shown in Figure 5.8. More specifically, we identified a total of 78 outliers for the 60% accuracy, 36 outliers for the 80% accuracy, and no outliers for the 100% accuracy. The main effect of *Accuracy* on *lnNonSuggested* was not found to be significant ($F_{1,11}$=1.669, p = .223).

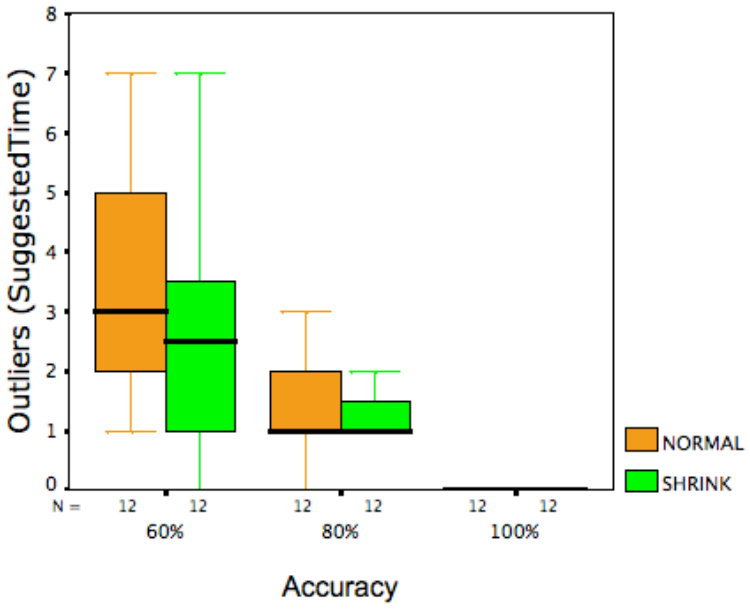


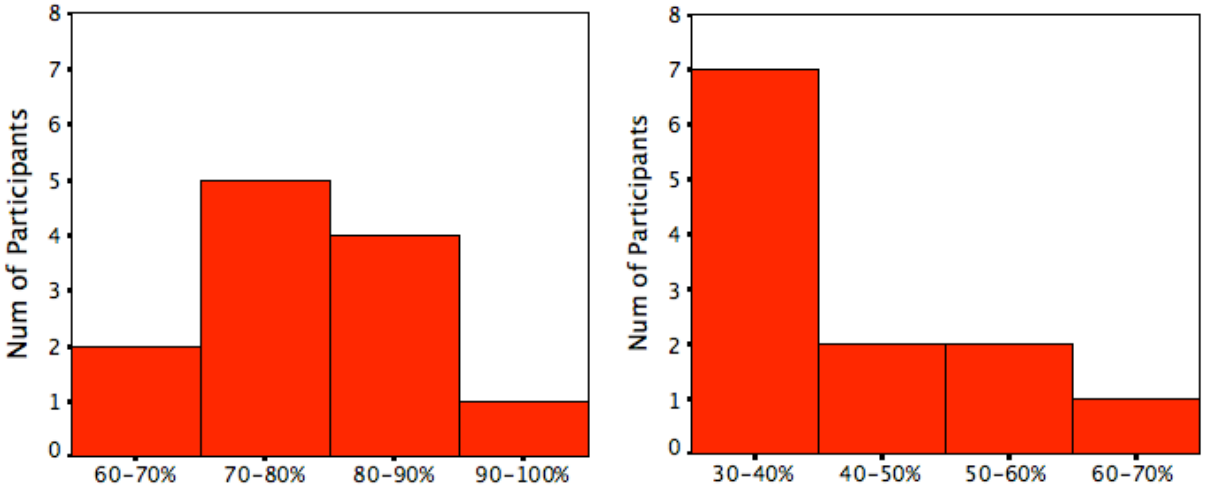
Figure 5.8. Boxplot showing the mean number of outliers (*SuggestedTime* > 8 sec) per experimental condition.

The number of suggestions also affected user performance. The mean time needed to select a correctly suggested item was significantly slower, when 8 instead of 4 items were suggested ($F_{1,11}$=211.09, p<.0001). On the other hand, the number of suggestions did not have a significant effect on the mean time needed to select items that were not suggested by the system ($F_{1,11}$=1.55, p=.238). We observed, however, a significant interaction effect between *Suggestions* and *Accuracy* ($F_{1,11}$=12.959, p=.004), also illustrated in Figure 5.7(b).

According to several participants' comments, item suggestions often helped them to chunk the list and scan its items faster. Surprisingly, participants reacted differently when the accuracy level was 80%. Apparently, they scanned suggested items more carefully in this case, and as a result, they spent more time when the number of suggestions was larger.

5.4.3 Errors

The SHRINK technique generated a large number of errors when accuracy was imperfect. In more detail, a total of 105 errors were recorded in this case, as opposed to 42 errors recorded for the NORMAL technique (60-80% accuracy). This result can be explained by the fact that the space available for clicking on a non-suggested item was smaller when the SHRINK technique was used. In Section 5.5, we discuss how this problem could be addressed in future designs of the technique.



(a) Estimations for the 80% accuracy (b) Estimations for the 60% accuracy

Figure 5.9. Distribution of participants' answers when asked to estimate the adaptation accuracy for the conditions that they had experienced.

5.4.4 Qualitative Results

Participants were asked to select from a range of accuracy levels that best approximated the percentage of times that the goal item had been correctly suggested (see Appendix B.2).

They were asked to give separate estimates for the low-accuracy condition (60% accuracy) and the high-accuracy condition (80% accuracy). As Figure 5.9 demonstrates, although most participants gave a correct estimate of the high accuracy level, the great majority of participants highly underestimated the level of low accuracy. More specifically, 9 out of the 12 participants believed that more than 50% of the times the system failed to suggest the goal item. Several participants noted that they felt frustrated when the system's suggestions were regularly incorrect. It is likely that this fact radically decreased their confidence about the system's ability to correctly adapt the list.

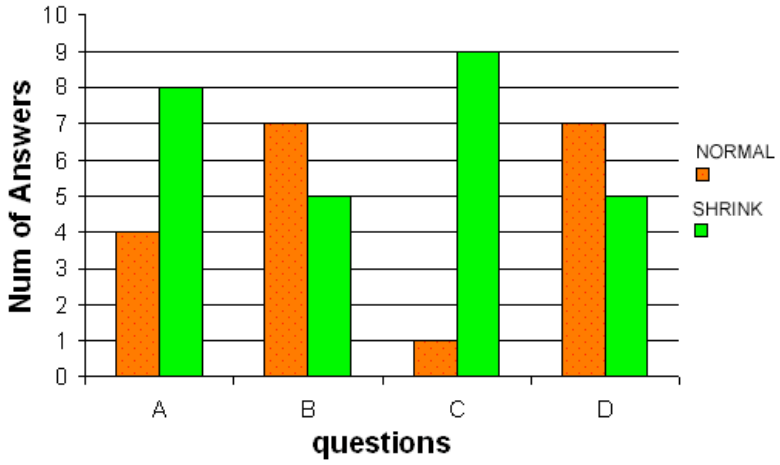


Figure 5.10. Distribution of participants' answers on which technique (NORMAL vs. SHRINK) (1) helped them to locate A. highlighted items faster, and B. non-suggested items faster, and (2) would be preferred when system's predictions were generally C. accurate, and D. inaccurate.

Participants were also asked to evaluate the two adaptation techniques. Figure 5.10 illustrates that according to their answers, the SHRINK technique would be mostly preferred if adaptation was highly accurate, whereas the NORMAL technique was more favourable in the case of low accuracies. Furthermore, most participants felt that the SHRINK technique was faster when selecting items successfully suggested by the system. On the other hand, most participants believed that this technique slowed down selection when the goal item had

not been suggested. These results are consistent with the quantitative results that we presented earlier.

5.5 Conclusions and Discussion

In conclusion, our results indicate that the effectiveness of an adaptation technique highly depends on the accuracy of the adaptation mechanism. Different techniques bear different costs and benefits when the system succeeds or fails, respectively, to anticipate the real user needs.

A striking result of the experiment was that accuracy affected not only the overall user performance but also the ability of participants to locate items that were correctly suggested by the system. This result, however, is consistent with previous work that has studied human trust on automation (Lee and See, 2004). It can be explained by the decrease of user reliance on the system's suggestions as accuracy deteriorated and can be further justified by taking into account the participants' subjective responses. It is also surprising that although participants gave a good estimate of the 80% accuracy level, they undervalued the system's competence when accuracy was 60%. In accordance to the above results, we suggest that designers should develop adaptation techniques with respect to the levels of accuracy that they expect to observe in the target system. Similarly, we recommend that researchers should always report the accuracy observed in their evaluation studies so that their results can be interpreted correctly.

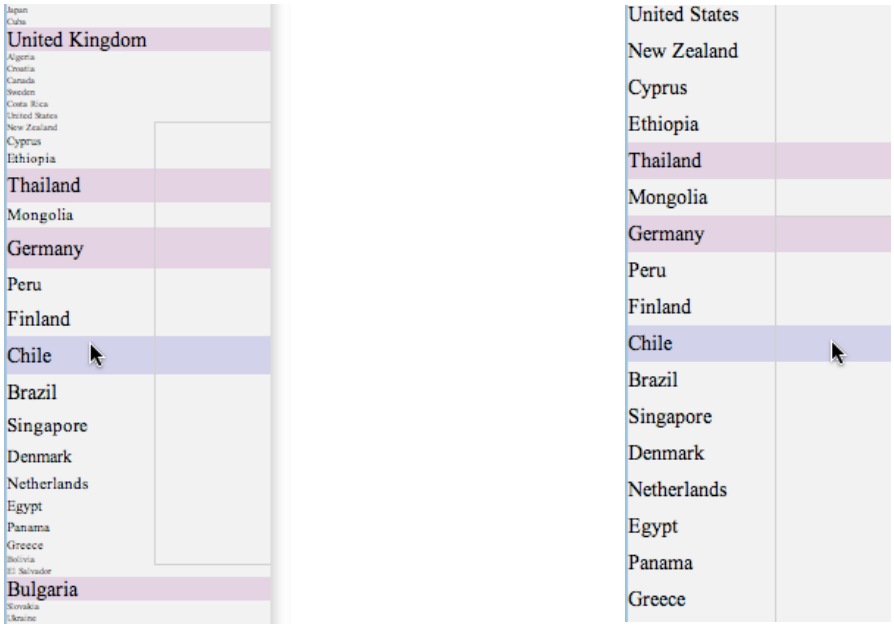
To our best knowledge, the first user studies that have taken into consideration our recommendations were conducted by Gajos et al. (2006). As discussed in Chapter 4, Gajos et al. (2006) compared three different interfaces of adaptive toolbars in Microsoft Office. In their first study, they compared these interfaces under two different adaptation algorithms: a recency-based and a frequency-based algorithm. In their second study, they compared the two top performing interfaces under a recency-based algorithm. For this experiment, they

created two classes of tasks, which resulted in their recency-based adaptation algorithm being either 30% or 70% accurate. As expected, they found that accuracy had a significant main effect on user performance. Furthermore, they found a significant interaction effect between user interface type and accuracy, confirming our results that adaptation techniques with higher costs for incorrect adaptations are more sensitive to the differences in the accuracy of adaptation mechanisms. Note that accuracy does not have a unique definition, and a variety of different measures such as precision and recall (see Chapter 2) could be used to quantify the competence of an adaptation mechanism.

We acknowledge that our results do not answer whether and when adaptive behaviour was effective in terms of user performance compared to no adaptation. Answering this question was out of the scope of the experiment. However, we can argue that, for the accuracy levels that we tested, adaptation was always beneficial. Specifically, the speed benefit coming from the suggestion of a small subset of items was considerably larger than any observed cost. Even when accuracy was 60%, the mean time to locate an item using the slowest adaptation technique (SHRINK) was 6.3 seconds. On the other hand, the mean time to locate a non-suggested item using the NORMAL technique was 8.73 seconds. Given the fact that we did not observe any main effect of the number of suggestions on *NonSuggestedTime*, we can expect that the mean time to locate an item without adaptation would not be much lower than 8.73 seconds.

Shrinking information can be valuable, since it reduces the size of the visualized space, preserving at the same time valuable context information. This approach, however, was shown to delay the location of items that were not suggested by the system. For that reason, the performance of the technique degraded as the accuracy of the system's suggestions became low. Yet, according to the experimental setup, there was always enough space to display the whole length of the normal non-shrinking lists. If space were limited, scrolling would be required to access items in a long list. In addition, suggestions might not be all

visible at the same time. We hypothesize that shrinking is more valuable in such situations, since it provides context about the whole set of suggestions and allows users to quickly move to any position within a long list without scrolling. Besides, the "focus lock" mode supported by fisheye menus (Bederson, 2000) could enhance the shrinking technique and enable the easy access of options in minimized areas of a list. Figure 5.11 illustrates an improved version of the technique that supports a "focus lock" mode. It allows users to move the cursor to the right portion of the list to freeze the fisheye lens and access items without being disturbed by additional movements of the lens.



(a) (b)

Figure 5.11. Improved version of shrinking lists that support a "focus lock" mode. (a) The box, shown at the right half of the list outlines the portion of the list that gets fully visible if the list is expanded. (b) The user moves the cursor to the right portion of the list to expand it.

Chapter 6

Bubbling Menus: A New Technique of Personalized Menus

This chapter documents the process that we followed to design bubbling menus, a new personalization technique for cascading drop-down (or pull-down) menus. The new technique bears similarities with the techniques that we have considered so far in the thesis. First, it preserves the original structure of the interface and, second, it provides several mechanisms of direct user control. However, in contrast to Chapters 3 and 4, where our analysis focused on techniques that aid navigation and visual search, this chapter focuses on pointing performance.

The process for the design of bubbling menus involved several iterations. It started with an early experiment, moved to the first design of the technique, continued with the evaluation of the first design, and ended with a second design and its final evaluation. This process has been conducted in accordance with our recommendations presented in Chapter 4. In particular, the effect of adaptation accuracy has been greatly taken into account. The

design process has involved four user studies. A first study was conducted to test the limitations of user-initiated target expansion in accelerating pointing performance. User-initiated target expansion is the core of the interaction model supported by the proposed design of menus. Two other user studies were conducted to evaluate two design iterations of bubbling menus. The first evaluation tested our first design in the context of automatic adaptation, taking into consideration the effect of adaptation accuracy. The second one evaluated our second design in the context of user-driven customization. An additional small study was conducted as a follow-up to the first evaluation study. The results of the four studies have helped us identify strengths and limitations of the proposed technique and come up with recommendations for its use.

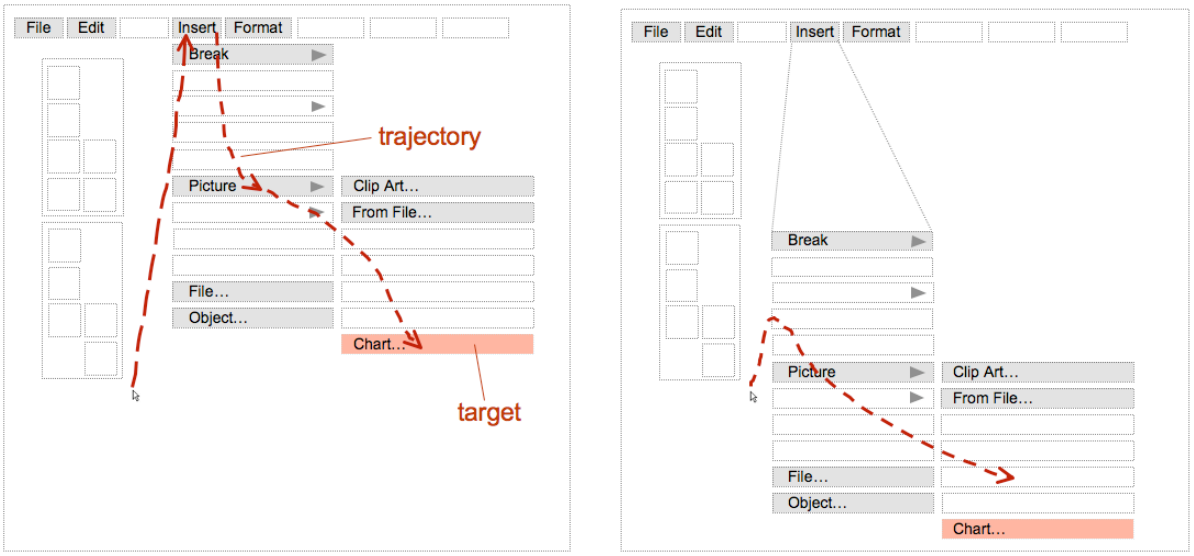
The research described in this chapter has appeared in the proceedings of the CHI 2007 ACM Conference on Human Factors in Computing Systems (Tsandilas and schraefel, 2007).

6.1 Goals

The goal of our design was to accelerate selection in hierarchical drop-down menus. Concentrating on pointing performance, we envisioned menus that could be accessed with minimal mouse movement. Figure 6.1 illustrates our vision: menu items are selected with rough, single-stroke gestures. Our vision required the use of personalization, since only a subset of menu items could be accessed that way. In addition, it required that personalization would preserve the original structure of menus, so that users could depend on their previous knowledge to select items. We viewed personalization as an alternative mode of interaction, deliberately activated by users.

As discussed in Chapter 2, we are not the first to study personalized menus. Dynamically reordered menus (Greenberg and Witten, 1985; Mitchell and Shneiderman, 1989), split menus (Findlater and McGrenere, 2004; Sears and Shneiderman, 1994), Microsoft's col-

lapse-expand design (see Figure 3.1), and the multiple interface design introduced by McGrenere et al. (2002) are designs that have been proposed in the past. Unfortunately, none of these designs preserves the original structure of menus. Therefore, we could not use them as a basis for our design.



(a) (b)

Figure 6.1. Our vision of menus contrasted with regular menus. Only items that the user selects regularly are shown. (a) Selection in a regular menu requires the user to follow a highly constrained trajectory and perform several movements. (b) Our vision was to allow users to select menu items with rough, single-stroke gestures.

6.2 Background

Before moving to our design process, we review previous work on menu selection and target acquisition. This work has served as ground for our design approach.

6.2.1 Menu Selection

Various models have been proposed to predict selection times in menus (Landauer and Nachbar, 1985; K. L. Norman, 1991). These models consider two factors affecting performance in menu selection: visual search and pointing (target acquisition). Visual search de-

pends on the ordering of menu items as well as the user expertise. If items are sorted, e.g., alphabetically, search time can be predicted by Hick's Law (Hick, 1952; Landauer and Nachbar, 1985), which states that the time to locate an item is a logarithmic function of the menu size. When menus are not alphabetical, users have to scan them in a linear fashion to locate an item. Alternatively, if users have memorized the position of items in a menu, search time is constant.

Pointing time can be predicted by Fitts' law (Fitts, 1954), a highly successful model for predicting human movement time. According to Fitts' law, the movement time (*MT*) needed to acquire a target of width *W* at distance *D* is determined by the equation:

$$MT = a + b\log_2\left(\frac{D}{W} + 1\right) \tag{6.1}$$

where *a* and *b* are empirically determined constants. The logarithmic term is known as the task's Index of Difficulty (*ID*) and is measured in *bits*. The above formulation suggests that menu items that appear further down the menu have a greater *ID*. Not taking into consideration constraints in the shape of the motion trajectory, Fitts' law cannot accurately predict movement time in nested menus. If the trajectory is constrained and the cursor has to be moved (*steered*) along a tunnel, movement time is better modeled by the steering law (Accot and Zhai, 1997), which is given by the equation

$$MT = a + b\frac{d}{w} \tag{6.2}$$

where *MT* is the time needed to cover a distance *d* in a tunnel of width *w*, while *a* and *b* are empirically determined constants. According to the steering law, the *ID* is linearly rather than logarithmically linked to the distance-width fraction. The steering law has been used to model selection times in cascading pull-down menus (Ahlstrom, 2005; Zhai et al., 2003). Ahlstrom (2005) described menu selection tasks as compounds of vertical and horizontal motions, where vertical motion is modeled as a Fitts' law pointing task and horizontal mo-

tion is modeled as a steering task. Based on this model, Ahlstrom (2005) applied "force fields" by adapting the visual motion of the cursor to decrease the distance-width ratio. On the other hand, Kobayashi and Igarashi (2003) suggested that submenus should pop up at the position where horizontal motion occurs so that the steering distance is minimized. Both approaches assumed that traditional menus require users to perform perfect steering motions to keep submenus open. In fact, menu behaviour in modern operating systems is different than the behaviour tested by these approaches. In Microsoft Windows XP, for instance, submenus stay open for a small time window even if the cursor has exited the boundaries of the associated parent item. So any movement within this time window is unconstrained. Mac OS X follows a better design, and according to Miller (2006) it "gets a Hall of Fame nod". Figure 6.2 demonstrates activation of menus in Mac OS X. As shown in the figure, after a submenu has been activated, its menu items can be selected with a single motion. The width of the constrained steering motion is considerably wider than the width of the selection, and therefore, selection is faster.

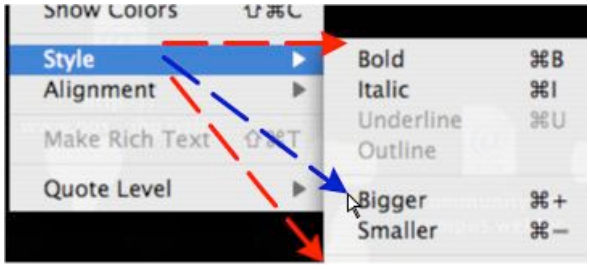


Figure 6.2. Selection in nested menus (Mac OS X). Motion is constrained within the triangular area outlined by the red (outer) arrows. When the cursor exits the boundaries of the selection ("Style"), for a brief time window, the user can move the cursor towards the submenu without causing the selection to change.

A different technique was introduced by Cockburn and Gin (2006), who showed that menu selection times could be reduced if enlarging the activation area of parent menu items and removing any delays before popping up submenus. A brief delay preceding a submenu

popup is commonly used to (1) prevent fluttering and (2) force users to target the correct parent item before starting a steering motion, and (3) allow for optimal diagonal movements as shown in Figure 6.2. When the activation area of a parent item grows, targeting this item becomes easier, and the need for such a delay disappears. The results reported by Cockburn and Gin (2006) suggest that a delay might be inappropriate even if the activation area of parent menu items was not enlarged. This result challenges exiting practices in commercial software, but Cockburn and Gin (2006) acknowledge that a zero delay could "harm acquisition because users must accurately steer across the item to reach the correct cascade menu". We examine this issue in more detail later in this chapter.

6.2.2 Improving Pointing Performance

Several interaction techniques have used Fitts' law to improve target acquisition either by decreasing the distance D (Baudisch et al., 2003) or by increasing the width W (Cockburn and Firth, 2003; McGuffin and Balakrishnan, 2002; Zhai et al., 2003). Decreasing the distance can be achieved by either bringing a target closer to the cursor's position (Baudisch et al., 2003) or by jumping the cursor closer to the target (Guirard et al., 2004). The width of a target can be increased by simply expanding the target as the cursor approaches the target (McGuffin and Balakrishnan, 2002; Zhai et al., 2003). This technique is used by the MacOS X Dock. Instead of expanding the actual target, Cockburn and Firth (2003) tested a similar technique where a bubble of a fixed radius (e.g. 40 pixels) appears around the target as it is approached by the cursor within a fixed distance (e.g., 50 pixels). McGuffin and Balakrishnan (2002) showed that dynamically expanding targets can improve selection time even when expansion occurs after 90% of the distance to the target has been traveled. Zhai et al. (2003) revalidated this result and found that selection time can improve even when target expansion is unpredictable. Nevertheless, they observed that target expansion inflated error rates.

Other approaches have tried to decrease the *ID* of a target acquisition task by dynamically adjusting the control-display (C-D) gain (Blanch et al., 2004). Benefits can be achieved by increasing the gain when the cursor approaches a target and decreasing it as the cursor moves inside the target. Finally, the bubble cursor (Grossman and Balakrishnan, 2005) is a dynamically resized cursor that allows for selecting targets with respect to their distance from the current position of interaction. As shown in Figure 6.3, the bubble cursor resizes so that, at each moment, the target closest to the cursor's center is selected. Grossman and Balakrishnan (2005) showed that bubble cursor performance can be accurately modeled using Fitts' law, where width *W* is represented by the expanded area of activation of a target. Compared to the other techniques, the bubble cursor has two main strengths: (1) it provides continuous visual feedback making the selection of targets predictable; and (2) it makes maximum use of the free space. This free space, however, is not equally allocated to all the targets, and as with other techniques, the success of the bubble cursor highly depends on the density of the targets and their position in space. If targets are stacked one on top of the other as in lists, there is no benefit.

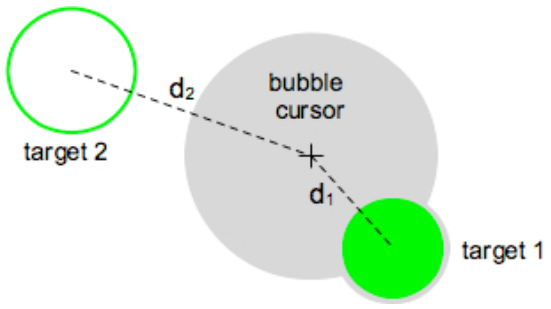


Figure 6.3. Overview of the bubble cursor (Grossman and Balakrishnan, 2005). The size of the cursor dynamically changes as the cursor moves. In this example, the bubble cursor selects *target 1*, as its distance d_1 from the center of the cursor is shorter than the distance of the center of the cursor from any other target.

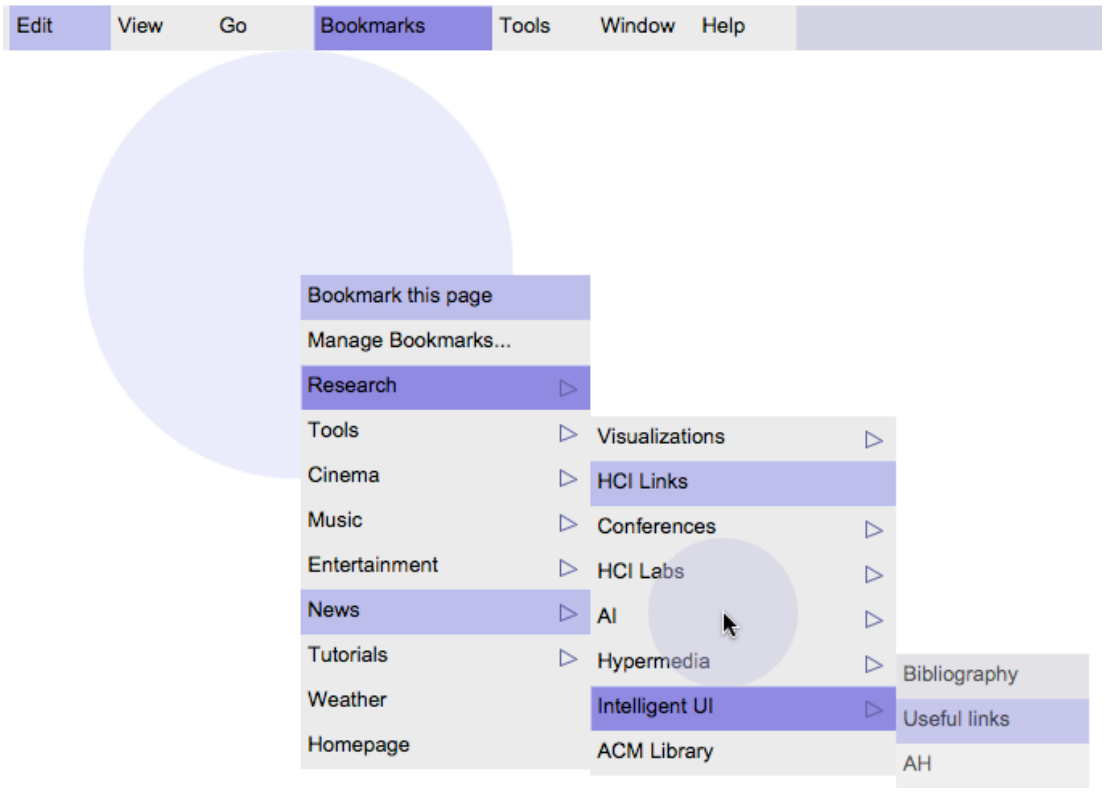


Figure 6.4. Overview of bubbling menus. Bubble cursors are used to select blue (hot) items in an alternative view, activated through mouse-dragging gestures. Blue items are defined by either a manual or an automatic customization mechanism.

6.3 Bubbling Menus

Figure 6.4 illustrates our proposed technique of cascading menus. The new technique is named the *bubbling menus*. Bubbling menus make use of the bubble cursor to expand the activation area of *hot* menu items. Here, by "hot", we refer to the menu items promoted by the personalization technique. Such items could be frequently selected menu items or items whose selection is important given a state of user interaction.

Bubbling menus satisfy our design goals and comply with our vision presented in Section 6.1. Users can use single-stroke mouse gestures to switch to an alternative personalized view. In this view, hot items are enhanced with larger activation areas, which results in faster movement. Moreover, personalization does not affect the original structure of menus. This

property makes the proposed design particularly useful for expert users, who, having memorized a menu structure, can select items with directional mouse gestures. At the same time, it does not prevent novice users from learning the position of items in a menu. Besides, unlike other designs, bubbling menus let users activate pull-down menus by initiating the selection gesture far from a menubar.

Bubbling menus support two different views, the goal of which is to provide a clear separation between the traditional behaviour of menus and adaptation. When users use the left mouse button to interact with bubbling menus, the menu's behaviour is almost identical to the behaviour of regular menus. The difference is that hot items are highlighted with a subtle background colour, letting users know which items could be accessed with the bubble cursor. The bubble cursor appears when users switch to the alternative view of the menus. Switching to the alternative (adapted) view of a menu is initiated by pressing and dragging the right mouse button. As shown in Figure 6.4, interaction can result in the activation of two bubbles: the first bubble is used to select a menu category from the menubar; and the second bubble is used to select a menu item within an open menu. The design incorporates several motion-aware techniques to improve motor control and facilitate menu selection.

Selection in bubbling menus requires users to make decisions about which of the two views to use to select menu items. If users knew beforehand which items could be selected with the bubble cursor, such decisions would be fast. However, a user may not be always able to remember or predict which items are classified as hot. Our work has investigated this problem and tried to explore designs that would minimize the overhead associated with decision-making. As a first step, we conducted a preliminary experiment, testing the cost of decision-making in the context of simple pointing tasks. Taking into consideration the results of this experiment, we designed a first version of bubbling menus. This version did not include the full capabilities of our final design. For instance, it did not support menu activation far from a menubar. It allowed us, however, to test several aspects of our approach through two

user studies and identify its limitations. The design was refined and a final evaluation was conducted. The steps of this design process are documented in the following sections.

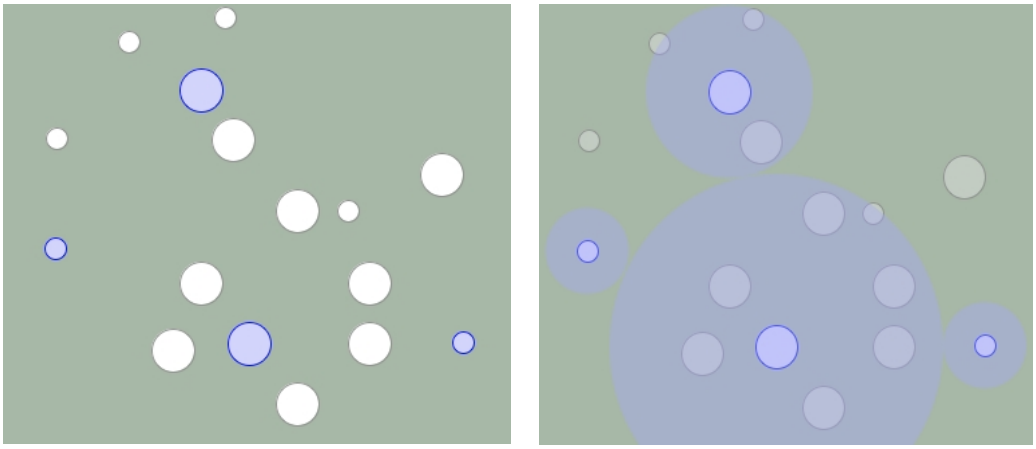
6.4 Testing Multimode Pointing

As discussed in Section 6.3, interaction with bubbling menus requires switching between two different views, a default static view, and an alternative view that boosts the selection of hot menu items. The advantage of this approach is that the decision of whether to adapt a menu is made by users themselves based on their goals. On the other hand, its application requires that switching between views is quick so that benefits coming from adaptation are not canceled by the cost of view switching. Furthermore, it assumes that users can predict or remember whether a menu item is "considered" hot so that they can switch views effectively. Remembering whether an item is hot or not is a binary decision. Therefore, it is less demanding than the use of keyboard shortcuts, which requires the remembering of key sequences. However, cognitive costs increase when hot items are automatically chosen by an intelligent mechanism. In such cases, users have to deal with the uncertainty about which items are hot.

By colouring items, we help users identify hot items before they make any decision about switching views. At the same time, colouring facilitates visual search. Unfortunately, this approach does not eliminate the problem of uncertainty. Users do not receive any visual feedback until a menu opens. Therefore, decision-making has to be performed after the menu opens, which delays the task. According to extensive experimental work in Cognitive Psychology on response times, the cognitive cost of two-choice decision-making in response to simple visual stimuli is roughly 150-200 ms (Luce, 1986).

To systematically assess the cost of mode switching and decision-making on pointing performance, we conducted a preliminary experiment. The experiment tested whether benefits would be possible if users were given the chance to expand a small number of hot tar-

gets. We examined expansion initiated by simple mode-switching techniques such as dragging the mouse or pressing a modifier key. Tasks were designed as simple Fitts' Law pointing tasks on a 2-D plane. Expecting that decision-making would be partially performed in parallel with the movement of the mouse and knowing that benefits from target expansion can happen even if the target expands late in the movement (McGuffin and Balakrishnan, 2002; Zhai et al., 2003), we hypothesized that a mode-switching approach to select targets would be beneficial. The results, however, revealed that logarithmic benefits coming from expansion were counterbalanced by the constant costs of mode switching and decision-making even when the task *ID* was decreased by 2-3 bits. Below, we present the experimental design and results in more detail.



(a) (b)

Figure 6.5. The two modes of interaction supported by multimode pointing. (a) Default mode – Expandable targets have been highlighted. (b) Alternative mode – Highlighted targets have been expanded.

6.4.1 Evaluated Techniques

The experiment contrasted multimode pointing that supports expansion against regular pointing with no expansion. Multimode pointing was performed by switching between two modes of interaction: (1) a default mode that allowed users to select targets without affecting their original geometry, and (2) an alternative adaptive mode that allowed users to access a

small subset of targets (hot targets), hypothetically faster, by expanding their motor space. Targets were represented as circles and were spread in a 2D space, as shown in Figure 6.5. Expandable targets were highlighted with a light-blue background colour.

As shown in Figure 6.5, expansion was implemented by introducing a bubble around the expanded target (Cockburn and Firth, 2003). The bubble of a target could cover the area of non-expandable targets. Only expanded targets could be acquired when the adaptive mode was activated. Semitransparent bubbles were used to minimize visual occlusion. We tested two techniques for switching between modes and selecting expended targets. The first technique required the user to press a key (the key "z") to switch from the default to the adaptive mode. After releasing the key, the default mode was activated again. In the alternative mode, expanded targets were selected by clicking within the area of their bubble while the key was pressed. The second technique did not require the use of a keyboard. The user could drag the mouse while pressing the right mouse button to activate the alternative mode. A target was selected by releasing the button within the area of the target's bubble.

6.4.2 Apparatus and Participants

The experiment was conducted on a 2GHz P4 PC with 1GB RAM, running Windows XP. A 21-inch monitor was used at a resolution 1280 by 1024 pixels. The software was implemented in Java. Six male and six female volunteers, 24-35 years old participated in the experiment. All the participants used the right hand to interact with the mouse.

6.4.3 Task

Each participant had to perform a series of 2D pointing tasks. For each task, the participant had to move the mouse to a home position marked by a small red circle, rest there for 0.5 second, and start moving to the target as soon as it appeared on the screen. The home position was different for each task. The goal target was marked with a red overlaying circle and was surrounded by a set of 15 distracter targets (see Figure 6.6). The diameter of targets was

either 16 or 32 pixels. Each participant tested three techniques to select targets: (1) normal clicking (*Static*), (2) clicking plus switching to the adaptive mode by key pressing (*KeyPress*), and (3) clicking plus switching to the adaptive mode by dragging (*Dragging*). In the case of *KeyPress* and *Dragging*, either two or four out of the 15 targets were marked as expandable. The goal target was expandable with a 50% probability. Its size was expanded by a factor of four or eight in an unpredictable manner.

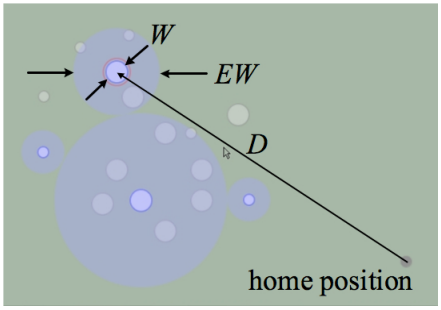


Figure 6.6. Experimental task. After the task begins, the participant has to select the target within the red circle. Blue targets are expanded by switching to the alternative mode.

The experimental task simulated the situation in which an intelligent system identifies a small number of hot targets and suggests them to the user by highlighting them. After being highlighted, targets become expandable. Ideally, the intelligent system will always suggest the targets that the user looks for. The experimental task tested a scenario in which system suggestions were wrong with a 50% probability. Trying to control the uncertainty about when the system fails to highlight a goal target, we tested two different conditions. Under the first condition, participants knew whether a goal target was expandable before starting a task (predictable adaptation). Under the second condition, participants had no information about whether the goal target was expandable (unpredictable adaptation). The first condition simulated the situation in which either the prediction mechanism is transparent to the user or target suggestions are static, e.g., they have been manually set by the user, or change slowly over time. Predictability was simulated by informing participants before the beginning of

each task about whether the goal target was expandable or not. Before a participant started a task, a blue square surrounding the home position indicated that the goal target would be expandable. The lack of the blue square indicated that the goal target was not expandable.

6.4.4 Design and Procedure

A full factorial within-participants design was used. The independent variables were the predictability condition *Predictable* (*True*, *False*), the selection technique *Technique* (*Static*, *KeyPress*, *Dragging*), the type of goal target *Suggested* (*True*, *False*), the distance *D* (256, 512, 1024 pixels), the width *W* (16, 32), the expansion-width-to-width ratio *EW/W* (4, 8), and the number of expandable targets *ExpandNum* (2, 4). Each participant completed two blocks for each combination of the variables *Predictable* and *Technique*. Each block consisted of 48 trials, presented in a random order. In total, 576 trials were completed by each participant in one session lasting from 45 to 60 minutes.

The order in which the two predictability conditions and the three techniques were presented was balanced among the 12 participants. For each condition and technique, each participant had to complete a series of practice trials. Participants were instructed to complete the tasks as quickly as possible, while trying to keep the error rate around 2 - 4%. An estimation of the within-block error rate based on their ongoing frequency of errors was constantly shown. In the case of an error, participants had to continue with the task until the goal target was selected. This prevented participants from deliberately making errors to complete tasks faster.

6.4.5 Measures

As Zhai et al. (2003), we analyzed three dependent variables: movement time *MT*, the time elapsed from the beginning of the movement until releasing the mouse button over the goal target, response time *RT*, the time elapsed between the presentation of the targets and the be-

ginning of the movement, and error rate, the ratio of errors over the total number of tasks. *MT* was analyzed separately for suggested goal targets and non-suggested goal targets.

6.4.6 Hypotheses

Our main hypotheses were as follows.

Hypothesis 5.1. *KeyPress* and *Dragging* will improve movement time (*MT)*.

Hypothesis 5.2. Response time (*RT*) will increase under the uncertainty condition, i.e., when *Predictable* is *False*.

Hypothesis 5.3. Movement time (*MT*) will be successfully described by Fitts' Law for the selection of both non-expandable and expandable targets.

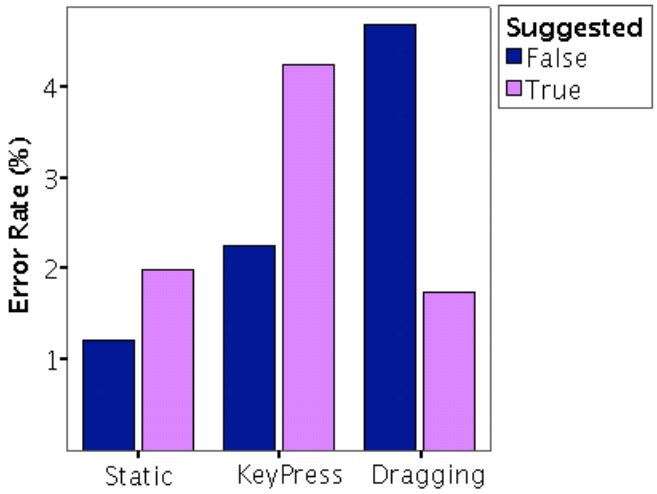


Figure 6.7. Distribution of errors

6.4.7 Results

Errors and Outliers

Errors and outliers accounted for a 2.9% of the total number of trials. Mean error rate (2.69%) was within the range of error rates of typical Fitts' Law experiments. As shown in Figure 6.7, *Dragging* resulted in a relatively high error rate (4.7%) when the goal target was not expandable. The reason for this error inflation is that *Dragging* did not provide any

mechanism for safely backtracking from the alternative mode to the default mode. If the user mistakenly started dragging the mouse, an error occurred.

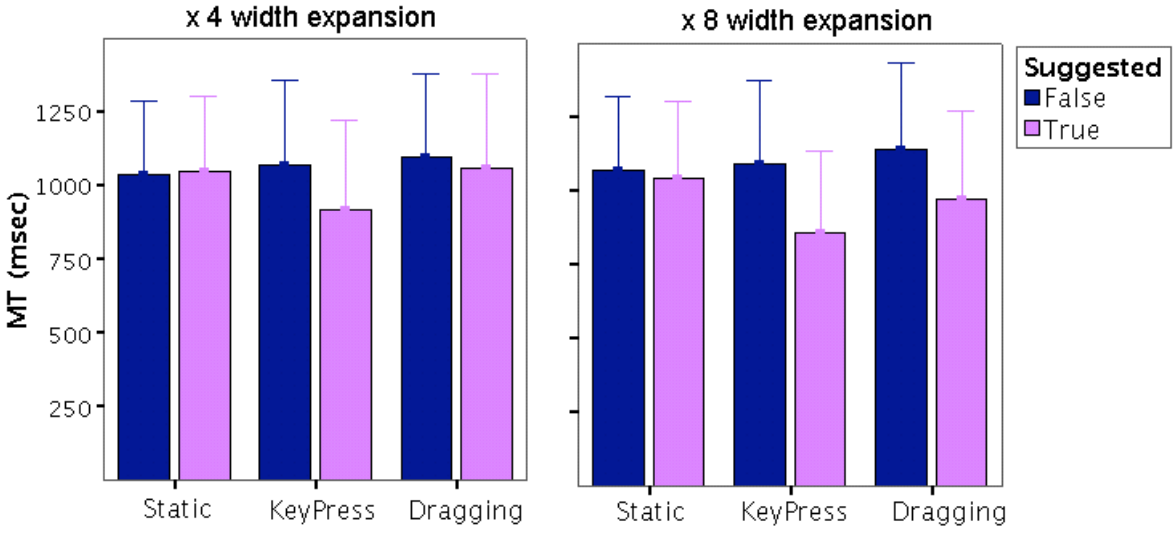


Figure 6.8. Results for movement time (MT)

Movement Time

The overall results for movement time (*MT*) are demonstrated in Figure 6.8. As shown in the figure, benefits from expansion are rather limited. Differences become only apparent when target widths were expanded by a factor of eight. After isolating errors and outliers, we conducted an ANOVA analysis treating *Technique*, *Block*, *Highlighted*, *Predictable*, *ExpandNum*, *D*, *W*, and *EW/W* as repeated measures, and *MT* as the dependent variable. Main and interaction effects are summarized in Table 6.1. As shown in the table, the main effect of *Technique* on *MT* was found to be significant ($F_{2,11} = 6.81$, $p = .005$). However, a post-hoc analysis using Bonferroni's adjustment did not reveal any significant difference between *KeyPress* and *Static* ($p = .07$) or between *Dragging* and *Static* ($p = 1$). Therefore, Hypothesis 5.1 was not confirmed in the general case. However, differences were clearer when comparing the performance of the three techniques for correctly suggested targets. More specifically, the effect of the interaction *Technique* × *Highlighted* was significant ($F_{2,22}=18.341$, $p < .0001$), and a pairwise comparison using Bonferroni's adjustment showed that *KeyPress* was

significant faster than *Static* (p = .002) and significantly faster than *Dragging* (p = .014) when the goal target had been successfully highlighted. No significant mean differences were found between *Dragging* and *Static* (p = 1).

The effect of *Predictable* on *MT* was not found to be significant ($F_{1,11}$=4.156, p = .066), but its interaction with *Technique* had a significant effect on *MT* ($F_{2,22}$=12.686 , p = .0002). However, as shown in Figure 6.9 (a), differences in *MT* between the two predictability conditions were marginal.

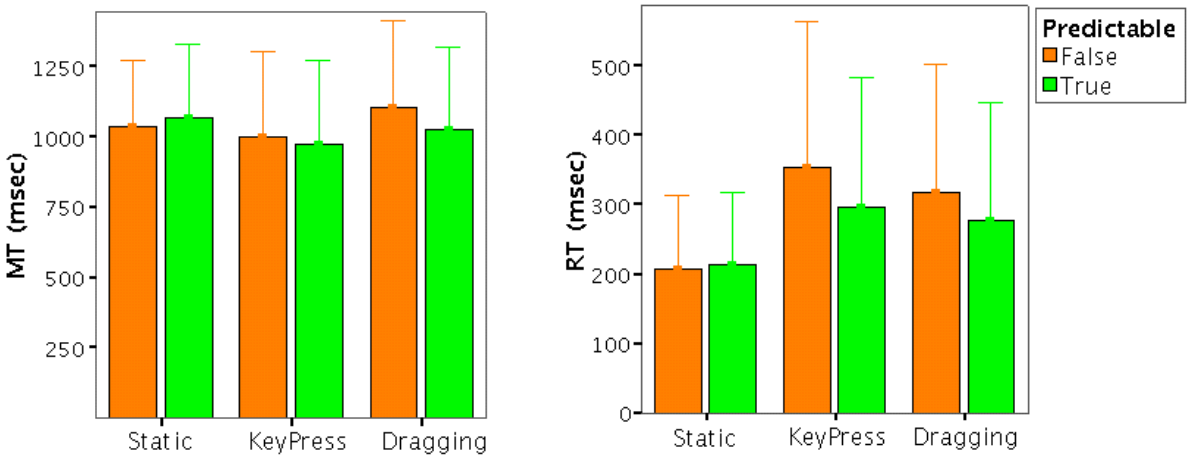
Table 6.1. Summarized Results from ANOVA with Repeated Measures on MT.

Measure	df	df (Error)	F	p
Technique	2	22	6.81	.005 *
Block	1	11	.028	.871
Highlighted	1	11	43.976	< .0001 *
Predictable	1	11	4.156	.066
ExpandNum	1	11	.156	.700
D (Distance)	2	22	238.404	< .0001 *
W (Width)	1	11	236.527	< .0001 *
EW/W	1	11	2.993	.112
Techn. × Block	2	22	.650	.532
Techn. × Highlighted	2	22	18.341	< .0001 *
Techn. × Predictable	2	22	12.686	.0002 *

** statistically significant at the .05 level*

Figure 6.9 (b) shows the distribution of response times over technique and predictability. As expected, the two expansion techniques delayed response time, because they required users to make additional decisions and regularly switch between selection modes. *Technique* significantly affected *RT* ($F_{2,22}$=23.74, p<.0001), and pairwise comparisons showed significant differences between the *Static* technique and the two expansion techniques (p=.001).

The extra cost was at the level of 100 ms. The analysis did not reveal any significant main effect of *Predictable* on *RT* ($F_{1,11}$=4.17, p=.066), i.e., Hypothesis 5.2 was not confirmed. The interaction effect *Predictable* × *Technique* was significant though ($F_{2,22}$=7.751, p=.003). Surprisingly, predictability reduced but did not eliminate the extra cost. This result can be attributed to: (1) delays caused by switching from the default mode to the alternative mode before the beginning of the movement; and (2) cognitive costs caused by the intermixing of two selection techniques. As no significant effect of *Suggested* on *RT* ($F_{1,11}$=2.121, p =.173) was found, the second explanation seems to better justify this result.



(a) (b)

Figure 6.9. The effect of predictability on (a) Movement Time (MT) and (b) Response Time (RT)

Fit to Model

Finally, we tested Hypothesis 5.3. Figure 6.10 demonstrates the regression lines for the measured data over the *ID* of both the original and expanded targets. The fit to the model was good for non-expandable targets (R^2 > .95). It was less precise when studied over expanded *IDs* (R^2 = 0.9193 for *KeyPress*), which can be explained by the fact that, sometimes, participants did not expand highlighted goal targets.

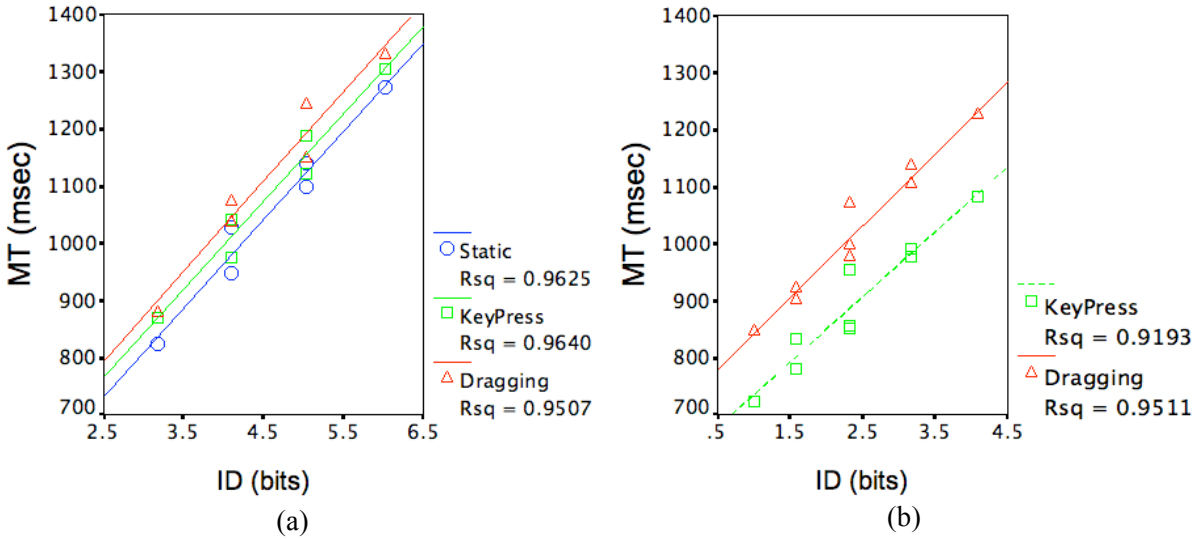


Figure 6.10. Fit of model for *MT*: (a) over original *IDs* for non-suggested goal targets, and (b) over expanded *IDs* for suggested goal targets.

6.4.8 Discussion

The results of the experiment show that multimode pointing is generally not promising. Although Hypothesis 3 was confirmed, benefits coming from target expansion were counterbalanced by the increased cost of decision-making and mode switching. As a result, Hypothesis 1 was not confirmed. Nevertheless, the experiment examined a worst-case scenario. It required participants to always start a task from the default mode, in which targets were not expanded. Yet, participants were only able to switch to the alternative view of the space after targets had been displayed on the screen. In a real situation, users would be able to switch to the alternative view earlier, before the display of the targets. Second, the extent of target expansion was hidden from users until they switched to the alternative view. Expansion levels were randomly distributed in each block, and therefore, participants could not plan the pointing task accordingly. These are also reasons why Hypothesis 2 was not confirmed. Although we noticed that unpredictability inflated response times, this inflation was not found to be statistically significant. We believe that such hidden effects as well as the

fatigue due to continuous mode switching might have blurred the real effect of unpredictability.

Furthermore, pointing tasks as tested by the experiment cannot fully describe selection in cascading menus. Pointing in cascading menus can involve multiple pointing subtasks, with a total *ID* higher than the *ID*s tested by the experiment. We hypothesized that multimode pointing could be beneficial in such cases as long as mode switching was kept minimal. We also hypothesized that extra gains would be possible if tasks involved steering in addition to pointing.

6.5 First Design

In this section, we present our first design of bubbling menus. This design concentrated on pointing performance, considering that menus were activated directly from a menubar, as in regular menus.

We limited our attention to mode-switching techniques that do not require the use of a modifier key. The experiment presented in Section 6.4 showed that dragging the mouse was slower and more error prone than using a modifier key to expand targets. However, our design addresses the main limitations of dragging. First, it provides mechanisms for switching back to the regular view of a menu. Second, it minimizes the number of mouse presses needed to perform a selection task. The design was finalized after running a pilot study with two participants.

6.5.1 Visual and Interaction Design

Figure 6.11 demonstrates basic interaction with the first design of bubbling menus. In their default view, bubbling menus behave as regular menus (see Figure 6.11 (a)). In their alternative view (see Figure 6.11 (b)), a semitransparent bubble cursor appears, which can only select hot items. A light-blue background colour is used to highlight hot items in both views.

Interaction with the bubble cursor is extended beyond the geometric boundaries of a menu box. The bubble cursor can select a menu item even if its center is in the space that surrounds the menu. Switching between views is entirely based on the use of the mouse. The alternative view of a menu is activated by dragging the mouse. In a typical course of interaction with this view, the user presses on the menu label and without releasing the button, drags the mouse towards the goal item. A selected item can be activated by releasing the mouse button. Consequently, a sequence of actions press-drag-release is sufficient for the selection and activation of a hot menu item. The alternative view can be activated by dragging the mouse in any position within the menu. Dragging has to exceed a minimum distance, e.g., 20 pixels, before the menu switches to its alternative view.

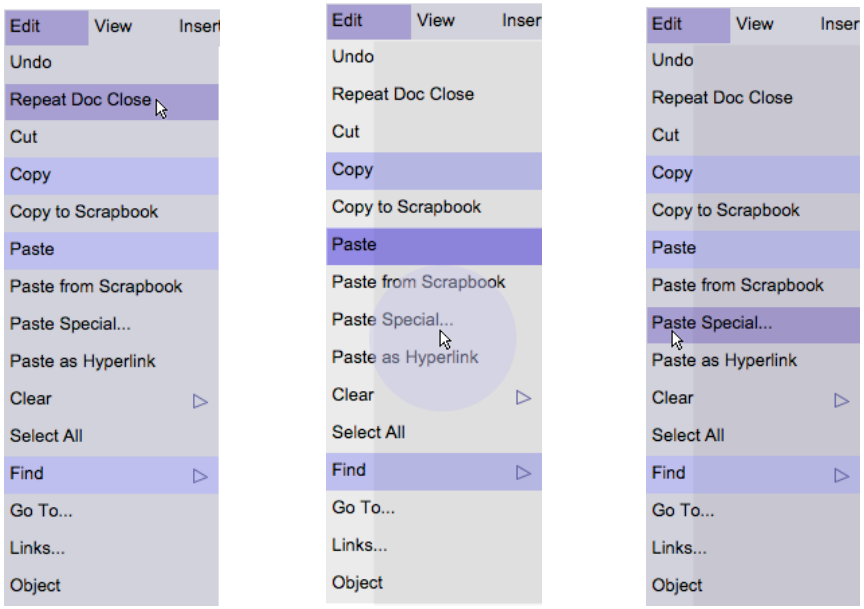


Figure 6.11. User interaction with bubbling menus. (a) Default view - A small number of hot items are highlighted with a light-blue color. (b) Alternative view - The user drags the mouse and a bubble cursor selects highlighted items. (c) When the cursor moves to the left sub-area of the menu, the bubble cursor disappears.

A difficulty that we faced during the design stage was coming up with a quick mechanism that would enable users to switch an adapted menu back to its default view. The pre-

liminary experiment stressed the importance of such a mechanism in minimizing errors and reducing the cognitive load of decision-making. We dealt with this issue by using free space surrounding a menu for switching views: while the space beneath and right to the menu is used to select items with the bubble cursor, the space above and left to the menu is reserved for error correction. If the user drags to the latter portion of the space and releases the button, the menu returns to its default view. An additional quicker mechanism is demonstrated in Figure 6.11 (b-c). The area of an adapted menu is split into two distinct sub-areas. The right dark sub-area is dedicated to the selection of hot items with the bubble cursor. The bubble cursor disappears when the mouse enters the left sub-area (see Figure 6.11 (c)). Within this sub-area, any item can be activated by simply releasing the mouse button over the item's boundaries.

Clearly, benefits from the use of the bubble cursor occur only if hot items are sparsely spread along menus. However, real data on usage patterns (Findlater and McGrenere, 2004; McGrenere and Moore, 2000) show that such an assumption is reasonable.

6.5.2 Submenus

The bubble cursor can be used to access items in any level of nesting in a menu hierarchy. Interaction with the bubble cursor moves forwards and backwards to subsequent levels of nesting. To accelerate interaction with submenus, and in addition to the use of a bubble cursor, we made several changes to the interaction model of regular cascading menus. First, the enlargement of the activation area of menu items allowed us to remove the delay that follows the selection of a parent item before the associated submenu is displayed. Second, we enhanced motor control by allowing submenus to follow the movement of the cursor, floating along the vertical direction. Third, we added simple interactions that allow users to switch from the adapted to the normal view of a submenu, avoiding errors. As opposed to Cockburn and Gin (2006), who removed all the delays associated with submenus, we removed the de-

lay preceding a submenu popup. In addition, following the example of Mac OS X (see Figure 6.2), we further enhanced steering control by allowing for diagonal steering movements, without affecting the selection of the parent item.

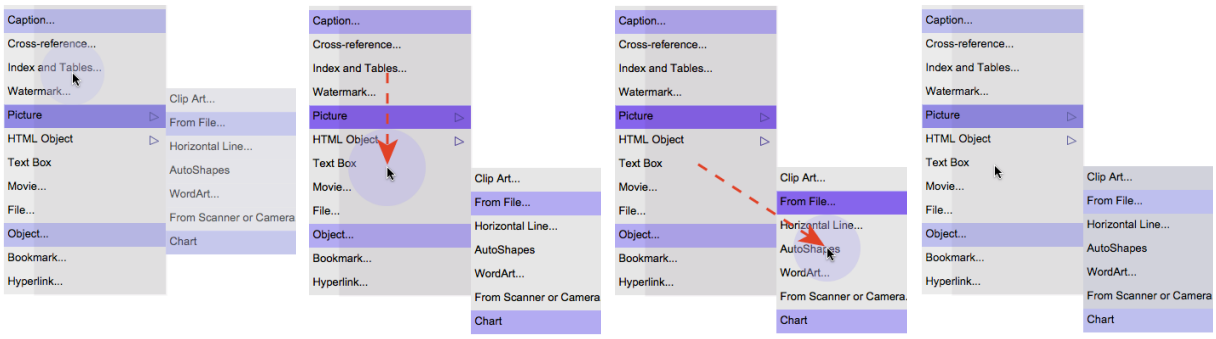


Figure 6.12. Interaction with submenus in bubbling menus: (a) selection of parent item; (b) vertical movement; (c) diagonal movement; and (d) release of mouse button. While the user drags the mouse, the bubble cursor appears. Arrows show the direction of mouse movement.

Figure 6.12 summarizes the interaction with the alternative view of cascading bubbling menus. As soon as the bubble touches a parent menu item, the associated submenu appears. The user can detect which submenu items are highlighted and decide whether to continue the motion towards the submenu or release the mouse button to activate the submenu in its regular non-adapted view (see Figure 6.12 (c-d)). Figure 6.12 (b) shows that submenus float along the vertical position of the bubble cursor's center. When the mouse moves towards the submenu though, the submenu freezes so that the user can target items without being disturbed by additional movements.

The above interaction model eliminates time spent with regular menus opening a parent item by halting the cursor or clicking on it. As Figure 6.13 demonstrates, users can select hot items in any level of a menu hierarchy with uninterrupted single-stroke mouse gestures, without having to be accurate in their movements. As opposed to first-level menus, submenus do not provide any mechanism for selecting non-highlighted items while the user

drags the mouse. Splitting submenus into sub-areas could not be applied without sacrificing the effectiveness of the design. Error correction is solely based on backtracking: the user can drag the mouse to the left of a submenu to move interaction to the previous level of nesting.

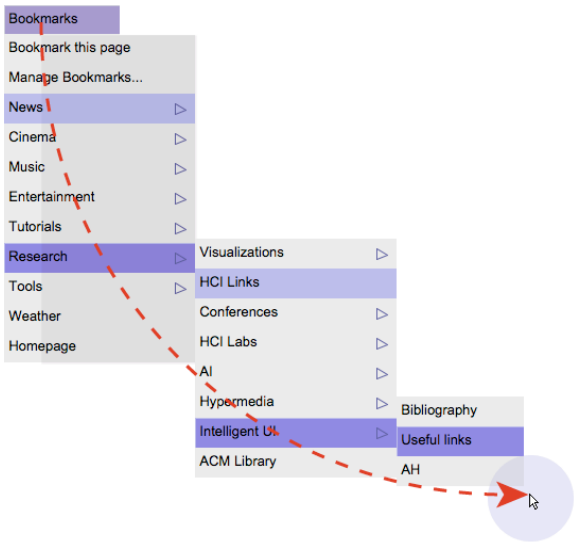


Figure 6.13. A nested item in bookmarks is selected with a single-stroke gesture.

6.6 Evaluation of the First Design of Bubbling Menus

We conducted an experiment to evaluate the first design of bubbling menus. The goal of the experiment was to test the success of the technique in supporting pointing performance. We were particularly interested in testing how the technique would perform if personalization was not accurate, i.e., in situations in which the goal item was not always highlighted. Given the results of our research presented in Chapter 4, we expected that accuracy would have a great impact on the performance of bubbling menus. Thus we examined the performance of the technique under both high and low accuracy levels. Accuracy was treated as the proportion of tasks in which the path of the goal menu item had been successfully suggested (highlighted).

6.6.1 Experimental Conditions

The experiment compared bubbling menus against regular static menus. The interaction design of static menus was based on the Mac OS X interaction model (Figure 6.2):

- A menu item was selected after releasing the mouse button over its boundaries; i.e., an item could be selected by either clicking or by dragging and releasing.
- A submenu was activated by either clicking on its parent item or by keeping the cursor over its boundaries for a short period of time (300 msec).
- Items within a submenu were selected according to the interaction model demonstrated in Figure 6.2. The time window in which motion was constrained by the triangular area shown in the figure was set to 400 msec.

Participants could use the selection strategy that best fitted their past experience. The same interactions were supported by the default view of bubbling menus with the exception that dragging for more than 20 pixels activated their adaptive views.

6.6.2 Apparatus

The experiment was conducted on a PowerBook G4 12-inch laptop with screen resolution 1024x768 and 768 MB RAM, running Mac OS X 10.4.4. A USB mouse was used as input device. The experimental software was implemented in Java 1.4.2 and used the Piccolo framework (Bederson et al., 2004).

6.6.3 Participants

Six female and ten male volunteers, 24-35 years old, participated in the experiment. All the participants had experience interacting with pull-down menus and a mouse. 15 participants used the right hand to interact with the mouse and one participant used the left hand.

6.6.4 Task

Participants completed a series of menu selection tasks. For each task, they had to select an item that appeared either at the second or third level of nesting. Selections were made from four different menu categories. As shown in Figure 6.14, a label "CLICK ME" guided the selection (not necessarily by clicking) of menu items. A task started as soon as the participant pressed on the label of the menu and finished when the goal item was successfully selected.

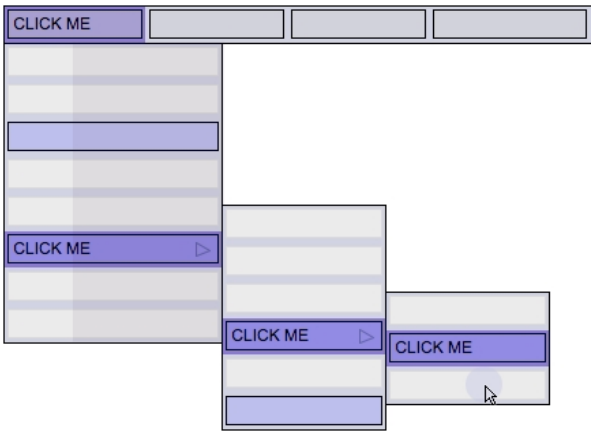


Figure 6.14. Demonstration of the experimental task.

The experimental trials were structured in blocks of 35 randomly ordered tasks. These 35 tasks were variations of the ten base tasks shown in Figure 6.15. Base tasks were cases where system suggestions were perfect, i.e., the "CLICK ME" item was always suggested. In their variations, suggestions were imperfect. For the static menus, there were no suggestions, and as a result, variations were identical to the base tasks. Tasks 1-5 required the selection of a second-level item. There was one variation for each of these tasks in which suggestions were wrong at the second level, and one variation where suggestions were wrong from the first level. Tasks 6-10 required the selection of a third-level item. For each of these tasks, there were three variations in which suggestions were wrong from the third, the second, or the first level.

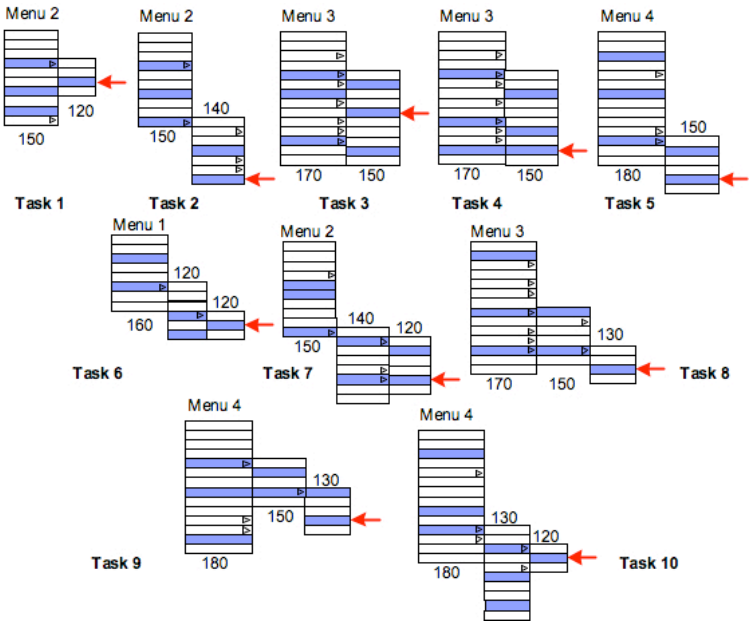


Figure 6.15. Base experimental tasks. Goal items are marked by an arrow. Numbers specify the width of menus in pixels. The height of each item was 30 pixels.

Suggestions were constrained as follows: menus with 1-4 items had one suggestion; menus with 5-9 items had two suggestions; and menus with 10-14 items had three suggestions. A menu did not include any suggestions if its parent item was not suggested.

6.6.5 Design and Procedure

A mixed factorial design was used. Accuracy of menu suggestions was treated as a between-participants factor. Participants were split into two groups with equal sizes. Each group was exposed to a different accuracy level. For the first group, the base tasks and all their variations appeared with the same probability, and as a result in only 10 out of the 35 tasks (28.6%) of each block suggestions were perfect. For the second group, the base tasks accounted for 30 out of the 35 tasks of each block, so accuracy was 85.7%. Consider that real menu selection data on one-level menus reported by Findlater and McGrenere (2004) show that selection patterns allow for predictions with accuracy levels over 90% even if simple

heuristics such as selection frequencies are used and a small number of items, e.g. 3 out of 15, is suggested.

Tasks were randomly ordered within each block. In other words, we simulated a worst-case scenario of adaptive behaviour, according to which participants could not predict how menus were adapted before starting a task. Each participant was exposed to both bubbling menus and static menus. The design can be summarized as follows:

2 accuracy conditions (*low*, *high*)

× 8 participants

× 2 techniques (*static*, *bubbling*)

× 4 blocks

× 35 tasks

= 4480 trials in total.

As bubbling menus was a new technique to which participants were not previously exposed, we tried to minimize the learning curve in the recorded data by including training sessions adapted to the individual needs of each participant. More specifically, participants started the experiment after they felt that they had learned how to use the technique. Also, for both techniques, before the four main blocks, we added an extra block not included in the analysis. For this block only, participants were instructed to start completing the tasks slowly but accurately and accelerate as soon as they felt confident. For the four main blocks, they were asked to complete the tasks as fast as possible, trying to avoid errors. Each participant completed the experiment in one session lasting 45-60 minutes. The order in which the two menu techniques were presented was balanced among participants.

6.6.6 Measures

We analyzed the total time *TT* to complete a selection task as well as the response time *RT* measured from the beginning of the task until the cursor entered the menu. We also conducted a separate analysis for the total time ($TT_{perfect}$) needed to complete tasks for which system suggestions were correct.

6.6.7 Hypotheses

Our hypotheses were as follows.

Hypothesis 5.4. Bubbling menus will decrease total selection time (*TT*) in high accuracy.

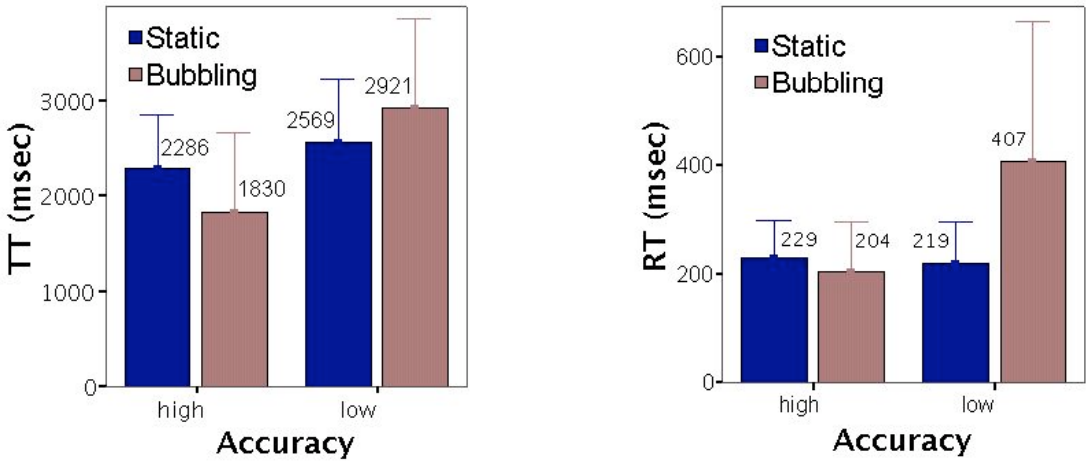
Hypothesis 5.5. Bubbling menus will increase total selection time (*TT*) in low accuracy.

6.6.8 Results

Errors due to wrong item selections or accidental collapses of first-level menus were removed from our analysis. Error rates were 1.68% for static menus and 3.41% for bubbling menus. Although higher, the error rate for bubbling menus is reasonable if taking into consideration the novelty of the technique and the unpredictability of suggestions. Besides, this error rate was considerably lower (2.59%) for the high-accuracy condition compared to its value (4.22%) for the low-accuracy condition.

Figure 6.16 (a) demonstrates mean times as measured for the two accuracy conditions. Hypotheses 5.4 and 5.5 were confirmed. Bubbling menus improved mean selection speed by 20% when accuracy was high (Hypothesis 5.4). However, they reduced mean performance by approximately 14% when accuracy was low (Hypothesis 5.5). An ANOVA analysis with accuracy treated as a between-participants variable and technique, block, and task treaded as repeated measures showed that the main effect of accuracy on *TT* was statistically significant ($F_{1,14}$=35.308, p<.0001). Its interaction effect with technique was also significant ($F_{1,14}$=36.846, p<.0001). A post hoc comparison using Bonferroni's adjustment showed that

bubbling menus significantly improved performance (p=.0003) in high accuracy and significantly decreased performance (p=.002) in low accuracy. No significant learning effects were found, i.e., the main and interaction effects of the block variable were not found to be significant.



(a) Mean Total Times (b) Mean Response Times

Figure 6.16. Overall results. Error bars represent standard deviations.

The poor performance of bubbling menus in the low-accuracy condition can be partially explained by the inflation of response times as shown in Figure 6.16 (b). The results indicate that participants who experienced the low accuracy tended to spend more time "thinking" before starting moving the mouse. However, a deeper analysis of the results showed that response times were not evenly distributed among these participants. Different participants followed different strategies, which explains the great variance shown in the figure. Figure 6.17 shows that some participants exposed to the low-accuracy condition did not get any benefit from the use of the bubbling menus even when suggestions were perfect.

As shown in Figure 6.18, not only did low accuracy hurt overall performance, it delayed menu selections even when suggestions were perfect. This result is consistent with our previous results presented in Chapter 4, indicating that when user trust over automation (Lee and See, 2004) declines, correct adaptations become less effective. An ANOVA analysis applied on the ten base tasks of each block showed a significant main effect of accuracy

($F_{1,14}$=9.68, p=.008), and a significant main effect of technique ($F_{1,14}$=34.27, p<.0001) on *TT*. Their interaction effect was not observed to be significant though ($F_{1,14}$=3.23, p=.094). As shown in Figure 6.18, bubbling menus were particularly effective when targets appeared in 3rd level menus. Selections in 3rd level menus involve two steering motions, and therefore, the strengths of the technique became more apparent.

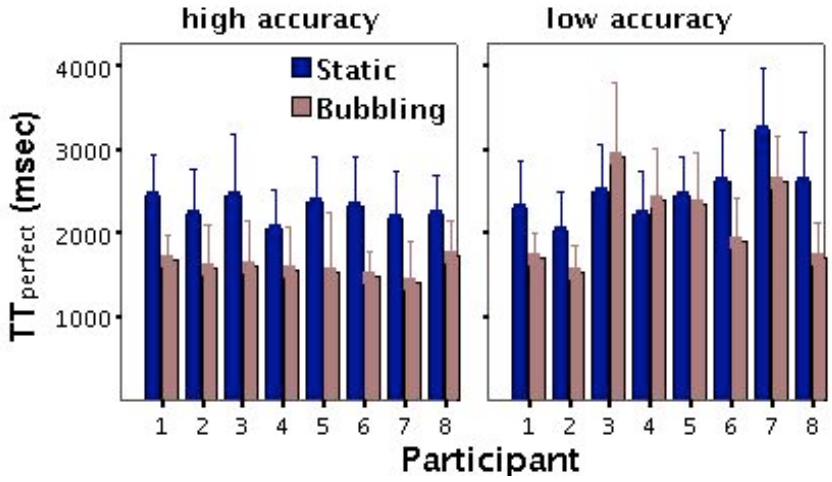


Figure 6.17. Performance of each of the sixteen participants when suggestions were perfect.

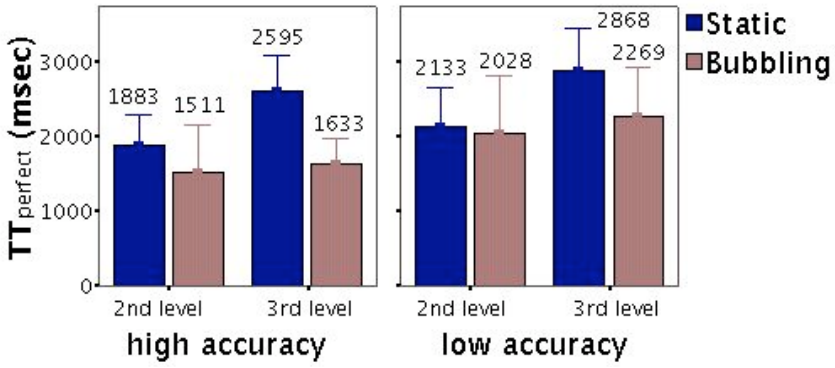


Figure 6.18. Performance for perfect suggestions shown separately for 2nd and 3rd level menus.

6.6.9 Subjective User Feedback

Most participants stated that bubbling menus helped them access suggested items faster and commented that they would use the new design as long as suggestions were generally accu-

rate. Several participants were very enthusiastic about their use. On the other hand, one participant was very negative. Exposed to the low-accuracy condition, he felt that interaction with bubbling menus added unnecessary complexity to a rather simple task. Another participant, also exposed to the low-accuracy condition, mentioned that sometimes, she had to "be attentive to too many details", which was "time-consuming".

Several participants disliked the fact that splitting menus into sub-areas was only applied to first-level menus. Although they found the mechanism useful, they felt that it was not applied consistently.

6.6.10 Conclusions

In conclusion, bubbling menus performed significantly better than static menus when accuracy was relatively high, but their performance was worse in the low-accuracy condition. Note that the experiment tested a worst-case scenario, where suggestions were completely unpredictable. As a participant commented "if this was an actual system I used, it is very likely that I would know which items are highlighted and which are not. In that case I would choose my strategy before starting the action".

Furthermore, participants were instructed to select highlighted items with the bubble cursor as frequently as possible. As participants were not aware of how menus had been adapted, they had to spend time deciding about their selection strategies and frequently switch between interaction modes. In real environments, usage patterns often change slowly and semi-static predictable adaptation schemes can be applied. As opposed to other adaptation techniques, bubbling menus do not disrupt the order of items in a menu and do not enforce the use of dragging gestures. We hypothesize that in low-accuracy environments, during, for instance, the learning stage of a classification mechanism, users would choose not to activate the alternative view of the menus. On the other hand, we expected that as soon as

they anticipated that the system had learnt their selection patterns, they would (optionally) take advantage of the technique according to their needs.

6.7 Supplementary Experiment

As discussed in Section 6.2, results by Cockburn and Gin (2006) suggest the hypothesis that removing delays from the interaction with submenus might improve performance even if activation areas were not increased. If this hypothesis was true, someone could attribute gains shown by our results to the elimination of such delays. To clarify this issue, we conducted a supplementary experiment with two male and two female participants. The experiment compared the regular menus tested in our main experiment (Delay) against menus with no delays (No Delay). We used the same experimental setup as the one presented in Section 6.6, but we kept only two blocks per technique. As in the main experiment, each block consisted of 35 menu selection tasks. The four participants were divided into two equal groups that were exposed to the two techniques in a different order. Each session lasted approximately 15 minutes.

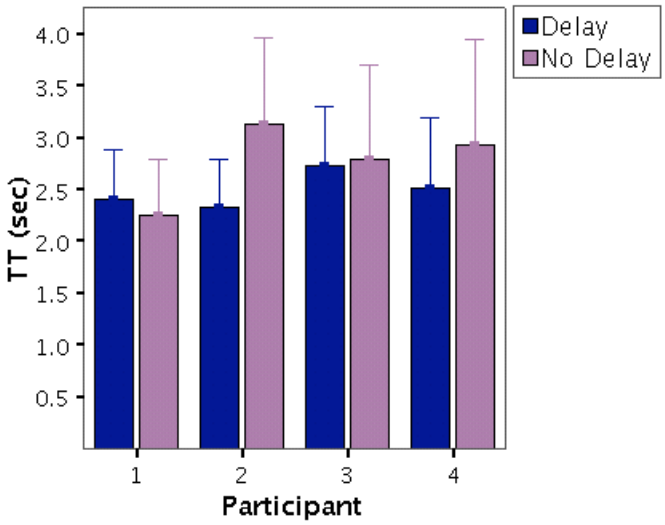


Figure 6.19. Results. Mean selection times (TT) per participant.

Mean selection times are presented in Figure 6.19. Participants 1 and 3 tested the Delay technique first, whereas Participants tested the No Delay technique first. The removal of the delay has only slightly improved the performance of Participant 1 (+6.7%). On the other hand, it harmed the performance of Participant 2 (-34.2%) and Participant 4 (-16%). The performance of Participant 3 was not affected.

The results show an advantage of Delay over No Delay, although a repeated measured ANOVA analysis did not show any significant difference between the two techniques with respect to selection times ($F_{1,3}$=1.745, p=.28). It seems that the order of exposure to the two techniques resulted in learning effects that obscured the results. Although a clear answer concerning the validity of the tested hypothesis would require a larger number of participants and blocks, the experimental results indicate that removing the delay would hurt rather than improve performance. Subjective feedback given by participants verified this fact. All the four participants preferred the version of menus that preserved delays, as it did not require them to perform perfect steering motions. One participant reported that he had to be very attentive to avoid errors when using the No Delay technique. In conclusion, existing evidence does not justify the removal of delays from the interaction with submenus if activation areas are not expanded.

6.8 Extended Design

In this section, we present the last iteration of our design. Trying to maximize the benefits of our approach and reach our initial goals, we extended the design so that selection gestures could start far from a menubar. As stated in Section 6.1, our goal was to allow users to select frequently selected menu items with rough, uninterrupted mouse strokes, instead of requiring them to move the mouse to the menubar, click on the menu label and then start a new movement to select the menu item.

Menu labels in a menubar are placed across a horizontal direction, which is normally perpendicular to the movement direction. Therefore, we first considered adopting selection techniques that use information about direction such as drag-and-pick (Baudisch et al., 2003) and object pointing (Guirard et al., 2004). However, such an approach would require the use of two different techniques to select items: one for the activation of the menu from the menubar and one for the selection of the goal item within the activated menu. In order to minimize the complexity of the design, we finally decided to use a single technique, the bubble cursor, for the activation of menus. Besides, compared to the drag-and-pick and object-pointing techniques, the bubble cursor gives richer visual feedback and is easier to control and use to correct errors.

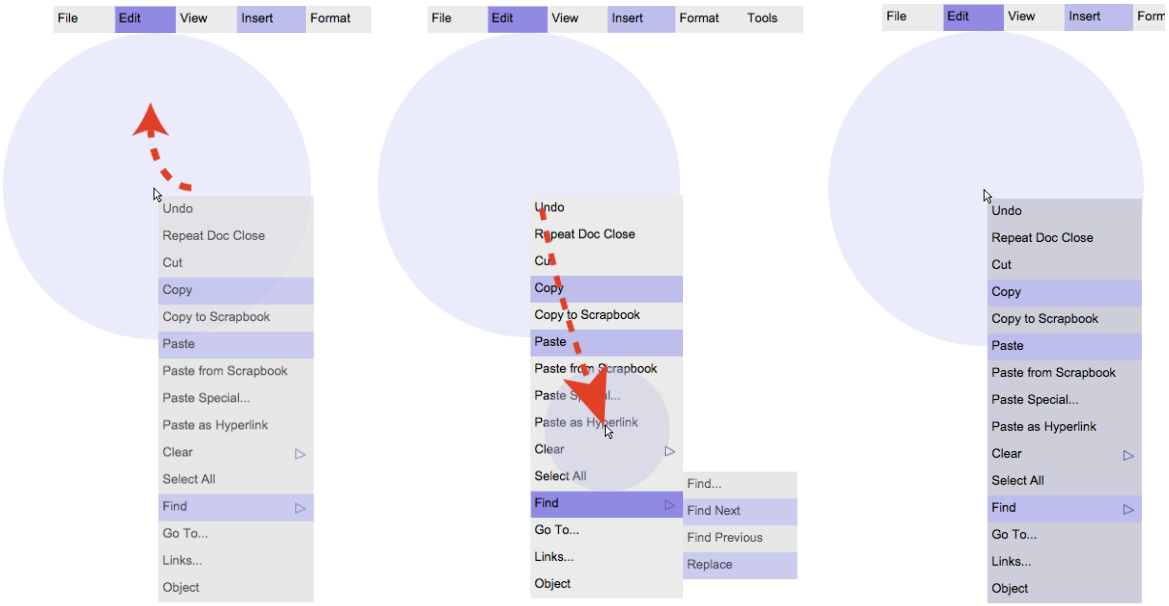
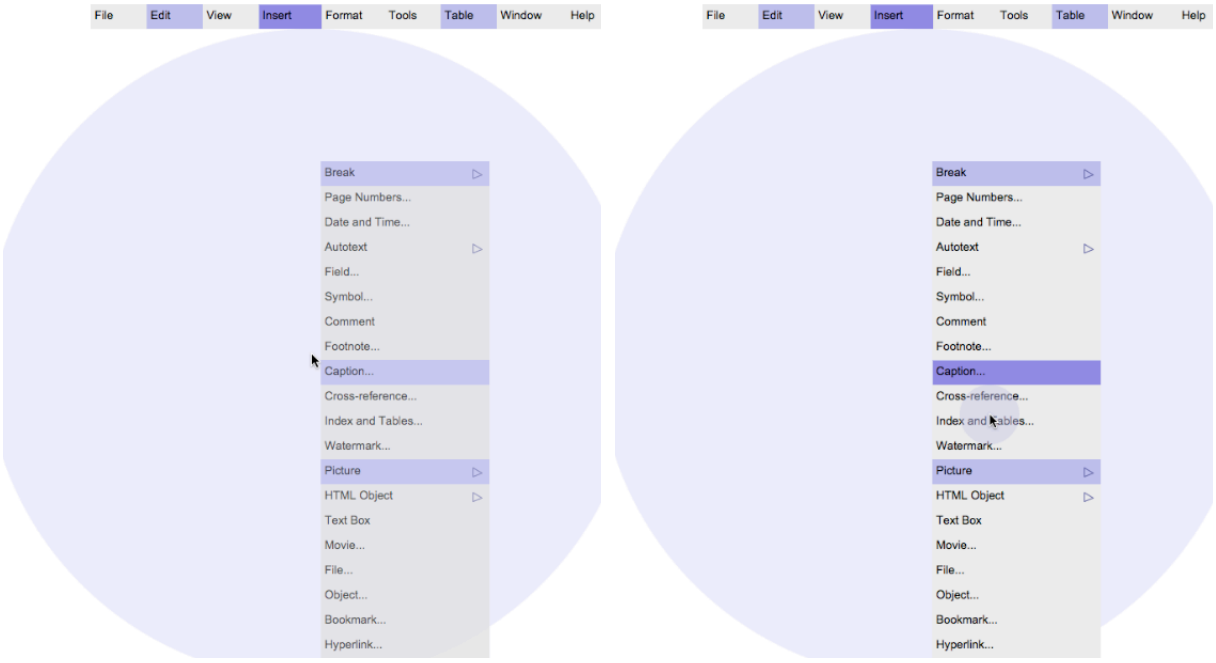


Figure 6.20. The extended design of bubbling menus. (a) When the user drags the right mouse button, a bubble appears that selects highlighted menu categories. A preview of the corresponding menu follows the cursor as the cursor's center moves towards the menubar. (b) The user moves the mouse downwards while dragging. The position of the menu freezes and a second bubble allows for the selection of highlighted items within the menu. (c) Alternatively, the user can release the button to activate the default view of a menu.

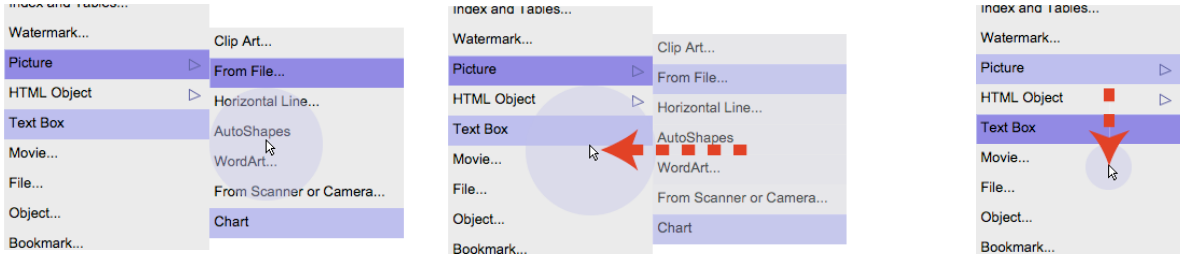
The extended design is illustrated in Figure 6.20. As shown in the figure, hot menu items can be selected with single-stroke gestures starting from any position on the screen. Again, dragging the mouse to activate the bubble cursor is optional, initiated by users based on their own intentions and needs. The new design makes use of two bubble cursors, activated at different stages. The outer bubble cursor selects highlighted menu categories from a menubar. The nested bubble cursor selects items within menus like in our first design. The first bubble cursor is activated after dragging the mouse for a small distance (20 pixels) while pressing the right button. This interaction enables its direct application to a wide range of applications in Microsoft Windows, where contextual menus are activated after the right mouse button is released. In Mac OS X, contextual menus are activated when the right button is pressed. However, its integration into Mac OS X would be feasible with minor changes. For example, it could be implemented by adding a brief delay before the activation of contextual menus, so that sensing a dragging motion could be possible.

The outer bubble cursor is enhanced with menu previews that follow the movement of its center. Such previews are always fully visible even when dragging starts far from the top of the screen, as shown in Figure 6.21. Expecting that menu previews would reduce the need for error corrections and taking into consideration participants' feedback from the previous evaluation, we decided to remove the left sub-area of first-level menus and keep the same interaction model for all the levels of nesting. We also improved the backtracking mechanism. Some participants complained that sometimes, an active submenu unexpectedly collapsed when they backtracked, planning to select a non-highlighted item within the submenu. Our solution, shown in Figure 6.22, addresses this problem by freezing the selection of a parent menu item when moving back to a previous level.



(a) (b)

Figure 6.21. Activating a long menu far from a menubar while pressing the right mouse button. (a) The menu preview appears close to the mouse cursor so that it is fully visible. Its location follows the cursor but when (b) it moves downwards and towards its boundaries, the alternative view of the menu is activated, and the user can use the inner bubble cursor to select hot items in the menu.



(a) (b) (c)

Figure 6.22. Improved backtracking. (a) The user enters a submenu while dragging. (b) If moving to the back level, the bubble selects the activated parent item ("Picture") rather than selecting the nearest highlighted item ("Text Box"). (c) The user slightly moves the mouse vertically to update the selection.

6.9 Evaluation of the Second Design of Bubbling Menus

A last user study was conducted to evaluate the second design of bubbling menus. This study provided mostly qualitative data about strengths and weaknesses of our approach in a more realistic setting than the previous user studies. Participants performed common menu selection tasks using a simulation of the menu structure of Microsoft Word 2004 for Mac (MSWord). Rather than testing an adaptive version of bubbling menus, we evaluated a customizable version, in which users manually highlighted items. The evaluation had three main objectives: (1) to establish useful criteria and strategies of customization/adaptation based on needs of various users; (2) to test how users would take advantage of bubbling menus when interacting with a familiar menu structure; and (3) to collect feedback about the usability and potential of our approach.

6.9.1 Techniques

To better satisfy our third objective, we contrasted our design against a design of customizable split menus. The version of split menus that we tested (see Figure 6.23) extends the original design of split menus (Sears and Shneiderman, 1994) by permitting the placement of submenu items in the top section of customized menus. Following the suggestion of Gajos et al. (2006), we changed the original design so that items were copied rather than moved to the top section. This approach is less intrusive as it does not prevent users from accessing the original structure of menus. Finally, we used a customization mechanism similar to the one proposed by Findlater and McGrenere (2004), but instead of using virtual buttons attached to the menu, users pressed the Page Up/Page Down keys while hovering over an item to control the item's position. Bubbling menus were customized by pressing the spacebar key, which caused items to get highlighted or return to their regular non-highlighted form.

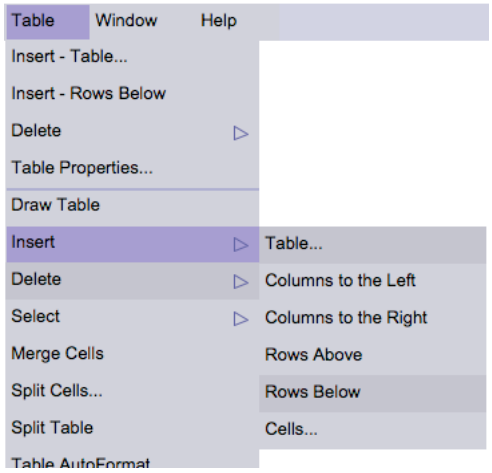


Figure 6.23. Our version of cascading split menus. Hot items can be copied to the top area of the menu from any level of nesting. The original copy of these items is slightly grayed.

Figure 6.24. An instance of the software used in the study. Here, the user is asked to select the "Format Style" menu item. The next two items to be selected are also shown. The user has to instantly hover over the red rectangle in order to start the task.

6.9.2 Apparatus

As in the previous two studies, a PowerBook G4 12-inch laptop was used with screen resolution 1024x768 and 768 MB RAM, running Mac OS X 10.4.4. Participants interacted with a USB mouse. A screenshot from the software used in the study is shown in Figure 6.24. The small red rectangle shown in the figure indicates the starting point for the next selection task. Its position varies for different tasks. The bottom-left part of the screen shows the next item to be selected as well as the two following menu items. The rationale behind revealing the next three tasks rather than one task was to imitate more realistic scenarios, in which users are aware of the context of their tasks and can plan their next actions accordingly. For instance, users always know that a "Paste" command will follow a "Copy" command or that an "Insert Table" command will be followed by a "Format" or an "Insert Row" command.

6.9.3 Participants

Six volunteers participated. The background of the participants is as follows: two Ph.D. students in Computer Science (females, 29 and 30), a Master's student in Architecture (male, 24), a professional engineer and programmer (male, 33), a high-school teacher in Physics (male, 31), and a civil servant (male, 39). All the participants were users of MSWord.

6.9.4 Procedure

At first, participants were asked to complete a questionnaire (see Appendix B.4) about their familiarity with MSWord and about strategies that they used to activate commands in office applications. Then participants were presented the menu structure of MSWord and were asked to freely explore it for 2-3 minutes. To test their familiarity with the menus, the experimenter asked them to locate and activate specific commands. After this step, participants were introduced to the two tested techniques. Order of exposure to the techniques was balanced among participants.

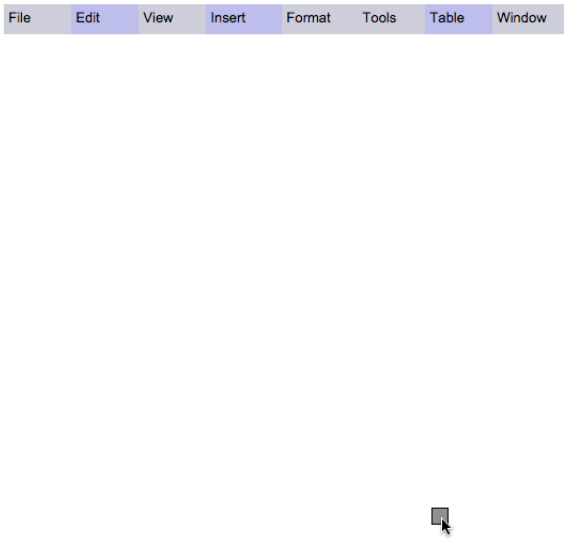


Figure 6.25. When the user places the cursor over the red rectangle, the rectangle's colour changes to grey and the user can move to select the target.

For each technique, the following procedure was followed. Initially, participants were explained the selection and customization mechanism supported by the technique. Then they were asked to customize the menus based on their personal needs while thinking aloud. Lastly, they were asked to complete two tasks. The first task acted as a training session, allowing participants to develop their customization and selection strategies. Each task had three steps. First, participants completed 38 menu selection trials without using the technique. The order of trials simulated sequences of common commands, needed to complete realistic tasks such as inserting and formatting pictures and tables. Second, participants were asked to customize the menus according to their experience through the first step. They were also asked to justify their customization strategy. Third, they were asked to complete 50 menu selection trials. 94% of these trials asked for items appearing in the first step with a similar frequency. 70-75% of the trials were first-level menu selections and the rest were second-level menu selections. To start a trial, participants placed the cursor over a small red rectangle, that appeared at various positions on the screen (see Figure 6.24). As shown in Figure 6.25, the colour of the rectangle was switched to grey instantly after the cursor was

placed over its boundaries, notifying the participant to start the selection task. Together with the colour change, a brief beep sound was produced as audio feedback

Participants were instructed to follow strategies that would best facilitate their tasks without rushing. The use of the customization and selection mechanisms supported by the techniques was optional. At the end, participants were given a questionnaire (see Appendix B.4) to evaluate the two techniques and rank them against traditional menus. Evaluation sessions lasted from 80 to 120 minutes.

6.9.5 Results

Familiarity with the MSWord menus varied across participants. Two participants (Architecture student and civil servant) spent time searching before being able to locate several commands. The rest of participants could select nearly all the commands required by the tasks without any searching. The following paragraphs summarize our results. The summary is based on data recorded in log files, notes taken by the experimenter during the sessions, and answers given to the questionnaires.

Customization Strategies

Although frequency of use was the primary criterion of customization for all the participants, customization strategies varied greatly among them. For split menus, the maximum number of items copied to the top section of a menu ranged from four up to seven items. Participants' comments indicated four distinct strategies used to sort items within the top section of a split menu: (1) sorting items according to the frequency of their selection from top to bottom; (2) preserving the original order of items; (3) grouping items based on logical relationships, e.g., keeping Cut, Copy and Paste together; and (4) ignoring order. Copying nested items to the top section was a common strategy. According to two participants, replicating frequently selected items that were either nested or appeared near the bottom of a long menu was particularly useful.

For bubbling menus, the maximum number of highlighted items in a menu ranged from four to ten. Proximity between menu items did not seem to determine the customization patterns of participants. Neighbouring items such as Undo, Cut, and Copy were all highlighted as they were all used. A participant explained that he chose to highlight all the items belonging to frequent command sequences. This strategy helped him to easily remember how items had been customized and minimized the need for switching between different selection techniques. Various strategies were used for customizing the menubar. Two participants highlighted all the menu categories as long as they were selected at least once throughout the task. Other participants did not highlight menu categories if they did not contain a minimum number of frequently selected items, e.g., more than two items. A participant observed that highlighting both the File and Edit menus reduced the effectiveness of the bubble cursor. He explained that File was an important menu but its items were less frequently selected. Therefore he preferred highlighting only the Edit menu. Finally, two participants stated that if hotkeys were available, they would use the customization mechanisms only for commands not usually being selected through hotkeys.

Selection Patterns

After split menus had been customized, items could be found in the top section of split menus with an average success rate of 68%. In bubbling menus, the average success rate for highlighted goal items and highlighted top menu categories was 73% and 87%, respectively. Error rates due to incorrect selections were 1.7% for split menus and 2.6% for bubbling menus.

Surprisingly, one participant (civil servant) did not use any dragging gestures to interact with bubbling menus. He explained that the use of bubbling menus increased the mental load required to complete selection tasks. He kept, however, customizing the menus because, as he explained, highlighting improved visual search. The other five participants used the technique heavily. On average, in 80% of the trials, users activated the outer bubble cursor.

Also, in 70% of the trials, the goal command was selected with the bubble cursor. Besides, results indicate that the five participants remembered how menus had been customized and used the bubbling menus selectively. More specifically, the probability that highlighted goal items were not selected with the bubble cursor was only 4%. Also, the probability that a bubble cursor was falsely activated to select a non-highlighted goal item under a non-highlighted menu category was 12%. Overall, for these five participants, the alternative view of bubbling menus was falsely activated in approximately 7% of the total number of trials. The same participants "missed" activating the bubble cursor in approximately 3% of the total number of trials.

Preferences

Three participants, a computer scientist, the Physics teacher, and the professional engineer, ranked bubbling menus as their first choice, split menus as their second choice, and traditional menus as their last choice. According to the first participant, bubbling menus "allow eyes-free selection and gracefully deal with more items than split menus". The second participant stated that bubbling menus "are not very easy to learn but when you do learn they are very fast in use". He also noted that "you don't have to be very accurate with the mouse", as the activation area of menu items is larger than in normal menus. The third participant commented that bubbling menus would be more appropriate for expert users. He explained that they better supported selection speed, whereas split menus might be more appropriate for menu-browsing tasks as opposed to goal-oriented tasks.

The second computer scientist and the civil servant ranked split menus as their first choice followed by bubbling menus. The former explained that split menus were faster than traditional menus and "less problematic to control" than bubbling menus. She noted, however, that bubbling menus did "not require accurate motor control" and if she had "mastered" the technique, bubbling menus might have been ranked as a first choice. Finally, the Architecture student ranked split menus as his first choice followed by traditional menus. He

found that bubbling menus were sometimes “confusing” stating that “speed is the strength of the mechanism, but it needs awareness”.

Participants were asked whether they would prefer a different version of split menus, where items were moved instead of copied to the top section. Five out of the six participants preferred our version of split menus because it supported memorization and allowed them to ignore the top section. On the other hand, one participant observed that copying instead of moving menu items overloaded menus with redundant information.

6.9.6 Conclusions

In conclusion, five out of the six participants activated the bubble cursor regularly and rather effectively. On the other hand, participants’ preferences varied greatly. Only half of the participants preferred bubbling menus to split menus.

Results suggest that bubbling menus could be more appropriate for experienced users, who having familiarized with the menu structure can make selections with single-stroke gestures. We expect that if customization remains constant over time, experienced users can use bubbling menus in a fashion similar to using marking menus (Kurtenbach and Buxton, 1993). On the other hand, we recognize that some participants found that bubbling menus were harder to use than traditional menus and split menus. A common difficulty that participants encountered was using the backtracking mechanism to cancel the bubble cursor. More intuitive view-switching mechanisms, such automatically canceling the bubble cursor when the cursor’s center is halted over a menu option, would allow for reducing the cognitive load associated with decision-making and error correction.

6.10 Summary and Discussion

This chapter presented a user-centered design process to develop bubbling menus, a new personalization technique for cascading drop-down menus. Bubbling menus facilitate the

selection of a subset of menu items, for example, frequently selected items. The design has been based on the bubble cursor (Grossman and Balakrishnan, 2005), directional mouse-gestures and floating menus to accelerate menu selection. Bubbling menus do not disturb the structure of menus and allow users to decide on their own on whether and when to initiate adaptation. These have been major goals for our design approach, significantly differentiating it from previous work on adaptive and adaptable menus.

The proposed technique has evolved through two design iterations and has been evaluated extensively. In particular, we have conducted four user studies. Results and observations coming from these studies have suggested that bubbling menus have several strengths:

1. Menu selection is quick. Menus can be accessed with rough, single-stroke mouse gestures. The user does not have to move the mouse over a menubar to initiate a selection task.
2. The use of dragging gestures to initiate the bubble cursor is optional. By default, users can access menus in their traditional form. Yet, even if they choose not to activate the bubble cursor, users can benefit from the fact that "hot" items are highlighted.
3. Users can initiate the bubble cursor at will, without having to interrupt their ongoing selection tasks.
4. Bubbling menus allow for simple customization mechanisms. Customization can be performed incrementally, in parallel with menu selection.

On the other hand, we have identified some limitations of the new technique.

1. Bubbling menus increase the complexity of the interface. Learning how to use them effectively requires practice. The additional complexity can discourage some users from using the technique.

2. Having to switch between two modes of interaction increases the cognitive overhead, particularly when users are uncertain about how menus are adapted. This additional overhead could hurt rather than improve performance.
3. Mainly due to the above two problems, bubbling menus can increase the error rate when compared to regular or split menus. The first evaluation study revealed an increase in error rate from 1.68% to 2.59% in the best case. Results from the second evaluation showed a similar trend. Although error inflation is a common problem of newly-introduced techniques that support fast target selection, e.g., see (Kurtenbach and Buxton, 1993), (Zhai et al., 2003), (Baudisch et al., 2003), and (Ahlstrom, 2005), it is a problem that designers should consider.

Given the above limitations, we suggest that the new design should be used in environments where any uncertainty about how menus are personalized is minimal. This is possible if menus are manually customized by the user or alternatively, if they are adapted based on usage patterns that quickly stabilize over time. In such scenarios, the cognitive overhead due to decision-making can be minimal. Notice that according to the first evaluation study, users can still benefit from the technique even if they do not have perfect knowledge of which items are highlighted. Low uncertainty levels in the range of 10-15% seem to be acceptable. Finally, as discussed in Section 6.9.6, we believe that the technique can improve if more intuitive mechanisms for switching between views are added. Such mechanisms could reduce the complexity of the design, improve error rates, and increase learnability.

Chapter 7

Conclusions and Future Directions

The goal of this dissertation has been to gain a systematic understanding of the design and evaluation of adaptive and adaptable user interfaces. With respect to this goal, its main objectives have been: (1) to design new adaptation techniques for a range of interfaces; (2) to explore tradeoffs between adaptive user interfaces and adaptable user interfaces; and (3) to investigate approaches for the systematic evaluation of adaptation techniques. These objectives have been met, within the scope of specific application domains.

7.1 Contributions

Below, we summarize the main contributions of the dissertation.

7.1.1 Design of Techniques for Adaptive and Adaptable Hypermedia

The dissertation has introduced a range of techniques for adapting hypermedia applications. We have focused on how automation and user control can be effectively coupled. Specifically, we have presented two prototypes that introduce new techniques to help users person-

alize the presentation of Web content, hyperlinks on Web pages, and browsing histories. The prototypes include mechanisms that allow users to define their own classification schemes, represent the parameters of these schemes by sliders, and manipulate the sliders to filter information on Web pages. We have demonstrated how such interactions can be realized in a Web environment. We have also explored several interaction techniques that let users control the adaptation of hypermedia content: zoomable tags to represent parameters of a user model, popup sliders to control the user model, popup glosses to provide feedback about hidden information, and animation to support fluid transitions between adapted views of Web content. The dissertation documented two small user studies that evaluated these techniques.

7.1.2 Systematic Treatment of Accuracy Effects in Experimental Designs

As opposed to static user interfaces, adaptive user interfaces are built on top of user modeling and decision-making mechanisms, whose actions are out of the direct control of users. A result of this is that the success of an adaptive interface relies on the ability of the underlying adaptation mechanisms to infer the needs of users and make correct decisions. If an adaptation technique is tested on top of poor inference and poor decision-making, it is likely that no benefits will be observed.

The dissertation explored this issue in connection with previous work on the evaluation of adaptive user interfaces. It suggested that evaluations of adaptive user interfaces should separate the user interface from the underlying adaptation mechanism, ensuring, at the same time, that variable properties of the adaptation mechanism are identified and controlled or treated as independent variables. Our work primarily focused on the effect of adaptation accuracy on the performance of adaptation techniques. To explore this effect, we conducted an experiment with 12 participants that compared two adaptation techniques for long lists, under various accuracy levels. We found accuracy affects the overall success of an ad-

aptation technique and determines how it compares with others. For instance, scaling out items that are infrequently selected reduces the visual space of the list and facilitates the selection of frequently selected items. However, this technique can seriously hinder user performance if the adaptation mechanism cannot accurately predict the real selection patterns of the user. We also found that accuracy had a great impact on how users made use of automatic assistance. We observed that user reliance on adaptation decreases as accuracy becomes low. When interacting with adaptive lists, participants tended to miss system suggestions if there was a high probability that the suggestions would be wrong. We observed similar effects when, later, we evaluated a new design of personalized menus. When participants interacted with an adaptive version of the menus, they tended to be more cautious about system suggestions when accuracy was low than when accuracy was high. In particular, they spent more time "thinking" before following suggestions, even when suggestions were correct.

Based on our findings, we made recommendations about how accuracy should be considered when evaluating adaptive user interfaces.

7.1.3 Design and Evaluation of Bubbling Menus

The dissertation has introduced bubbling menus, a new design of personalized cascading menus. To our best knowledge, bubbling menus is the first widget implementation that makes use of the bubble cursor (Grossman and Balakrishnan, 2005). The new technique improves selection performance, allowing users to access menu items with rough mouse movements. Contrary to other designs, it does not change the original structure of menus to provide adaptation. Furthermore, the activation of the quick selection mechanism supported by its design is optional. Users can activate it at any time and only if they think that it can facilitate their task.

Bubbling menus have been developed through an extensive user-centered design process. This process involved two main design iterations and four user studies. First, an experiment with 12 participants was conducted, in the context of simple pointing tasks, to assess cognitive overheads associated with decision-making when target expansion is user-initiated. A second user study with 16 participants evaluated our first design of menus, focusing on motor performance. A third study with four participants tested a potential bias of the control condition tested by the second study. Finally, a fourth study with six participants was conducted to evaluate the final design of bubbling menus in more realistic tasks. The second study tested an adaptive version of the proposed design, whereas the fourth study tested a customizable version of the design, contrasting it with customizable split menus (Findlater and McGrenere, 2004).

We have concluded that bubbling menus are more useful for experienced users. We have also suggested that they are appropriate when uncertainty about how menus are adapted is low. Therefore, personalization in bubbling menus should be based on customization or selection patterns that become stable over time.

7.2 Future Directions

We see three main directions for future work: (1) improving our designs and extending them to other types of widgets and interfaces; (2) exploring aspects of adaptive behaviour that were not examined by this dissertation; and (3) establishing detailed design guidelines for adaptive/-able user interfaces through comparative evaluation studies.

7.2.1 Improving and Extending the Proposed Designs

There are many possibilities for improving and extending the interaction techniques presented in this dissertation. First, our proposed Web-based adaptation techniques have been applied to a small range of pages. Their generalization to a broader class of pages is not

straightforward. For instance, the fisheye-like adaptation technique cannot be applied directly to pages that contain multiple columns like a front page of a newspaper. New techniques should be developed for more general page layouts. Furthermore, we need to evaluate our designs in more realistic scenarios and verify whether users would make use of the proposed controllers to adapt Web pages.

The implementation of more effective mechanisms for controlling adaptation is another future goal. In Chapter 4 (Section 5.5), we have proposed an improved design of shrinking lists, which allows users to fluidly switch from shrunk views, that provide global context, to expanded views, that support local focus and better motor control. View switching in bubbling menus could be improved with mechanisms that do not require users to move the mouse to the right of a menu. A mechanism that we have considered is the use of time-sensitive target selection: when the user pauses over an item for more than a threshold time, the menu switches from the adapted to its normal view. We expect that this approach will reduce the cognitive overhead associated with decision-making under uncertainty. We also believe that such techniques can be useful for generic target-acquisition tasks. In particular, we have started experimenting with interaction designs, where frequently selected targets are selected with fast movements that expand their activation areas, while normal targets are selected with slower movements. Exploring time thresholds over which transitions between these two types of selection occurs is a challenging problem.

Another direction for future work is the application of bubbling menus to pen-based interfaces, where the absence of a keyboard disallows the use of hotkeys. Also, the technique could be extended to other types of widgets, such as contextual menus, toolbars and tree structures. When targets in an interface component cannot all fit on the screen, expansion of activation areas could be combined with distortion-based fisheye view techniques that visually shrink information to provide summarization. This approach would facilitate the access of frequently selected items in large lists of items.

Finally, it would be interesting to examine whether selection techniques other than the bubble cursor could be used to accelerate the selection of frequently selected menu items. The design of the bubble cursor does not take into consideration the direction of movement and other parameters of motion such as velocity and acceleration. Non-circular shapes of dynamically resizable cursors, e.g., ellipses, could be used to address this limitation. For instance, we have been considering designs in which the shape of a bubble cursor changes from circular to ellipsoid. Such designs can use information about motion and boost the selection of targets appearing along the movement direction. As an example, consider an ellipsoid cursor, whose major axis, parallel to the movement direction, grows as velocity increases, while the minor axis becomes shorter.

7.2.2 Studying Additional Parameters of Adaptation

The dissertation investigated the effect of accuracy, but other important parameters of adaptation have not been examined. For instance, we hypothesize that the stability of an adaptive user interface over time could greatly affect user performance. Slow changes in a user interface support predictability. On the other hand, slow changes cannot reflect rapid changes in user needs. Furthermore, Some widgets could be more sensitive to changes than others, e.g., menus compared to toolbars, depending on the frequency of their use and the type of tasks that dominate their manipulation, e.g., motor versus cognitive. Similarly, adaptation techniques that change the structure of the interface could be more sensitive to changes than techniques that simply annotate it. Testing the scope of these hypotheses will provide additional insight about the design of adaptation techniques.

Our evaluations were not conducted over real intelligent systems. On the one hand, this allowed us to control potential confounding variables. On the other hand, the effect of individual characteristics of inference mechanisms was not examined. Inference heuristics such as frequency of use and recency are easy to understand. Therefore, they are expected to

result in adaptive user interfaces with simple conceptual models. Adaptive menus in MS Office 2000 intermixed both recency and frequency of use (Findlater and McGrenere, 2004), possibly resulting in a complex conceptual model. Whether and to which extent this approach has affected the success of this interface is unknown. On the other hand, sophisticated inference mechanisms that combine multiple heuristics to predict user goals can be more accurate. Systematically studying this trade-off is a future goal.

Finally, we are interested in models that could describe performance in adaptive user interfaces. Cockburn et al. (2007) recently proposed a predictive model of menu performance, which models pointing time, as well as visual search and decision time. It also takes into consideration the transition of users from novices to experts. Using this model as a framework to study adaptation and model the performance of a wide range of adaptation techniques is a research direction worth of future investigation.

7.2.3 Establishing Detailed Design Guidelines for Adaptive and Adaptable User Interfaces

Despite the fact that adaptive user interfaces have existed for more than 20 years, research has not resulted yet in clear guidelines about the design of adaptive user interfaces. However, we envision that the systematic assessment of adaptation techniques through comparative studies will eventually lead to extensive guidelines about their design. Our experience has shown that adaptive user interfaces cannot completely change the way users interact with computers. Nevertheless, they can considerably improve usability, provided that they are carefully designed, take into consideration real user needs and respect well-established design principles. Some general guidelines about the design and evaluation of adaptive user interface, coming from our own research, as well as the work of other researchers, are summarized below.

- Expected benefits coming from the use of adaptation should be large enough to outweigh any potential costs. If benefits are expected to be tiny, adaptation should not be considered as an alternative solution, since adding complexity to the user interface might introduce new costs and hinder rather than help users.
- Adaptation techniques applied to an interface should be selected with respect to the expected accuracy. If accuracy is expected to be low, the technique should be as less intrusive as possible. Also, it should support mechanisms that let users overcome inaccurate system actions with minimal cost. The cost of inaccurate system actions could be further reduced by making adaptive behaviour transparent, helping the user predict its outcome and develop appropriate interaction strategies.
- Allowing users to adapt a user interface on their own could be more effective than automatically adapting it. Designers should consider effective ways to combine automation with adaptability.
- User characteristics such as user expertise should be carefully considered when designing adaptation techniques. For instance, adaptive behaviour should not disrupt the past experience of expert users, since they highly depend on it to complete their tasks. Novice users, on the other hand, might not notice changes in an adaptive interface, as their mental model is incomplete. However, in the long run, such changes could prevent them from learning to use the interface effectively.

Future work needs to explore these issues more systematically in various application domains and find the best trade-offs between benefits coming from adaptation and its costs.

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Appendix A Consent Forms for Main User Studies

A.1 Experiment on Adaptive Lists

CONSENT FORM

I agree to participate in a study that investigates the usability of various techniques on adaptive lists. I understand that my participation is entirely voluntary.

The following points have been explained to me:

1. The purpose of this research is to compare human ability to use various user interface techniques when interacting with adaptive systems. I understand that I will be asked questions about my previous computer experience. The benefits I may expect from the study are: (a) an appreciation of research on user interfaces, (b) an opportunity to contribute to scientific research. I do not expect any other benefits or any other kind of compensation apart from the aforementioned. I also understand that the results of this study will be submitted for publication.

2. The procedure will be as follows: I will perform various information-locating tasks lasting approximately 1-1:30 hour in total (including breaks). I will interact with a desktop computer using a mouse device.

3. The researchers do not foresee any risks to me for participating in this study, nor do they expect that I will experience any discomfort or stress.

4. I understand that I may withdraw from the study at any time.

5. I understand that I will receive a copy of this consent form.

6. All of the data collected will remain strictly confidential. Only people associated with the study will see my responses. My responses will not be associated with my name; instead, my name will be converted to a code number when the researchers store the data.

7. The experimenter will answer any other questions about the research either now or during the course of the experiment.

8. Upon completion of my participation, I will receive an explanation about the rationale and predictions underlying this experiment.

_____	_____	_____
Participant's Printed Name	Participant's Signature	Date
Experimenter Name: Theophanis Tsandilas	_____ Participant Number	

A.2 Experiment on Multimode Target Acquisition

CONSENT FORM

I agree to participate in a study that investigates the usability of various forms of adaptable user interaction. I understand that my participation is entirely voluntary.

The following points have been explained to me:

1. The purpose of this research is to compare human ability in using various techniques that have been designed to accelerate targeting performance in desktop environments. The research is part of the Ph.D. thesis of the experimenter. I understand that I will be asked questions about my previous computer experience. The benefits I may expect from the study are: (a) an appreciation of research on user interfaces, and (b) an opportunity to contribute to scientific research. I do not expect any other benefits or any other kind of compensation apart from the aforementioned. I also understand that the results of this study may be submitted for publication.

2. The procedure will be as follows: I will perform various targeting tasks lasting approximately 40-50 minutes (including breaks). I will interact with a desktop computer using a mouse device and a keyboard.

3. The researchers do not foresee any risks to me for participating in this study, nor do they expect that I will experience any discomfort or stress.

4. I understand that I may withdraw from the study at any time.

5. I understand that I will receive a copy of this consent form.

6. All of the data collected will remain strictly confidential. Only people associated with the study will see my results. The results will not be associated with my name; instead, my name will be converted to a code number when the researchers store the data.

7. The experimenter will answer any other questions about the research either now or during the course of the experiment.

8. Upon completion of my participation, I will receive an explanation about the rationale and predictions underlying this experiment.

_____ _____ _____

Participant's Printed Name Participant's Signature Date

_____

Experimenter's Name: Theophanis Tsandilas Participant Number

A.3 First Study on Bubbling Menus

CONSENT FORM

I agree to participate in a study that investigates the usability of various forms of adaptable user interaction. I understand that my participation is entirely voluntary.

The following points have been explained to me:

1. The purpose of this research is to compare human ability to use various user interface techniques that have been designed to facilitate selection in pull-down menus. The research is part of the Ph.D. thesis of the experimenter. I understand that I will be asked questions about my previous computer experience. The benefits I may expect from the study are: (a) an appreciation of research on user interfaces, (b) an opportunity to contribute to scientific research. I do not expect any other benefits or any other kind of compensation apart from the aforementioned. I also understand that the results of this study may be submitted for publication.

2. The procedure will be as follows: I will perform various menu selection tasks lasting approximately 1 hour (including breaks). I will interact with a laptop using an external mouse device.

3. The researchers do not foresee any risks to me for participating in this study, nor do they expect that I will experience any discomfort or stress.

4. I understand that I may withdraw from the study at any time.

5. I understand that I will receive a copy of this consent form.

6. All of the data collected will remain strictly confidential. Only people associated with the study will see my responses. My responses will not be associated with my name; instead, my name will be converted to a code number when the researchers store the data.

7. The experimenter will answer any other questions about the research either now or during the course of the experiment.

8. Upon completion of my participation, I will receive an explanation about the rationale and predictions underlying this experiment.

_____ _____ _____

Participant's Printed Name Participant's Signature Date

_____

Experimenter Name: Theophanis Tsandilas Participant Number

A.4 Second Study on Bubbling Menus

CONSENT FORM

I agree to participate in a study that investigates the usability of various forms of customizable user interfaces. I understand that my participation is entirely voluntary.

The following points have been explained to me:

1. The purpose of this research is to evaluate various customization techniques that have been designed to facilitate selection in pull-down menus. The research is part of the Ph.D. thesis of the experimenter. I understand that I will be asked questions about my previous computer experience. The benefits I may expect from the study are: (a) an appreciation of research on user interfaces, (b) an opportunity to contribute to scientific research. I do not expect any other benefits or any other kind of compensation apart from the aforementioned. I also understand that the results of this study may be submitted for publication.

2. The procedure will be as follows: First, I will be asked questions concerning my previous experience with using menus in office applications. Then, I will perform various menu selection tasks using two different techniques. Finally, I will be asked questions concerning my experience with the techniques presented to me. The whole procedure will last approximately 90-100 minutes (including breaks). I will interact with a laptop using an external mouse device and a keyboard.

3. The researchers do not foresee any risks to me for participating in this study, nor do they expect that I will experience any discomfort or stress.

4. I understand that I may withdraw from the study at any time.

5. I understand that I will receive a copy of this consent form.

6. All of the data collected will remain strictly confidential. Only people associated with the study will see my responses. My responses will not be associated with my name; instead, my name will be converted to a code number when the researchers store the data.

7. The experimenter will answer any other questions about the research either now or during the course of the experiment.

8. Upon completion of my participation, I will receive an explanation about the rationale and predictions underlying this experiment.

Participant's Printed Name	Participant's Signature	Date

Experimenter Name: Theophanis Tsandilas

Participant Number

Appendix B Research Instruments

B.1 Study on Control Mechanisms Applied to Hypermedia

Questionnaire

Please, complete all the questions below. Your feedback is important. Thanks for your time and help.

A. Complete the following information.

Sex: Male ( ) Female ( )

Age:

B. For each statement check the answer that best describes what you think.

1. I could easily understand the reaction of the system without any visual aid, i.e., glosses and labels.
   strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree ( )

2. I found hard to complete any task when no visual aid was provided.
   strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree ( )

3. I found the glosses disturbing.
   strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree ( )

4. The glosses helped me comprehend the reactions of the system.
   strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree ( )

5. The glosses helped me discover information and complete the given task.
   strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree ( )

6. The zooming labels were redundant and did not add any value.
   strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree ( )

7. The zooming labels helped me understand the system's behaviour and complete the given tasks.
   strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree ( )

8. The popup sliders were NOT helpful.
   strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree ( )

9. The popup sliders were very easy to use.
   strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree ( )

10. The animation was disturbing.
    strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree ( )

11. The animated pages helped me understand the transitions between their views.
    strongly disagree ( ) disagree ( ) neutral ( ) agree ( ) strongly agree ( )

C. Rate the following versions of the interface (1: best, 4: worst).

No visual aid (only animated pages):

Only glosses:

Both glosses and zooming labels but not sliders:

Everything (glosses, zooming labels, popup sliders):

D. Other comments:

B.2 Experiment on Adaptive Lists

Questionnaire

Please, complete the following questionnaire. Your feedback is important. Thanks for your time and help.

Complete the following information.

Sex: Male ( ) Female ( )

Age:

1. LOW ACCURACY: I think that about _____ of the cases the system's suggestions were correct:

   (a) 30-40% (b) 40 – 50% (c) 50-60% (d) 60 – 70%

2. HIGH ACCURACY: I think that about _____ of the cases the system's suggestions were correct:

   (a) 60-70% (b) 70 – 80% (c) 80-90% (d) 90 – 100%

Rate the three techniques that you used

(a) helped locate suggested items faster

normal sizes ( ) small sizes ( )

(b) helped locate non-suggested items faster

normal sizes ( ) small sizes ( )

(c) preferred when the system's predictions are accurate

normal sizes ( ) small sizes ( )

(d) preferred when the system's predictions are not very accurate

normal sizes ( ) small sizes ( )

B.3 First Study On Bubbling Menus

Questionnaire

Please, complete the following questionnaire. Your feedback is important. Thanks for your time and help.

Complete the following information.

Sex: Male ( ) Female ( )

Age:

Mark the answer that best describes your opinion about the statements presented in the following table regarding the menu-selection techniques that you tried.

	Strongly Agree	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
I have previous experience with interfaces that require dragging the mouse to select targets.					
Learning to select menu items by dragging the mouse was relatively easy.					
Having to identify whether a goal item was highlighted or not disturbed my task.					
Filtering the menus by dragging the mouse helped my to access highlighted items faster.					
Overall, using normal menus was more effective than using the menu-filtering technique.					
Given the option, I would use the menu-filtering technique as an alternative to access menu items.					

Report any problem that you may have experienced when interacting with the menus.

B.4 Second Study on Bubbling Menus

Cover Page for Participation (a)

Code of participant: C1 C3 C5

Checklist

A. Introduction

Give the consent form and have the participant sign it. ☐

Give the background questionnaire. ☐

Present the traditional menus and let the user explore them. ☐

B. Bubble Menus

Present the bubble menus (only menu items are highlighted). ☐

Press F1 to show how bubbles can reach menus in the menubar. ☐

Explain the customization mechanism. ☐

Press F2 and ask the user to customize the menus based in his/her own experience. Ask him/her to think aloud and justify his/her strategy. Take notes. ☐

Press F3 and ask the participant to complete menu selections, trying to remember which items have appeared. ☐

After the end of the section the participant will have to customize the menus. ☐

Press F4 and ask the participant to complete the selection tasks using the technique (optionally). ☐

After the end of the tasks, press F8, and have the participant to complete a new series of tasks. ☐

Customization starts again. Ask the participant to think aloud, and justify the customization strategy. Take notes. ☐

Press F4 and ask the participant to complete the selection tasks using the technique (optionally). ☐

Ask the participant to explain his/her strategy to select menus using the technique. ☐

Take a 5-minutes break. ☐

C. Split Menus

Present the split menus	☐
Explain the customization mechanism.	☐
Press F2 and ask the user to customize the menus based in his/her own experience. Ask him/her to think aloud and justify his/her strategy. Take notes.	☐
Press F3 and ask the participant to complete menu selections, trying to remember which items have appeared.	☐
After the end of the section the participant will have to customize the menus.	☐
Press F4 and ask the participant to complete the selection tasks using the technique (optionally).	☐
After the end of the tasks, press F8, and have the participant to complete a new series of tasks.	☐
Customization starts again. Ask the participant to think aloud, and justify the customization strategy. Take notes.	☐
Press F4 and ask the participant to complete the selection tasks using the technique (optionally).	☐
Ask the participant to explain his/her strategy to select menus using the technique.	☐

D. Feedback

Give the participant to complete the feedback questionnaire.	☐

Cover Page for Participation (b)

Code of participant: C2 C4 C6

Checklist

A. Introduction

Give the consent form and have the participant sign it.	☐
Give the background questionnaire.	☐
Present the traditional menus and let the user explore them.	☐

B. Split Menus

Present the split menus	☐
Explain the customization mechanism.	☐
Press F2 and ask the user to customize the menus based in his/her own experience. Ask him/her to think aloud and justify his/her strategy. Take notes.	☐
Press F3 and ask the participant to complete menu selections, trying to remember which items have appeared.	☐
After the end of the section the participant will have to customize the menus.	☐
Press F4 and ask the participant to complete the selection tasks using the technique (optionally).	☐
After the end of the tasks, press F8, and have the participant to complete a new series of tasks.	☐
Customization starts again. Ask the participant to think aloud, and justify the customization strategy. Take notes.	☐
Press F4 and ask the participant to complete the selection tasks using the technique (optionally).	☐
Ask the participant to explain his/her strategy to select menus using the technique.	☐
Take a 5-minutes break.	☐

C. Bubble Menus

Present the bubble menus (only menu items are highlighted).	☐
Press F1 to show how bubbles can reach menus in the menubar.	☐
Explain the customization mechanism.	☐
Press F2 and ask the user to customize the menus based in his/her own experience. Ask him/her to think aloud and justify his/her strategy. Take notes.	☐
Press F3 and ask the participant to complete menu selections, trying to remember which items have appeared.	☐
After the end of the section the participant will have to customize the menus.	☐
Press F4 and ask the participant to complete the selection tasks using the technique (optionally).	☐
After the end of the tasks, press F8, and have the participant to complete a new series of tasks.	☐
Customization starts again. Ask the participant to think aloud, and justify the customization strategy. Take notes.	☐
Press F4 and ask the participant to complete the selection tasks using the technique (optionally).	☐
Ask the participant to explain his/her strategy to select menus using the technique.	☐

D. Feedback

Give the participant to complete the feedback questionnaire.	☐

Background Questionnaire

The purpose of this questionnaire is to see if you will be a good fit for the study and collect background information concerning your experience in using menus in office applications. Note that all information provided will remain strictly confidential.

Section I: Personal Information

1. Age:

2. Gender:

Male [ ] Female [ ]

3. Occupation:

Section II: Use of Office Applications

4. Which operating systems do you currently use on a regular basis? Tick all that apply.

MS Windows [ ] Mac OS [ ] Linux [ ] Other(s), please specify: _____

5. Please indicate your experience with the following word processors.

MS Word	Not Used [ ]	Occasionally Used [ ]	Frequently Used [ ]
Open Office	Not Used [ ]	Occasionally Used [ ]	Frequently Used [ ]
Word Perfect	Not Used [ ]	Occasionally Used [ ]	Frequently Used [ ]
LaTeX	Not Used [ ]	Occasionally Used [ ]	Frequently Used [ ]
Other: _____	Not Used [ ]	Occasionally Used [ ]	Frequently Used [ ]

6. How would you characterize yourself in terms of your overall knowledge of MS Word?

I have basic knowledge	[ ]
I have moderate knowledge	[ ]
I have extensive knowledge	[ ]

7. How do you execute commands in office applications that you use regularly (e.g., print, save, open, copy, paste)? Tick all that apply.

Command	Select from pull-down menu	Select from toolbar	Use a hotkey
Print	[ ]	[ ]	[ ]
Save	[ ]	[ ]	[ ]
Open	[ ]	[ ]	[ ]
Copy	[ ]	[ ]	[ ]
Paste	[ ]	[ ]	[ ]
Insert Picture	[ ]	[ ]	[ ]
Insert Page Break	[ ]	[ ]	[ ]
Format Paragraph	[ ]	[ ]	[ ]
Insert Table	[ ]	[ ]	[ ]
Word Count	[ ]	[ ]	[ ]
Search for a word	[ ]	[ ]	[ ]

8. Please indicate how often you do the following activities when using word processors and other office applications. For the activities that you are unfamiliar with, tick the first box rather than using the scale.

1 = Never 2 = Seldom 3 = Occasionally 4 = Frequently

	Unfamiliar				
I create/edit styles	[ ]	1	2	3	4
I edit the format of the text and the paragraphs	[ ]	1	2	3	4
I create/edit tables	[ ]	1	2	3	4
I insert and format graphics (images, figures, charts)	[ ]	1	2	3	4
I insert captions to figures and tables	[ ]	1	2	3	4
I search for specific words occurrences in the text	[ ]	1	2	3	4

Feedback Questionnaire

The purpose of this questionnaire is to evaluate the techniques that you experienced, and help us improve menu-selection techniques. The questions concern your experience through the experiment with the following types of menus.

Split menus: These menus are split into two regions. The top region contains copies of a small number of items as specified by the user.

Bubble menus: Some items in these menus are highlighted with a light blue colour. The user can activate a *bubble* to select these items by dragging the mouse.

Traditional menus: These are the traditional menus as implemented in today's operating systems.

Section I: Split Menus

Please, answer the following questions concerning your experience from using the split menus.

1. Rank the menus with respect to the questions presented below. For each question, circle a single number from 1 to 7.

How easy was the use of the customization mechanism? (1 = hard, 7 = easy)	1	2	3	4	5	6	7
How easy to learn was the menu selection mechanism? (1 = hard to learn, 7 = easy to learn)	1	2	3	4	5	6	7
How high was the mental demand required for using the menus? (1 = HIGH demand, 7 = LOW demand)	1	2	3	4	5	6	7
How high was physical demand required for using the menus? (1 = HIGH demand, 7 = LOW demand)	1	2	3	4	5	6	7
How high was the performance of menus in terms of selection speed? (1 = LOW performance, 7 = HIGH performance)	1	2	3	4	5	6	7
How confusing was the customized view of the menus? (1 = confusing, 7 = NOT confusing)	1	2	3	4	5	6	7
How would you rate your overall experience with the split menus? (1 = unsatisfactory, 7 = satisfactory)	1	2	3	4	5	6	7

2. If an application gave you the option to customize your menus by splitting them, how frequently do you think you would take advantage of this customization mechanism?

never [ ] seldom [ ] occasionally [ ] frequently [ ]

3. **According to your opinion, which are the main strengths and/or the main weaknesses of split menus?**

4. **In the version of split menus that you tested, items were *copied* to the top region of the menus when customized by the user. Would you prefer a different version of menus in which items were *moved* to the top region instead of being copied?**

I prefer copying rather than moving the items	[ ]
I am not sure about which approach is better	[ ]
I prefer moving rather than copying the items	[ ]

5. **Briefly justify your answer to the previous question.**

6. **Would you fancy an automated version of split menus in which customization is automatically performed based on past usage patterns (e.g., frequently selected items are placed on the top region of the split menu)?**

I am **negative** to any automation in the customization of split menus	[ ]
I am **neutral**	[ ]
I am **positive** to the automatic customization of split menus	[ ]

7. **Briefly justify your answer to the previous question.**

Section II: Bubble Menus

Please, answer the following questions concerning your experience from using the bubble menus.

1. Rank the menus with respect to the questions presented below. For each question, circle a single number from 1 to 7.

How easy was the use of the customization mechanism? (1 = hard, 7 = easy)	1	2	3	4	5	6	7
How easy to learn was the menu selection mechanism? (1 = hard to learn, 7 = easy to learn)	1	2	3	4	5	6	7
How high was the mental demand required for using the menus? (1 = HIGH demand, 7 = LOW demand)	1	2	3	4	5	6	7
How high was physical demand required for using the menus? (1 = HIGH demand, 7 = LOW demand)	1	2	3	4	5	6	7
How high was the performance of menus in terms of selection speed? (1 = LOW performance, 7 = HIGH performance)	1	2	3	4	5	6	7
How confusing was the customized view of the menus? (1 = confusing, 7 = NOT confusing)	1	2	3	4	5	6	7
How would you rate your overall experience with the bubble menus? (1 = unsatisfactory, 7 = satisfactory)	1	2	3	4	5	6	7

2. If an application gave you the option to customize your menus by using the bubble-menus mechanism, how frequently do you think you would take advantage of this customization mechanism?

never [ ] seldom [ ] occasionally [ ] frequently [ ]

3. According to your opinion, which are the main strengths and/or the main weaknesses of bubble menus?

4. **Would you fancy an automated version of bubble menus in which customization is automatically performed based on past usage patterns (e.g., frequently selected items are highlighted)?**

   I am **negative** to any automation in the customization of bubble menus [ ]
   I am **neutral** [ ]
   I am **positive** to the automatic customization of bubble menus [ ]

5. **Briefly justify your answer to the previous question.**

Section III: Overall Experience

1. **Given the option to choose among Traditional Menus, Split Menus, and Bubble Menus, which would be your 1st, 2nd and 3rd choice?**

____Traditional Menus _____Split Menus _____Bubble Menus

2. **Why have you ranked them this way?**

3. **Do you have any other comments about the above versions of menus or your participation in this study?**

Notes taken by the experimenter

Section I: Bubble Menus

(a) Customization based on personal experience

While you customize the menus, please, explain your decisions by thinking aloud.

Briefly justify your customization strategy.

(b) Customization based on given task

While you customize the menus, please, explain your decisions by thinking aloud.

Briefly justify your customization strategy.

(c) Menu Selection

Explain your strategy to select menus.

Section II: Split Menus

(a) Customization based on personal experience

While you customize the menus, please, explain your decisions by thinking aloud.

Briefly justify your customization strategy.

(b) Customization based on given task

While you customize the menus, please, explain your decisions by thinking aloud.

Briefly justify your customization strategy.

(c) Menu Selection

Explain your strategy to select menus.