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Culturally Adaptive User Interfaces

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Abstract

One of the largest impediments for the efficient use of software in different cultural contexts is the gap between the software designs – typically following western cultural cues – and the users, who handle it within their cultural frame. The problem has become even more relevant, as today the majority of revenue in the software industry comes from outside market dominating countries such as the USA. While research has shown that adapting user interfaces to cultural preferences can be a decisive factor for marketplace success, the endeavor is oftentimes foregone because of its time-consuming and costly procedure. Moreover, it is usually limited to producing one uniform user interface for each nation, thereby disregarding the intangible nature of cultural backgrounds.

To overcome these problems, this thesis introduces a new approach called ‘cultural adaptivity’. The main idea behind it is to develop intelligent user interfaces, which can automatically adapt to the user’s culture. Rather than only adapting to one country, cultural adaptivity is able to anticipate different influences on the user’s cultural background, such as previous countries of residence, differing nationalities of the parents, religion, or the education level. We hypothesized that realizing these influences in adequate adaptations of the interface improves the overall usability, and specifically, increases work efficiency and user satisfaction.

In support of this thesis, we developed a cultural user model ontology, which includes various facets of users’ cultural backgrounds. The facets

were aligned with information on cultural differences in perception and user interface preferences, resulting in a comprehensive set of adaptation rules.

We evaluated our approach with our culturally adaptive system MOCCA, which can adapt to the users' cultural backgrounds with more than 115'000 possible combinations of its user interface. Initially, the system relies on the above-mentioned adaptation rules to compose a suitable user interface layout. In addition, MOCCA is able to learn new, and refine existing, adaptation rules from users' manual modifications of the user interface based on a collaborative filtering mechanism, and from observing the user's interaction with the interface.

The results of our evaluations showed that MOCCA is able to anticipate the majority of user preferences in an initial adaptation, and that users' performance and satisfaction significantly improved when using the culturally adapted version of MOCCA, compared to its 'standard' US interface.

Zusammenfassung

Eines der grössten Hürden, die dem effizienten Umgang mit Software durch Menschen verschiedener Kulturen entgegensteht, ist die Diskrepanz zwischen dem Software-Design, welches normalerweise nach westlichem Verständnis von Benutzbarkeit und Ästhetik entworfen wird, und den Benutzern, die die Software nach ihren ganz eigenen kulturell-geprägten Vorstellungen benutzen. Dieses Problem gewinnt zunehmend an Relevanz, nachdem die Mehrheit der Einnahmen der Softwareindustrie heutzutage nicht mehr nur aus marktdominierenden Ländern, wie den USA, stammt. Dem gegenüber stehen Forschungsergebnisse, die zeigen, dass die Anpassung der Benutzerschnittstellen an den kulturellen Hintergrund der Benutzer ein entscheidender Faktor für den Erfolg im Markt sein kann. Solch eine Anpassung, genannt Lokalisierung, wird in der Umsetzung jedoch meist noch vernachlässigt, und dies vor allem weil der Prozess enorm zeit- und kostenintensiv sein kann. Zudem ist eine Lokalisierung, wenn überhaupt, meist auf die Produktion einer Benutzerschnittstelle pro Nation beschränkt und setzt den schwer fassbaren Begriff "Kultur" daher nur in stark vereinfachter Form um.

Um diese Probleme zu überwinden, stellt diese Dissertation einen neuen Ansatz zur Lokalisierung vor: "kulturelle Adaptivität". Die Idee ist, intelligente Benutzerschnittstellen zu entwickeln, die sich automatisch an die Kultur des Benutzers anpassen können. Statt sich einfach nur an ein bestimmtes Land anzupassen, ist kulturelle Adaptivität auch in der Lage, ver-

schiedene andere Einflüsse auf die Kultur des Benutzers miteinzubeziehen, wie zum Beispiel den Einfluss von Ländern, in denen der Benutzer möglicherweise früher gewohnt hat, den einer unterschiedlichen Nationalität der Eltern, der Religion oder des Bildungsgrades. Die Hypothese dieser Dissertation ist, dass die Einbindung solcher Einflüsse in adäquate Adaptionen der Benutzerschnittstelle die Benutzbarkeit insgesamt, aber insbesondere die Arbeitseffizienz und Zufriedenheit steigert.

Um diese Annahme zu untersuchen haben wir eine kulturelle Benutzermodellontologie entwickelt, die die vielzähligen Facetten von Kultur beinhaltet. Die einzelnen Aspekte wurden mit kulturellen Besonderheiten in der Wahrnehmung und mit bekannten kulturell geprägten Präferenzen in Verbindung gebracht, woraus wir Adaptationsregeln ableiten konnten.

Die daraus entwickelte Methode zur kulturellen Adaptivität wurde von uns mit Hilfe eines Prototypen, eines kulturell adaptiven Systems namens MOCCA, evaluiert. MOCCA bietet mehr als 115000 Kombinationsmöglichkeiten der Benutzerschnittstellenelemente an, so dass die Software überaus flexibel ist, um sich an die Präferenzen des jeweiligen Benutzers anzupassen. Zunächst stützt das System sich auf die oben genannten Adaptationsregeln, um ein passendes Layout zu erzeugen. Darüber hinaus kann MOCCA jedoch auch neue Regeln lernen oder existierende verfeinern. Dies geschieht mit Hilfe von Personalisierungstechniken, wie dem kollaborativem Filtern und dem Beobachten der Benutzerinteraktion mit der Schnittstelle, um davon Benutzerbedürfnisse und damit neue Regeln abzuleiten.

Die Ergebnisse unserer Experimente zeigen, dass MOCCA schon basierend auf den anfänglichen Adaptationsregeln die Mehrheit der Präferenzen unserer Benutzer erkennen kann. Zudem konnten wir eine signifikante Steigerung der Benutzereffizienz und -zufriedenheit nachweisen, wenn unsere Testkandidaten MOCCAs kulturell-adaptive Version benutzten, verglichen mit MOCCAs amerikanischer "Standard"-Schnittstelle.

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1

Introduction

The majority of software and web pages is still being provided by a few market dominating countries such as the USA, forcing users worldwide to adapt to embedded cultural values in user interfaces. In today's competitive market, however, companies are increasingly realizing the importance of adapting software programs and web sites to a particular language, culture, and local design requirements. These so-called localized web sites can reduce the risk of losing consumers to competitors, if they immediately convey values, such as trust, or professionalism, in a culturally-appropriate way. After all, the first impression also counts on the web [Lindgaard et al., 2006].

Localization can
increase market share

Google is a prominent example of the high interest in adapting user interfaces to different target nations. The company's classic minimalism (see Figure 1.1a for a screenshot of Google's Swiss search engine site) has shown to be highly successful in the western world, increasing their market share to over 90 % in many western countries [Sang-Hun, 2007], and about 81 % worldwide [MarketShare, 2009]. In South Korea, however, Google appears to be struggling to increase its market share of 1.7 % in 2007 [Sang-Hun, 2007]. In contrast, the home-grown

competition Naver.com has kept their seemingly unreachable market lead of 77 %. Most Swiss users would feel disturbed at the sight of the Naver page with its blinking graphics and bright colors (see Figure 1.2). Naver.com's market share in South Korea, however, speaks for itself.



(a) Google's Swiss web site



(b) Google's Korean web site

Figure 1.1: Google's web presence in Switzerland and Korea

Only recently Google dropped its western-oriented minimalist design for South Korea, adapting their web page to the Korean culture (see Figure 1.1b). The new design offers explorative animations that appear when the user hovers the mouse over the site's buttons. It also provides more functionalities, linking the page to the wide variety of Google products. Although ongoing changes to this web page indicate that Google might not yet be satisfied with the existing localization, Korean users have already responded positively to its new look [Sang-Hun, 2007]. The most recent usage figures suggest that Google has been able to slightly increase its market share to nearly 3 % [The Economist, 2009].

The example of Google shows the economic importance of localization for gaining market share. Like Google, many other companies operating worldwide, such as Microsoft, or IBM, have spent an increasing amount of money on adapting their software applications and web sites to users from different countries. This growing number of localized user interfaces can be also credited to many researchers who have demonstrated that considering culture in user interface design is the key to improving work efficiency and user satisfaction and thus, to customer loyalty in global marketplaces [Sheppard and Scholtz, 1999, Ford and Gelderblom, 2003].

Improvement of work efficiency and user satisfaction

The design process for localized user interfaces is typically undertaken by conducting ethnographical analyses in the target countries. However, due to this time-intensive endeavor, the manual localization of user interfaces has proven to be prohibitively expensive. And even if time and money did not play a role, there still remains another problem of localization: The appropriateness of assigning one interface to an entire nation. To date, localized user interfaces have been adapted to specific target countries, neglecting the fact that culture cannot be confined to country borders. In today's globalized world, however, this approach is highly contradictory. In fact, although a person's culture is certainly influ-

Problems of localization

The screenshot shows the Naver search engine homepage. At the top, there's a navigation bar with links for '메일', '카페', '블로그', '지식IN', and '쇼핑'. The Naver logo is prominently displayed in the center. Below the logo is a search bar with a search button and a dropdown menu. The main content area is divided into several sections: a top banner for '대한이민국시' (Korean Immigration and Citizenship) on February 14th, a news section with a headline about a 3.9% increase in a certain category, a '퀵뉴스 100주년' (Quick News 100th Anniversary) section, and a '쇼핑' (Shopping) section with various product recommendations. The left sidebar contains utility links like '로그인' (Login) and '회원가입' (Sign Up), and a '뉴스' (News) section with a '강성지수 36.5' (Strength Index 36.5) article. The bottom right corner features a '광고의견 쓰기' (Write Ad Feedback) button.

Figure 1.2: The web presence of the search machine naver.com

ened by his or her country of residence, other aspects such as previous stays in other countries, the parents' nationality, or the influence of a globalizing internet, also strongly impact the dynamic nature of cultural background [Rhoads, 2008].

In summary, the conventional approach to localization has two major drawbacks:

- Cultural background is elusive by nature, and does not allow the consideration of all people of a nation by just designing a single user interface per country. Instead, culture also comprises personal characteristics, therefore creating a

smooth transition between culturally embedded and personal user interface preferences. The manual localization of user interfaces, however, is unlikely to take into account the intangible nature of different users' cultural backgrounds.

- Localization requires the consideration of culture from the very start of the software engineering process, often including ethnographic analysis of the target groups, and creating specific versions of the software/web site for each country. This results in an extremely time-consuming and expensive development cycle.

The next section describes the main contribution of this thesis: The idea, how to overcome the limitations of localization.

1.1 General Idea of Cultural Adaptivity

As a consequence of economic factors and culture's elusive nature, conventional localization poses questions that are unlikely to be solved. In this thesis, we propose a new approach called *cultural adaptivity*: Personalized user interfaces that recognize the user's cultural background and automatically adapt to (cultural) user preferences.

Culturally personalized interfaces

The idea is to equip the computer with a form of 'cultural intelligence' [Earley and Ang, 2003], which – similar to the human ability to more or less adjust to the behavior of other cultures – enables computers to derive his or her cultural background, observe the user, and learn over time.

A major advantage of cultural adaptivity is that it takes into account more than the user's current whereabouts, but also incorporates other influences on culture, such as former countries of residence, or the user's computer literacy. Moreover, cultural adaptivity is flexible enough to adapt to these influences beyond changing date and time formats, or the language, but by personalizing the whole look & feel of the interface.

Based on this, our first hypothesis is the following:

Hypothesis I: Cultural adaptivity improves both work efficiency and user satisfaction compared to non-adapted user interfaces.

Additionally, we can assume that an adaptive approach to localization is more likely to incorporate the preferences of numerous different cultures, while not adding the costs of ethnographical analyses. Thus, provided that it is possible to design adaptive systems that are able to flexibly adapt their interface to a large variety of preferences, culturally adaptive user interfaces will be cheaper in their production process. We therefore hypothesize:

Hypothesis II: It is possible to develop adaptive user interfaces that do not restrict the adaptations to a finite number of countries, and that this method reduces the process of localization to a fraction of the time needed.

A well-known problem of adaptive user interfaces, and user modeling specifically, is the tedious collection of assumptions about the user's preferences when deploying the user model for the first time. This drawback, the so-called *bootstrapping problem* [van Kleel and Shrobe, 2007], is especially severe for systems that are not regularly re-visited. It is also a major reason why only a handful of applications employ user modeling techniques today. We believe that the knowledge about a user's cultural background can rapidly expedite the acquisition process; As many preferences are deeply-rooted in a person's cultural background, culture bundles information about a variety of partialities, such as information density,

navigational support, the level of hierarchy in the information presentation, or the learning style [Ford and Gelderblom, 2003]. Presenting an adequately personalized user interface from the instant a user accesses it, however, can be crucial for convincing him or her to stay. Thus, our third hypothesis proposes:

Hypothesis III: The knowledge about the user's cultural background can be used to provide a fairly suitable initial adaptation, thereby limiting the risk of losing users to the competition.

On the basis of our approach to cultural adaptivity, we have developed an adaptive system called MOCCA, which is able to adapt to different cultural backgrounds on the basis of (1) user input, (2) user interaction observation, and (3) by learning from other users' preferences. Evaluations of the system showed that it is able to accurately predict up to 65.8 % of user interface preferences (compared to 33 % which could have been achieved by chance), and that its user interfaces significantly improve the users' work efficiency and satisfaction compared to a non-adapted version.

1.2 Research Questions and Outline

In contrast to localization, cultural adaptivity requires the computer to gain knowledge about more than the user's current whereabouts by taking into account various cultural influences, such as previous countries of residence, or the parents' nationalities. This information can be saved in a so-called user model, which the computer employs as a personal knowledge base for each user. To know how to adapt to certain aspects

in this user model, the computer has to transform this knowledge into adaptation rules, which trigger changes in the user interface.

Against this backdrop, the approach spans a variety of research fields ranging from cultural anthropology to user modeling and adaptive user interfaces. I will discuss various questions arising from these fields (please refer to the page that is indicated in brackets after each question for answers on how we made use of previous research, and approached the different problems):

Questions about modeling the user's cultural background:

- Is there a tangible classification of the user's cultural background that can be used for the field of user interfaces? (Page 27)
- Is it enough to equate culture with a whole nation in our globalized and multicultural world? (Page 27)
- What are the effects of culture on user interface preferences? (Page 36)
- What is the best method to model the information about the user? (Page 53)
- How can we acquire the user's cultural background? (Page 58)

Questions about user interface adaptation:

- How flexible does the composition of user interface components have to be in order to allow for an adequate adaptation to different cultures? (Page 63)
- How can we define and adequately represent user interface adaptations? (Page 66)

- Which learning approaches are best suited to refine the user model and adaptivity strategy? (Page 70)
- Is it possible to learn from the preferences of users from similar cultural backgrounds? (Page 71)
- How can we adapt the user interface without violating usability principles? (Page 80)

Questions about the benefit of cultural adaptivity:

- To what extent can we predict the interface preferences of culturally ambiguous users if taking into account their current and former residences? (Page 83 and 112)
- Do people of similar cultural background share preferences so that we could learn from them? (Page 125)
- Does cultural adaptivity improve work efficiency and user satisfaction? (Page 145)

The thesis is based on several peer-reviewed papers, in which we have previously discussed some of these questions. After this introduction, Chapter 2 provides an overview of the related work. In Chapter 3, I investigate the understanding of culture in anthropology, its implications for use in IT, and the effects of different aspects of culture on user interface preferences. Parts of this chapter were written in collaboration with cultural anthropologist Sonja Schenkel and my advisor Abraham Bernstein, and appeared in [Reinecke et al., 2010] (reprinted by permission of the publisher).

Outline

Chapter 4 describes the approach of cultural adaptivity ranging from the cultural user model and the establishment of adaptation rules to a preliminary evaluation of the approach. The idea of the approach first appeared in [Reinecke and Bernstein, 2007], and was detailed in [Reinecke, 2007] and [Reinecke et al., 2007]. The preliminary evaluation of this ap-

proach, which concludes Chapter 4, has been published in [Reinecke and Bernstein, 2008].

Based on this approach, the thesis introduces our culturally adaptive system MOCCA in Chapter 5. MOCCA was first introduced in [Reinecke and Bernstein, 2009], and parts of its functionalities were later described in [Reinecke and Bernstein, 2010b]. Chapter 6 presents several evaluations of MOCCA's adaptation rules, such as an experiment on the preference prediction for culturally ambiguous users, which is based on [Reinecke and Bernstein, 2009], and a study on the preference prediction and similarity of users' choices within the three countries Rwanda, Switzerland, and Thailand [Reinecke and Bernstein, 2010b]. MOCCA's ability to learn from the preferences of culturally similar users was also previously described in [Reinecke and Bernstein, 2010b].

Chapter 7 concludes the thesis with an evaluation of the benefit of cultural adaptivity. The improvements in performance and user satisfaction achieved with our approach are described in [Reinecke and Bernstein, 2010a]. The thesis closes with a summary of contributions, a description of limitations and exciting possible directions of future work.

2

Related Work

The idea of culturally adaptive user interfaces requires knowledge about culture, a user model which contains this information, a rule-base that formulates adaptations for an uncountable number of different cultures, and a flexible user interface, which is able to automatically trigger the modifications. It therefore builds upon prior research in the areas of *international usability and culture*, *user modeling* and *adaptive user interfaces*. To date, very little effort has been made to combine these fields in an interdisciplinary manner for the aim of culturally adaptive software. In fact, the only work to our knowledge in this direction seems to be that conducted by Kamentz in the area of e-learning [Kamentz, 2006], and by Heimgärtner in the area of cultural adaptivity in navigation systems [Heimgärtner, 2005]. However, both these approaches have a different focus to ours:

Related research
areas

The work presented in [Kamentz, 2006] relies on a questionnaire to classify the user into one of a set of pre-defined cultural groups, and this classification triggered adaptations to an e-learning system. Since the adaptations were mainly aimed at improving the user's learning experience, she focussed on the learning style (e.g. an adaptation of instructions), and symbols. The adaptations did not comprise a full

re-arrangement of user interface components, as we anticipate is necessary for culturally adaptive software. While our aim is also to overcome some of the disadvantages of localization, such as the commonplace practice of disregarding culturally ambiguous users, Kamentz directed her work at only a few countries, therefore new adaptation rules would have to be generated when extending the number of (national) groups targeted by the e-learning system.

Heimgärtner [2005], in comparison, concentrated on the classification of users by their interaction patterns. He introduced a tool, which automatically classifies users based on their navigational patterns while carrying out predetermined tasks. His work has mainly focused on paving the way for culturally adaptive navigation systems [Heimgärtner et al., 2007], however, it demonstrates the feasibility of classifying the user's culture (proven for Chinese and German subjects) according to their interaction patterns.

Aside from the work of Kamentz and Heimgärtner, there are numerous findings in other related work, which could be useful for our approach to cultural adaptivity. In the following sections, I will therefore introduce the state-of-the-art in related fields, starting with the foundation of the idea, international usability.

2.1 International Usability

User interface designs are a matter of taste, as preferences vary from person to person. However, we can find commonalities in these preferences which are deeply-rooted in culture [Dormann and Chisalita, 2002]. In agreement with this, research has shown that people considered to belong to the same cultural group also perceive and process information in similar ways [Nisbett, 2003]. This phenomenon can be observed, for instance, when comparing locally developed web

sites in Asia with ones developed by European designers; While Asian web sites tend to offer colorful and often animated user interfaces, Europeans seem to prefer a more factual and structured information presentation. Such contrasts in the designs of user interfaces in different countries indicate that culture bundles a variety of these partialities, e.g. concerning the number of colors, navigational support, or the information density, and that many preferences are collectively shared by certain cultural groups [Callahan, 2005].

Correspondingly, the term *international usability* usually refers to localizing user interfaces for specific target countries. Considering such foreign markets in the software development process has often been motivated by improvements in usability as a result of (manually) localized user interfaces [Sheppard and Scholtz, 1999, Ford and Gelderblom, 2003]. Most studies in this direction were able to show an advantage with regards to aesthetic preferences and/or trust building [Corbitt et al., 2002, Siala et al., 2004]. In addition to this visual user satisfaction, much research assumes possible performance improvements with localized user interfaces [Barber and Badre, 1998, O'Neill-Brown, 1997, Gould et al., 2000, Sun, 2001, Marcus, 2001, Kamentz and Womser-Hacker, 2003]. This assumption was supported by [Ford and Gelderblom, 2003], who were able to demonstrate an increase in work efficiency for localized sites. In another study, Middle Eastern subjects were able to navigate and find information faster on Middle Eastern sites, than on US sites [Sheppard and Scholtz, 1999]. Furthermore, it was found that US participants performed better with a US web site design than with a Greek or Italian web site, regardless of which site they preferred visually [Badre, 2000]. A performance difference between American and Chinese participants was also demonstrated in [Choong and Salvendy, 1998], with Americans performing better with alphanumeric elements, and Chinese performing better with pictorial elements (icons).

Motivation for
localization

Cultural markers

While many researchers have pointed out strong variations in the designs of user interfaces in different countries, some researchers have specified which aspects of a user interface actually differ, and therefore form so-called ‘cultural markers’ [Barber and Badre, 1998], or ‘cultural fingerprints’ [Smith and Chang, 2003]. Analyzing many hundreds of web sites, they found that those elements of an interface that are significantly preferred by a specific culture, strongly influence the usability of user interfaces [Barber and Badre, 1998]. In [Sun, 2001] this concept of cultural markers was advanced by analyzing the preferences for certain cultural markers of internet users from China, Brazil and Germany. As a consequence, Sun states that “cultural sensitivity should be regarded as one metric in usability matrix” [Sun, 2001].

Localization refers to national culture(s)

In response to these findings, many multinational companies (e.g. Amazon, Credit Suisse, Nestle, Emirates, to name a few) have begun to adapt their web sites to foreign markets in order to gain customer loyalty and increase their market share [Sheppard and Scholtz, 1999]. After identifying the different target nations, the process of localization normally leads to an ethnographic analysis being carried out prior to the actual software localization [Yeo, 1996]. Many localized web sites typically require the user to select a specific country at first entry, thus reducing culture to national borders, and disregarding culturally ambiguous users. A Chinese user who has lived in the United States for half his life might, for example, select the USA from the list of countries, but may potentially be better off with a website adapted to Chinese preferences, or a mixture of both. Other web sites retrieve the users’ IP address, and thus their current whereabouts, but do not consider users currently residing in a foreign country. In this case, a German visiting the Google website in South Korea, for instance, would be redirected to the South Korean version of Google, although this is most likely not the intent.

Hence, the process of localization bears another disadvantage: the mapping of one interface to a whole nation despite today's globalized world (please refer to Chapter 3 for an extensive discussion of this).

Restrictions of today's localization

In addition, localization usually excludes the less visible interface aspects, such as workflows. Most localized user interfaces are able to adapt to users of different countries by modifying aspects such as language, colors, images, or more rarely the content arrangement. In most cases, however, software localization excludes the adaptation of the software's core. Some researchers have therefore suggested an entire "software culturalization" which distinguishes "culture-dependent components from other components of the core" [Kersten et al., 2002]. Similarly, other researchers have emphasized the need to adapt not just the most visible aspects, but also workflows and functionalities [Röse, 2001].

Some ideas as to how workflows should distinguish between different levels of guidance, for example, can be inferred from work, such as [Kamentz and Womser-Hacker, 2003, Marcus and Gould, 2001]. Such 'guidelines', however, are usually based on theoretical research, and typically restricted to only a few countries. Often, they also need to be interpreted for specific domains, which can in turn lead to misinterpretations.

Localization guidelines

Most previous localization guidelines (see, e.g., [Microsoft, 2010]) still only concentrate on the most visible aspects of the interface. In an attempt to create and refine such localization guidelines, many researchers have mapped culture to different user interface designs. Equating culture with one country, studies mainly aimed to analyze and compare web sites of two or more different countries [Yeo, 1996, Barber and Badre, 1998, Gould et al., 2000, Zhao et al., 2003, Burgmann et al., 2006], thereby revealing ubiquitous design preferences for the investigated countries. Although such studies provide a good insight into differences between certain countries, they are

rarely comparable due to their diverse experimental designs. In addition, research on single country comparisons is unlikely to ever cover the countless number of cultures in this world.

More comprehensive approaches were chosen with evaluations that used so-called *cultural classifications* developed by anthropologists, such as Trompenaar and Hampden-Turner [1997], Hofstede [2003], or Hall and Hall [1990], as for example described in [Zahed et al., 2001]. The mapping of these classifications to user interface designs is more generalizing than investigating single countries, but it is more likely to cover numerous cultures, and thus, could be more useful as an approach to cultural adaptivity. I will therefore describe research in this direction in-depth in the following chapter.

Open questions

In summary, the research findings in the field of culture & usability provide information about how a user interface should be designed to appeal to users from a certain country. However, these findings raise several questions that define the state of the art, as well as important research gaps:

- Is it enough to provide users from the same country with one interface design, or do we also need to take into account a user's personal preferences?
- Can users be expected to classify their culture, or even judge their own preferences?
- How do we handle culturally ambiguous users, that is, people who have been influenced culturally by more than one country?

I will tackle these questions in Chapters 3 and 4, starting with a comprehensive explanation about the interpretation of culture in anthropology, before deriving implications for the design of culturally adaptive systems.

2.2 User Modelling

While it is increasingly encouraged to consider culture in interface design, very little progress can be found towards modeling the users' cultural backgrounds for a more individual adaptation of the user interface. As I mentioned in the introduction to this chapter, work in this direction includes Kamentz's research [Kamentz, 2006], who investigated human aspects needed for cultural user modeling. She states that cultural adaptation must consider the context of the user's origin, while knowledge, aims and plans, preferences and individual user properties form important attributes that are to be modeled, but do not as such involve the cultural component. Apart from learner specific adaptivity, she also incorporated layout, interaction and navigation along with its cultural particularities in her studies. Specifically, she measured a person's attitude towards a set of questions ranging from general information technology and usage behavior, to preferences in the functional design of e-learning software. Applying machine learning to this questionnaire data, the work demonstrated that it is possible to derive a person's culture group (here generalized to a country) from their answers [Kamentz and Mandl, 2003]. Kamentz and Womser-Hacker [2003] applied the approach to the learning system SELIM, which automatically adapts its instructional design to the user's culture, as described in [Kamentz and Mandl, 2003]. The initial classification of the user is done after posing more than 25 learning style-related questions, before deriving an adequate guidance and support for the personalized version of her learning system. As of today, it is unclear whether a similar questionnaire could shed light on the design and layout preferences of users; however, it is also questionable whether users are willing to answer numerous questions to initialize the user model. Furthermore, Kamentz's approach clusters people from different countries, such as Russia with countries that had been part

of the Soviet Union, into having one and the same culture. Cultural adaptivity, in contrast, is aimed at overcoming the stereotypical assignment to one cultural group, by including a user's personal history of cultural influences (such as different countries of residence).

Application-specific
versus independent
user models

A disadvantage of the user model applied in Kamentz's work is that it only works with the e-learning system SELIM, and would have to be rewritten in order to become application-independent [Kamentz, 2006]. Until today, the use of such application-specific user models is common for adaptive systems, e.g. as deployed by Amazon.com [Linden et al., 2003] to provide personalized recommendations on what to buy. However, research has noted some advantages of application-independent, or distributed user models [Dolog and Nejd, 2003b], where user models are shared through ontologies¹ [Zhou et al., 2005]. Ontologies can provide the means to specify a common understanding of the user modeling domain. This way, the information about a user can be accessed by different applications, providing all of them with user-tailored adaptation rules. The benefit for the user is a holistic usability, where all applications and websites could access (and adapt to) his or her preferences.

Research towards such shared user models has been made in the area of e-Government with the Portal Adaptation Ontology [Stojanovic and Thomas, 2006], or in e-learning applications [Dolog and Nejd, 2003b, Henze and Nejd, 2004, Aroyo et al., 2006]. Further efforts include the General User Model Ontology (GUMO), which supplies a method "for the uniform interpretation of distributed user models in intelligent Semantic Web enriched environments" [Heckmann et al., 2005]. Parts of GUMO's user modeling functionalities have been used by the Personal Reader project, which provides an

¹In computer science, an ontology is a data model that describes a set of concepts within a domain and considers the relationship between these concepts.

environment for the construction of personalized Web content readers [Abel et al., 2007, Henze, 2005].

Apart from the representation of the user model, user modeling requires the acquisition of data throughout the user's interaction with the system. A key concern when ascertaining user modeling information is whether data should be gained through an integrated acquisition process in the background, or through separate acquisition that is discrete to the normal interaction between the user and the system [Kobsa and Schütt, 1993]. So far, almost all the organizing of user groups with common characteristics using stereotypes, or into common interests using communities, as suggested by Paliouras et al. [1999], have been carried out manually. This has proven to be difficult because it "involves the classification of users by an expert and/or the analysis of data relating to the interests of individual users" [Paliouras et al., 1999]. In regards to cultural user modeling, manual acquisition would also most likely encounter difficulties due to the intangible perception of cultural values.

Acquisition of data

Such challenges in the manual construction process can be lessened through the use of machine learning techniques for the automatic acquisition of data for the user model [Pitschke, 1994, Kobsa, 1995, Pohl, 1996, Langley, 1997, Paliouras et al., 1999, Kamentz and Mandl, 2003]. One such system that interactively acquires user preferences in order to learn input parameters for adaptive software was introduced in [Gajos and Weld, 2005].

Some personalization mechanisms construct their user model by analyzing navigational behavior [Eirinaki and Vazirgiannis, 2003]. A more detailed approach to tracking user behavior is described in [Schmidt et al., 2007]: Here, a semantically rich user model is built by combining the web development technique AJAX with the Semantic Web. Advantages of this approach are on-the-fly adaptation, which removes the need for reloading a page and the ability to record scrolling,

Acquiring information by tracking the user's interaction

mouse-over and keystroke events [Schmidt et al., 2007].

Similarly, an approach to dynamically classify novice vs. skilled use without a previously specified task model was introduced in [Hurst et al., 2007]. The approach concentrated on the selection of menu items: Users who slowly traversed a menu, for instance, were classified as novice, while users with a more directed navigation behavior were assigned to a group of skilled users.

Difficulty of acquiring
visual preferences

In general, the acquisition of information to fill the user model mostly concentrate on tangible concepts and a clear classification into different stereotypical groups. Wherever personalization is targeted at more subtle presentation preferences, it is difficult to acquire this information about users. Hence, adaptive systems on presentation level require sophisticated information acquisition processes, presuming knowledge about the preferences of users. However, since users are usually not aware of their preferences themselves [Pu and Chen, 2008], it is not feasible to acquire this information by asking them. For the same reason, the manual personalization of user interfaces by the user cannot be seen as an alternative to an automated adaptation.

Open questions

Since culture cannot be very easily defined, the main challenge in the area of user modeling will be to establish a classification that is applicable for the field of culturally adaptive user interfaces. Furthermore, we will have to develop an acquisition procedure, which combines previous approaches in obtaining information about the user, but is especially suitable for cultural user interface preferences. In Chapter 3, I describe these challenges, and explain the approach employed towards a cultural user model.

2.3 Adaptive User Interfaces

Today, many companies offer some kind of adaptivity on their site: Google and its personalized advertisements adjusted to

the user's most recent search queries, Amazon with its product recommendation mechanism, or Pandora, the personalized radio station playing music that corresponds to previously selected music, artists, or genres - these are just a few industry examples of personalized systems that have proven highly successful.

Not all of these systems are truly adaptive : If users are able to explicitly customize different aspects to their own preferences, one usually refers to these as *adaptable systems* [Jameson, 2008]. *Adaptive systems*, in contrast, adapt themselves to the user by acquiring information and triggering suitable adaptations. Some of these systems ask users about their preferences, such as in a questionnaire, before the adaptation takes place [de Bra, 1999]. On the basis of the user's profile, they provide personalized versions, or advertisements (e.g. as on the social networking platform Facebook, or the e-mail service provider GMX). Often, they also implicitly acquire user profiles by monitoring the (navigation) behavior and adapting different parts of the content or information presentation [de Bra, 1999]. Examples of this are the above-mentioned companies Google, Amazon, and Pandora, but also many research projects that have aimed to extract preferences from the user's navigation behavior [Agichtein et al., 2006, Abel et al., 2007], for instance, to personalize news according to what a user has previously accessed [Aggarwal and Yu, 2002, Henze, 2005].

Note that many systems pursue a combined approach: To speed up the initial information acquisition process (and thus, to overcome the cold-start problem [Mehta and Nejd, 2007]), they use a questionnaire or dialog, but additionally observe the user to verify or extract further information [de Bra, 1999]. Although explicitly provided information might be deemed more reliable, some knowledge is better suited to being automatically inferred. For example, in case of Google's advertisement strategy, it would be difficult for users to name all their

Adaptable and adaptive systems

Implicit acquisition of information

Combination of explicit and implicit information acquisition

interests, and not everyone would be comfortable with providing this information, or updating his or her profile every so often.

For our approach to cultural adaptivity, we have adopted a two-pronged approach (described in Chapter 4) to avoid a cold start by asking the user a few questions, but subsequently deriving further information from observations. Similarly to other systems, the adaptations in our approach are also based on the behavior of users (e.g. Amazon recommends books on the basis of what other users have bought, but also assembles information from observing which books the user looks at himself).

In contrast to most such systems today, our approach does not aim to personalize the content, but rather the way the information is presented to the user. One reason why most industrial systems do not offer a flexible and automatic rearrangement of all user interface elements might be that the advantages and disadvantages of providing generically filtered information are relatively easy to evaluate. Besides, it can be assumed that the objections to adaptivity at the user interface level has also led to a stagnation of research in this area [Benyon, 1993]. In reference to this, Shneiderman [2002] points out that “machine initiated changes to user interface features seem to be troubling to users”.

Advantages
of adaptivity

On the other hand, it was suggested that adaptive systems “represent the most promising solution to the contradiction between striving to achieve cost-savings on the one hand and [...] customer satisfaction on the other” [Maier, 2005]. In addition, much research supports the thesis of user performance improvement with the help of adaptive interfaces (see e.g. [Greenberg and Witten, 1985, Sears and Shneiderman, 1994, Höök, 1997, Gajos et al., 2008, Findlater and McGrenere, 2008, Findlater et al., 2009]). If doubts persist, it is because none of these results can to date be readily generalized. Thus, many objections stem from “a fear that intelligence at the in-

interface will violate usability principles” [Höök, 2000]. An important issue in this regard is the choice between automatic or computer-supported adaptation, the latter leaving more control to the user. Kobsa and Schütt [1993] state that computer-supported adaptation is the better alternative if adaptations only rarely occur but are nevertheless important. This is fundamental for changes in the user interface since the user attention might have to be drawn to the new possibilities [Kobsa and Schütt, 1993]. Our approach integrates such computer-supported adaptation; the details of this are described in Section 4.4.3.

With the increasing awareness of human factors, and of the benefit of adapting interfaces to individuals beyond the “one size fits all” approach [Höök, 2000], research has increasingly investigated adaptivity at the presentation level. Popular application areas for this have been adaptations for people with disabilities [Stephanidis et al., 1998, Gajos et al., 2008], or adapting to different skill levels in computer use [Hurst et al., 2007]. Furthermore, the growing number of different devices has led to investigations into the adaptation and rearrangement of user interface elements. Examples of this are different strategies for displaying the same content on various screen sizes [Menkhaus and Pree, 2002, Grundy, 2003, Gajos et al., 2005]: Menkhaus and Pree [2002], for example, developed a new approach to dynamic user interface adaptation by remodeling “the widgets of a window into a new composition of ‘small’ windows”, basing it on a “linking strategy” of two graph hierarchies. This method was originally developed to provide adaptation possibilities for a range of displays, input devices and mobile computing gadgets. Likewise, it has proven to be applicable for the flexible rearrangement of user interface components on the basis of a hierarchical structure of windows.

Gajos et al. [2005] later proposed to use declarative models of the interface and desired hardware device (i.e. a spec-

Adapting the information presentation

ification of the screen size) in order to generate personalized user interfaces based on decision-theoretic optimization. The approach was applied in the context of personalized user interfaces for users with motor impairments, demonstrating the ability of adapting the size and distance of user interface elements, for example, to facilitate interaction [Gajos et al., 2008]. Individual user preferences were acquired with a one-time motor performance test [Gajos et al., 2008].

While the techniques mentioned above can be classified as the restructuring of components with the basic interface remaining the same, several approaches have proposed offering different interfaces. Shneiderman's idea of a multi-layer design for complex systems, for example, associates the user's experience with a certain interface layer. It thereby offers the user a lower level with less functionalities or a higher level with an augmented number of interaction possibilities [Shneiderman, 2002].

Open questions

For cultural adaptivity, it seems that none of the previous approaches can be readily applied. First of all, the kind of adaptations (i.e. providing different user interface elements, workflows, functionalities, as well as high-level adaptations such as colors) differ to what previous adaptive systems focused on. Secondly, our system should not just adapt to a limited number of stereotypes (e.g. to two different skill levels), but should provide personalized interfaces for all countries in the world, plus cater for culturally ambiguous users, and other aspects of cultural background. The degree of flexibility required for such an approach will be described in Section 4.3, and details of the implementation of cultural adaptivity in a web application are provided in Chapter 5.

3

Interpreting Culture for Use in Human-Computer Interaction

The related work in international usability (Section 2.1) shows that the conventional approach to localization equates culture with one nation, and thus, that culture is linked to national territory. Findings about user interface designs in different countries, further suggest that we could generalize user interface preferences for people of the same nationality (e.g. [Gould et al., 2000, Zhao et al., 2003, Burgmann et al., 2006]). Yet there are many counter-arguments to reducing culture to country borders, these range from the world's globalization that results in the exchange of cultural values, to the artificial definition of country borders in the first place. Likewise, it is questionable whether differences in user interface preferences can be merely ascribed to the level of national culture, seeing that the equation *country = nation = culture* is of limited validity.

In order to overcome this problem we have proposed to equip computers and their user interfaces with a human-like ‘cultural intelligence’ – a term that was coined by Earley and Ang [2003]. Moving beyond the concept of national culture, this shifts localization to another level: to that of the single user. The approach hypothesizes that we will be able to adapt user interfaces to a more precise cultural background than with the conventional approach to localization. In other words, it also assumes that we are able to model users’ individual cultural backgrounds.

The precondition for such an approach to cultural user modeling is, however, to know which cultural aspects influence which user interface preferences. In what we believe is one of the first collaborations between researchers in human-computer interaction (HCI) and cultural anthropology we have developed a more encompassing interpretation of culture for the field of user interfaces. The chapter deals with the alignment of this interpretation with cultural differences in perception and preferences, and further lists those cultural variables that are relevant to our approach to cultural user modeling.

3.1 Differences in the Understanding of Culture

Culture influences perception, and thus, the way we see and think of the world. This is also the case for our perception of user interfaces, our preferences, and how we generally receive and process information [Ito and Nakakoji, 1996]. It raises the question of what we need to know about culture in order to understand its influence on user perception and preferences. Is it enough to use culture as a synonym for the user’s country? Or do we need a more profound definition of the user’s cultural background?

In the following, I will first introduce the term culture as seen in anthropology in order to establish an idea of its intangible nature while still communicating a conceptual outline of the term. The subsequent section then contrasts this view with details on how culture has been incorporated in human-computer interaction.

3.1.1 An Anthropological View of Culture

One of the greatest obstacles of an approach to culturally adaptive user interfaces is the elusive nature of culture. In anthropology, culture has been described numerous times without generating an accepted definition, or generally assessing a common understanding of its concept. In 1952, Kroeber and Kluckhohn could already find over 164 varying definitions of the term culture [Kroeber and Kluckhohn, 1952], one of the earliest academically recognized one being by Sir Edward Tylor who defined culture as a “complex whole which includes knowledge, belief, art, morals, law, custom, and any other capabilities and habits acquired by man as a member of society” [Tylor, 1920]. From today’s point of view, Tylor’s definition does not take into account the dynamic nature of culture, nor how the view on its concept has changed with new findings and the spirit of the age. Indeed, the only constant of culture is change. Culture can therefore never be fully confined to a finite number of factors.

Tylor’s definition of culture

Furthermore, any concept of culture is biased by a set of assumptions about society that may not apply everywhere. In its most general sense, culture can be loosely described as based on shared values. People acquire values early in life through childhood socialization and education [Karahanna et al., 2005], influenced by such aspects as the language, or religion. Hofstede’s definition of culture as a “programming of the mind” [Hofstede, 1997] accurately expresses how culture forms these fundamental values and subconsciously con-

Hofstede’s understanding of culture

Cultural groups
and subcultures

trols our collective behavior. Thus, definitions of culture are mainly based on the understanding that people share commonalities, which can help to distinguish certain cultural groups, each characterized by their own concept of identity. Anthropology further differentiates between confined definitions of culture, which are linked to ethnic or cultural groups, and ones that entail subcultures, such as groups found in youth culture, or in a company's business culture.

All of these definitions, albeit slightly different, describe culture as a complex concept without setting boundaries to its meaning. Cultural anthropologists have found it increasingly difficult to define the term both on a theoretical level as much as in its methodological applications. The discussion has even led some researchers to call for an abolition of the term [Abu-Lughod, 1991].

The influence of glob-
alization on culture

As a consequence, many anthropologists have turned towards understanding culture and how it is influenced by the dynamics of globalization. As technical innovations linked to mobility and telecommunications have led to international work co-operations, worldwide communication, and also to increased migration, these new life-dynamics have resulted in an interchange of people, ideas, and resources, ultimately affecting those on the move as much as those at home [Appadurai, 1996]. The result are cultural groups that maintain their identities across nations and different territories – a phenomenon that is often described as “transnational public spheres”, which are independent of spatial proximity [Gupta and Ferguson, 1997].

The “deterritorialization of culture” [Appadurai, 1996] has had the effect that not only cultural references have been dispersed but also that its practice finds different expressions. Culture cannot be seen as an homogenous whole but is constantly changing. This is also true when excluding the influence of migration. In many large countries, such as the United States or Brazil, people refer to a national identity but at the

same time practice various regional or local customs and values.

In this regard, a person can belong to more than one culture, although we have to distinguish between affiliations as they are communicated within a social environment, in contrast to the individual practicing his or her conscious or unconscious cultural practice. An Indian software specialist residing in London, for instance, may claim affiliation to several cultural groups depending on his current environment, work place, home in London, or home back in India. His international background allows him to undertake different cultural practices and behavior depending on the situation. Asked about his cultural roots, however, he might immediately respond that he is Indian (especially when this question occurs outside of India). If someone poses the same question in India, he might name his state, or city of origin. Cultural affiliation becomes a matter of context. In the context of a communicated cultural affiliation, it reveals that people generally think of culture as linked to geographical location, and, thus, relate it to a certain territory. On the contrary, anthropology has found that people handle their cultural references in much more flexible and intermingled ways. People move within a culture or cultures. With that, they also apply related values or behaviors to a cluster of cultural practices.

Multiple cultural affiliations

As an additional point, anthropology views a person's culture as subject to change: People do not only acquire culture, but they are also part of its creation. In the context of globalization, change and exchange among different cultures are omnipresent. Analyzing the way people handle these exchanges and possible alterations of cultural identity, anthropologists have found that globalization does not transform different cultures into a homogeneous whole, and people do not necessarily absorb new cultural influences [Sahlins, 1993]. Instead, they either develop a certain resistance to external influences, or adapt these influences to their own cultural con-

Changes in culture

text, which sometimes even enhances their own cultural identity [Sahlins, 1993].

National culture

In contrast to ongoing discussions in cultural anthropology, however, the nation as a territorial concept remains today's most frequently used synonym for culture across various disciplines: The country of residence seems to persist as the most tangible factor that enables measurability between different cultures. Based on this simplification, many researchers trying to operationalize culture have attempted to find a set of tangible indicators of culture. One example are Hall and

Hall's cultural classification

Hall [1990], who described the term with the help of a number of values, such as Polychronic vs. Monochronic Time, meaning the ability to attend to multiple events simultaneously, or Context, which refers to the amount and specificity of information in a situation. In low context cultures, people expect each other to express information clearly, whereas people belonging to high context cultures usually put as much weight towards the context of a conversation, as to the communication itself [Hall and Hall, 1990].

Hofstede's cultural dimensions

Hofstede later described differences in national culture with the five cultural dimensions Individualism, Uncertainty Avoidance, Masculinity, Power Distance, and Long Term Orientation (see [Hofstede, 2003] for a detailed description). Starting in 1980, Hofstede's studies included a large-scale quantitative analysis of organizational culture, after which he assigned a score for all five dimensions to each of the 74 investigated countries. Figure 3.1 shows the world average scores for these dimensions: 55 for Power Distance, 43 for Individualism, 50 for Masculinity, 64 for Uncertainty Avoidance, and 45 for the dimension Long Term Orientation. The averages mainly provide the possibility to compare on country to 'the norm'. Malaysia, for example, has one of the highest Power Distance scores worldwide (104), which usually relates to the perception of power differences within society. Thus, in comparison to most other countries, Malaysians are much more

willing to accept an unequal distribution of power, and less powerful members of society do not necessarily insist on democratic rights [Hofstede, 2003]. Furthermore, many Latin American and Asian countries received rather low scores in the dimension Individualism, and are therefore classified as collectivist countries. In comparison to individualist countries, people in China, for example, act as members of a group, such as the family. In the US, or in the Netherlands (countries that are defined by high Individualism scores), people are more expected and willing to show their own personalities, and stand out from a group [Hofstede, 2003]. You can find world maps showing the distribution of Hofstede's dimension in the Appendix B.

With that, the cultural dimensions are an attempt to comprehend deeply anchored cultural values with the help of a tangible set of variables. Given the close association of nationality with the term culture, Hofstede's dimensions were often criticized for equating one country with one cultural background (see e.g. [McSweeney, 2002]). Nevertheless, or maybe because of this simplification, his dimensions have been widely used in various disciplines, such as to analyze cross-cultural communication between or within organizations, or to explain differences in learning style (cf. Chapter 2).

Hofstede criticism

In part by building up on Hofstede's work, Trompenaar has coined the analogy of culture as an onion, which must be peeled to get to the core values [Trompenaars and Hampden-Turner, 1997]. According to his definition, the outer layer of an onion makes up people's first impression of another person. The middle layer concerns norms and values that control people's behavior. As the most intangible part of culture, the core of the onion describes basic assumptions that we automatically use for problem-solving. It is this inner part of the onion that is the key to understanding other cultures. In his work, Trompenaar describes seven cultural dimensions, which partly overlap with Hofstede's model, and partly add

Trompenaar's cultural dimensions

new concepts to a cultural classification [Trompenaars and Hampden-Turner, 1997].

Although various other anthropologists have attempted to narrow down the term culture, the classifications of Hall, Hofstede, and Trompenaar remain most widely applied across many different disciplines. Anthropologists mostly agree that none of these classifications can fully confine the complex nature of culture; however, other fields of study often call for sets of cultural dimensions in order to pin down the influence of culture on various intercultural processes. We will describe this phenomenon in the next section, explaining the role of culture in human-computer interaction, and how cultural dimensions have been exploited in this field.

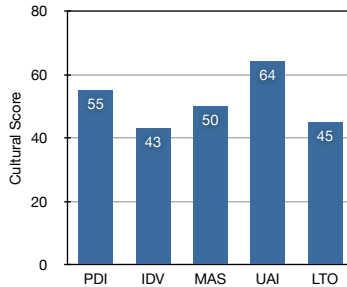


Figure 3.1: World averages for Hofstede's dimensions Power Distance (PDI), Individualism (IDV), Masculinity (MAS), Uncertainty Avoidance (UAI), and Long Term Orientation (LTO).

3.1.2 The Understanding and Use of Culture in IT

When considering the effects of culture on human-computer interaction, it is crucial to understand the role of global software companies and their internationally expanding markets.

Today, the world's largest software manufacturers, according to their sales revenues, come from the US [Software Top 100 Foundation, 2009]. The number one, and long-standing market leader Microsoft, for example, supplies a worldwide market with its operating systems and other software. The US also continues to lead in the number of Internet users per country. However, the majority of users (81.7 %) come from countries other than the US [Computer Industry Almanac, 2006]. Researchers have discussed this globalization of the internet, treating it as a "virtual cultural region" [Johnston and Johal, 1999] that "transcends the geographic-nationhood notion of culture" [Burgmann et al., 2006]. Yet discussions in anthropology point out that although such influences might create new cultural groups [Appadurai, 1996], they do not necessarily loosen the ties to one's origin [Sahlins, 1993].

Globalization on the web

Thus, reacting to the globalizing software market, companies have increasingly started to adapt their products to the local preferences of target countries. The localization usually involves adapting user interfaces to local languages, and taking account of different date and time formats. On top of this, many researchers have attended to more subtle variations in cultural preferences, such as adapting colors and images for better comprehensibility in a target country [Kondratova and Goldfarb, 2006]. The software's functionality and flow, that is, the arrangement of elements, the level of guidance, and the general way of handling are mostly ignored [Kralisch et al., 2005]. This 'halfhearted' adaptation turns into a problem if the user has a differing cultural background to that of the developers, who unconsciously integrate their cultural values into the functionalities and aesthetics. In this case, the developers, who indirectly communicate with the users through different interfaces, are not able to respond to differences between their own and the users' cultural backgrounds. Contrasting the fragmentary localization, research conducted on the usability of fully localized user interfaces

The user's versus the developers' cultural backgrounds

has demonstrated notable improvements in work efficiency and user satisfaction [Ford and Gelderblom, 2003].

Two reasons are generally named for the lack of holistically localized user interfaces: Firstly, an adaptation to different target countries is time-consuming and expensive [Reinecke and Bernstein, 2007], and secondly, research has yet to determine which parts of an interface need to be adapted in order to take into account the elusive nature of different cultural backgrounds [Marcus, 2001]. Companies and researchers have therefore called for guidelines that map certain aspects of culture onto user interface adaptations. The main problem so far has not been the definition of adaptable user interface aspects, but rather finding a definition of culture that maps these aspects to cultural variables. Ignoring newly developed ideas of the term culture in anthropology, cultural usability research has focused on applying the tangible definitions described in the previous section, such as Hall's cultural values, to user interface design. The effects of Hall's Monochronic Time on user interface design, for example, are a preference for linear navigation patterns, and for links emphasizing hierarchical structure [Kralisch, 2005]. Polychronic cultures, in contrast, show non-linear navigation behavior and tend to switch between several open pages [Kralisch, 2005].

Dunn and Marinetti [2002] used Trompenaar's cultural dimensions to point out that one must peel this onion "to get to the core values, the things that really matter" in order to plan for cultural adaptation. Later, Marcus and Baumgartner [2004] developed a set of cultural dimensions by ranking a given list of these dimensions with the help of 57 participants from 21 different countries around the world. Doing so, they were one of the first researchers to attempt to build a bridge from evaluations on culture and usability to their application.

While many researchers have analyzed the relationship between cultural values and user interface preferences, navigation patterns, or existing user interface designs, the cul-

tural dimensions found by Hofstede [2003] have been employed most frequently (cf. [Rogers and Tan, 2008]). One reason for this might be that his work produced five dimensions for 74 countries and regions, enabling the comparison of concrete scores. Thus, analyzing the 'cultural' differences between user interfaces from two countries can, with Hofstede's approach, simply be made on the basis of differences in these numbers.

Evaluations applying Hofstede's dimensions indicate the significance of at least some of them to certain interface aspects [Marcus and Gould, 2001]. The dimension of Uncertainty Avoidance, for example, predicates a society's tolerance for uncertainty and ambiguity, and a person's tolerance for unstructured situations [Ford and Gelderblom, 2003]. Thus, users from countries with a high Uncertainty Avoidance score usually prefer a linear navigation clearly indicating the current position [Baumgartner, 2003]. Similar mappings of Hofstede's dimensions to user interfaces have been made for all of his dimensions by different researchers, e.g. [Voehringer-Kuhnt, 2002, Marcus, 2001, Marcus and Gould, 2001, Dunn and Marinetti, 2002, Dormann and Chisalita, 2002, Ford and Gelderblom, 2003, Baumgartner, 2003, Hodemacher et al., 2005, Kamentz, 2006].

Research on cultural usability can, however, not presume that generic models of culture are universally valid. In [Smith and Chang, 2003] for example, the authors raised concerns over the significance of Hofstede's dimensions for the field of user interfaces, because they were originally developed for intercultural business communication. Generally, the applicability of Hofstede's dimensions seems to bring forward many discussions, which are often related to the process of localization itself: Is it enough to adapt user interfaces to a certain country and thereby rigorously restrict culture in a uniform way within country borders? According to the many discussions in an-

Applicability of cultural dimensions to user interface design

thropology, we can answer this question in the negative. Nonetheless, inconsistent results might also be due to the indefinable transition of cultural preferences to personal likes: In all cases above, culture is understood at a macro level, neglecting the individual, but focusing on nations and universal values [Rogers and Tan, 2008].

Our proposition to cultural user modeling could master these problems, if a user's cultural background included influences on culture beyond conventional approaches to localization. In the following, we will analyze such influences on user interface preferences.

3.2 The Effects of Culture on Interface Preferences

The previous section listed numerous perspectives on culture, yet their application to the field of human-computer interaction has raised the question of what we need to know about a user's culture in order to localize user interfaces to cultural preferences. Answering this question is once again hindered by the fact that culture is not an homogeneous construct.

Influence of personality and culture

First of all, cultural preferences are certainly biased by personal preferences, blurring the border between personality and culture, and culture and human nature [Hofstede, 1997]. But does this mean that we cannot model the users' cultural backgrounds when excluding their personal preferences?

Second, culture is a dynamic construct. As discussed in the previous section, cultures influence one another, and people can adapt to other cultures to a certain extent. The dominance of US software manufacturers and English web sites, for example, might influence users worldwide in that they adopt Western values [Nunberg, 2002]. If this is the case, how much of a user interface do we have to adapt, and where can

we expect users to adapt themselves without impairing usability?

Third, people do not necessarily belong to just one culture, but can be part of several different (forms of) culture/s. Thus, a user might belong to a certain national culture, but could differ from his neighbor by incorporating another business culture. Do all of the different forms of culture influence user interface preferences and perception?

The overall matter in question is what culture can tell us about the users' perception. Imagine a typical scenario in interpersonal communication, where two people from a different cultural background meet. Both of them will subconsciously observe each other's behavior, such as movements, habits, wording, or looks. In our mind, this information automatically forms an impression, which usually results in a stereotypical view of the other person. Such 'container thinking' enables us to form cultural patterns, to which we respond by adjusting our behavior. Thus, the process of interpersonal communication converts various information to internal adaptation rules – a procedure that we could adopt as an approach to cultural user modeling. Could – if we knew which information it is that we actually collect in our mind, and if we knew how humans respond to single variables contained in the overall information about other people.

Interpersonal
communication

In interpersonal communication, the ability to observe and adapt to other cultures is often measured by cultural intelligence [Earley and Ang, 2003]. Cultural intelligence for computers and their user interfaces requires knowing the user's culture, and knowing how this information can be transformed into adaptation rules in order to trigger culturally personalized user interfaces. The computer can acquire knowledge about the user's cultural background in different ways: (1) implicitly, by observing the user's behavior, or (2) explicitly, by directly asking about his/her cultural background, or about certain preferences. Both of these knowledge acquisi-

Cultural intelligence
for computers

tion processes are also possible for interpersonal communication. The difference, however, is that the computer has to be told how to compose this information and how to transform it into adaptation rules.

Cultural adaptation rules

In order to establish this connection between information about the user's cultural background and the adaptation rules, we have investigated the most common variables that ethnologists regard as part of culture and extracted those ones known to influence perception. Note that cultural background can be influenced by variables that do not constitute culture, but further refine cultural groups, or connect people of different cultural backgrounds and regions (such as the Portuguese language, which is spoken in Brazil, Portugal, and many other countries). Some other aspects are not directly cultural factors, but stand for affiliated cultural norms. Gender and age, for example, do not represent culture, but are often seen as connecting variables across various cultures. They can determine the affiliation to an additional cultural group, or specify a person's culture with their underlying norms, which in turn affects user interface preferences and perception. In the following, we will list these influencing aspects of culture and detail on their effects on human-computer interaction.

Nationality

The use of nationality as a synonym for culture implies two different meanings: Nationality describes the affiliation of a person to a certain nation, or it characterizes people with comprehensive traits, such as language, traditions, or customs. Hence, nationality could be equated with a certain country and its territory, but it can also refer to a person's ethnicity. Migrants, for example, can be affiliated with a certain country by citizenship, although their identity might be linked to a different country and/or ethnicity. Thus, on the one hand, equating nationality with culture reduces culture to country

Ambiguous meanings of the term nationality

borders, but on the other hand, the use of culture in this setting expresses possible affiliations to an ethnic group within, or in more than one country. The ambiguous meaning of this equation reflects the space and place discussion [Gupta and Ferguson, 1997] in cultural anthropology: While place refers to where a person is situated (meaning the nationality as a territorial concept), space describes the mental affiliation, which could differ from the country and/or nationality that the person's current whereabouts describe.

Consequently, characterizing a cultural background by nationality requires knowing a person's cultural identity across nations and territorial concepts. While we will not be able to cover the user's space (i.e. the mental affiliation) in all details, different territorial influences on the users' culture, such as information about a person's current, but also former residences, could be a more definite hint of their preferences than conventional localization is able to provide. In order to reveal these differences between single countries, researchers have often used Hofstede's cultural classification, because, as previously mentioned, its five dimensions per country facilitate the comparison of cultural differences between countries. In several studies, all of Hofstede's dimensions have been related to certain preferences, revealing that his generalized dimensions might not be applicable for all people in one country, but can nevertheless be used as a predictive means.

The majority of surveys have compared countries with a high score in a specific dimension, with countries that have been assigned a low score in the same dimension. Accordingly, the findings can be used for adaptation rules for users with a low and a high score, which summarize the findings for Hofstede's dimensions by [Callahan, 2004, Callahan, 2005, Corbitt et al., 2002, Dormann and Chisalita, 2002, Ford and Gelderblom, 2003, Gould et al., 2000, Hodemacher et al., 2005, Hofstede, 1986, Hofstede, 2003, Kamentz et al., 2002, Kamentz and Womser-Hacker, 2003, Kamentz and Mandl, 2003, Kralisch

Approximating place
and space

et al., 2005, Marcus and Baumgartner, 2004, Marcus, 2001, Marcus and Gould, 2000, Sheppard and Scholtz, 1999, Sturm, 2005]. We will introduce such adaptation rules in Section 4.3 (see Table 4.3 for a summary).

Unlike Hofstede, Hall never assumed such a strong connection of culture with nationality. Lacking tangible scores, his cultural values have been mainly employed for describing user interface differences, rather than for predicting preferences. The above-mentioned preference of polychronic cultures for non-linear navigations, for instance, can be roughly generalized for users living in Asia and Africa, but Hall never defined a list of countries that can be assigned to one or the other. This may be one reason why applying Hofstede's dimensions has been the basis of much more research than Hall's dimensions.

With the information about a user's nationality as a combination of space and place, we have localized the users' cultural background based on their affiliation to certain countries. The following variables provide further information, refining users' mental affiliations, and describing additional influences on their thinking and behavior.

Language

Language is known to shape a person's thinking [Nisbett and Masuda, 2003]. Languages are not culture-specific, and can certainly not serve as a synonym for culture [Rhoads, 2008]. Quite the contrary, one cultural group can inherent different languages, such as in multilingual Switzerland. Switzerland, however, is also an example of how different language groups form sub-cultures of their own, suggesting that culture is less dependent on country borders than on language.

Sub-cultural
language groups

Languages differ in the way they combine words, and their words differ in the way they are formed. It suggests itself that language plays an immense role in the cultural adaptation of

content; but does it also influence the perception of different arrangements of user interface elements?

One of the key distinctions between languages is the writing system orientation, which has evolved differently for many languages in this world. Some languages are generally written and read from left to right, some others from right to left, and some from top to bottom starting on the right. In each case, the writing system influences the spatial routines literate humans apply, which impacts expectations about the visual attention [Chan and Bergen, 2005]. The writing system orientation a user is familiar with not only needs to be implemented for textual parts of a user interface, but also applied to the layout of user interface constituents. Röse [2005], for instance, found that the writing system orientation influences the centre of attention on a screen. Thus, if a system wants to draw the user's attention to a certain part of the user interface (e.g. in the case of error messages), the placement decision has to consider the user's writing system orientation [Röse, 2005]. These results were supported by Chan and Bergen [2005] who demonstrated that visual attention is initially placed at the start location of the person's writing system orientation.

Influence on visual attention

In addition, language has been found to influence the perception of focal and background elements [Nisbett, 2003]. Western languages, for example, seem to force a preoccupation with focal objects as opposed to context [Nisbett, 2003]. Hence, languages do impact the way people observe the world (and thus, parts of it such as user interfaces). As Nisbett points out, however, the tendency to perceive things as given by Western or Eastern languages also depends on how the brain has been trained to think in other languages [Nisbett, 2003]. Asking participants from China and the US to group a number of words, they received different classifications for Chinese participants tested in their native language, and Chinese participants tested in English. In the latter case, participants seemed to adopt the Western way of thinking merely due to

Influence on focus

using another language. In further studies with two groups of bilinguals who had either learned a second language early or later in life, Nisbett found that Chinese who learned a Western language early in life also shifted towards Western thinking [Nisbett, 2003]. Considering these findings, it is advisable to incorporate knowledge about a user's first language, but also about his or her second language as well as how early this language was learnt.

Religion

Influence on trust Religious affiliation in user interface design is often expressed with symbols or colors. Analyzing this, Siala et al. [2004] conducted a study on the influence of religious affiliations on consumer trust in e-commerce. Muslim participants tended to prefer online shops that provided cues for the same religion, and also stated that religion highly influenced their general purchasing decisions. This was not the case for Christian participants, who preferred the neutral online bookshop www.bol.com. Their study suggests that religion can result in a more positive attitude towards web sites showing the same religious affiliation; however, they also found that this finding depends on the religious commitment [Siala et al., 2004]. Their findings imply that a culturally intelligent system should inquire about the user's religion, but also about the religious commitment. Adaptation rules could then relate religious meanings to color preferences, offering versions of user interfaces that feature those colors associated with a positive meaning.

Education

Cultural differences also emerge from varying education levels, but also from the form of education someone is most used

to. Students who have mainly received teacher-centered instruction, as opposed to participatory learning as with group work, are thought to also appreciate detailed instructions later in life [Reinecke, 2005]. Additionally, they are more prone to the lost-in-hyperspace feeling often felt navigating in non-linear hypertext structures. Thus, a dominance of teacher-centered instruction at school seems to result in a preference for linearly composed web sites, a higher level of support, and more instructions on subsequent options [Reinecke, 2005]. In contrast, students who are used to participatory learning, e.g. where they are able to propose their own thoughts in discussions, are more likely to appreciate the freedom of a non-linear navigation, and prefer exploring information themselves.

Form of education and support requirements

As opposed to the form of education, the education level mainly influences the intensity of cultural characteristics in a person. It is assumed that people who have rarely been exposed to other cultures have stronger cultural traits than culturally ambiguous people, that is, people who have interacted with other cultures or experienced them in another way. People become more aware of differences between cultures if they visit other countries, mix with friends of various cultural backgrounds, or have parents of another nationality. In this regard, the level of education can be a good predictor of the amount of international travel; the higher the education level, the higher the number of times someone has typically been abroad [Hayward and Siaya, 2001].

Education level and the intensity of cultural characteristics

As previously described, anthropologists note another important aspect of cultural influence: different forms of media such as the TV and the Internet that play an enormous role in cultural exchange today. If a higher education level usually results in more exposure to other cultures, we could also assume that those people with a high education level are also more open to adopt foreign cultural traits. Although more research is needed on the effects of user interface acceptance,

we can roughly assume that the higher the education level, the less users are impaired by non-localized web sites.

Education level and
computer literacy

Furthermore, the education level is often strongly related to computer literacy. In fact, education also obeys the rule: the higher educated a person is, the more he or she uses the computer [Microsoft, 2004]. If high computer literacy results in less need for navigational cues and support, a higher education level could also indicate this. Keeping in mind the difficulty of acquiring information about users without requiring them to fill in long questionnaires, we therefore suggest to include either computer literacy, or the education level in the acquisition process. The missing information in the user model can later be filled in by inference.

Political Norms and Social Structure

While the political orientation is understood to be part of culture [Hofstede, 2003], its influence on user interface design has mostly been indirectly investigated with the help of Hofstede's dimension Individualism versus Collectivism. In related work, communism has been mostly regarded as a form of collectivism, and thus, collectivist traits have been assigned to communist states such as the People's Republic of China, Republic of Cuba, or Democratic People's Republic of Korea (North Korea). In contrast, the division between Eastern cultures and Western cultures is often used to refer to Asia and Europe (sometimes with the addition of North America and Oceania). Instead of distinguishing between political systems, this division arose from religious affiliations, assigning Western cultures to Christianity, and Eastern cultures to Eastern religions, such as Buddhism, Hinduism, or Confucianism [Ankerl, 2000]. It is therefore difficult to determine whether differences found in perception between Western and Eastern cultures, or collectivist and individualist societies are a result

of religion, politics (e.g. through politically intended educational concepts), or both.

However, differences in perception between those two coarse classifications were indeed found in that people belonging to Eastern cultures paid more attention to interdependent relationships among items shown to them, while Westerners seemed to focus on individual objects [Nisbett, 2003]. Similarly, Westerners were found to categorize objects much more than East Asians, who preferred non-hierarchical structures between objects referring to them in their broad context [Nisbett and Masuda, 2003]. As a result, they also seemed to have greater trouble separating an object from its context [Nisbett, 2003].

Difference in perception between Easterners and Westerners

With regards to the arrangement of user interface elements, these last results are also reflected in differences in web site design between Eastern and Western cultures. Chinese web sites are often more complex, featuring various independent areas of content. In contrast, Western web sites are mostly organized around one main content area as a focus point, with additional images illustrating the content [Schmid-Isler, 2000]. These differences also mirror further preferences: While people belonging to Eastern cultures often opt for user interfaces with high information density, where they can browse through the information, many Westerners prefer less, but strongly structured information at once. In accordance with this, Nisbett notes that “the feeling in control is not as important for Asians as it is for Westerners” [Nisbett, 2003].

Differences in web site design

Such results have also been shown to relate to Hofstede’s dimensions of Uncertainty Avoidance and Power Distance (e.g. [Baumgartner, 2003]) and can, therefore, not simply be explained with the dimension Individualism. However, Asia has received mostly low to medium scores in the dimension Individualism, as measured by worldwide average scores [Hofstede, 1997]. Europe, North America, and Oceania, in contrast, mostly obtained a high score in Individualism. While

this distribution indicates the possibility of predicting the aforementioned preferences in information density and control with Individualism only, we suggest using this dimension as an initial predictor of user interface preferences. The information about the user's political orientation and habitual social structure could then be used to refine adaptations of the user interface. Further research is needed to reassess the exact effect of this information on user interface preferences.

Age

Age as a facilitator
for sub-cultures

As described above, age cannot be seen as a part of culture, but it can certainly connect people of different cultural groups. An elderly person in Japan, for instance, could feel much more understood by elderly people in the US, simply because in some respect cultural differences are less important and outweighed by age similarities. Although we cannot make generalizations on this, studies about differences in perception between younger and elderly people did demonstrate that these groups could have their very own partialities in handling computers [Shneiderman, 1989].

Influence on
spacial memory

Thus, while we cannot assume that age supercedes cultural difference, it does seem like an important indicator for user interface preferences and needs. Sjolinder [1998], for example, provided a detailed review on individual differences in spatial cognition and way finding. Age differences were found in spatial memory, with older adults tending to have a less holistic view of their environment. Older users might therefore need explicit verbal instructions to focus attention on the path or route [Sjolinder, 1998]. Similar recommendations have been made by Shneiderman [1989], who encouraged software designers to increase online help and clear navigation mechanisms for elderly users.

Age as a predictor
for computer literacy

In the Western world, age can be also used as a predictive variable of computer literacy: Computer usage is high-

est around 30 years of age, and steadily decreases in older age [Microsoft, 2004]. Inferring computer literacy from the user's age could therefore be used to initially predict user interface preferences, such as the need for more support. With different levels of computer usage in different occupational groups, however, this assumption could be strongly biased. We therefore recommend hedging against false assumptions about users by providing the possibility to judge their computer literacy themselves.

Gender

As with age differences, gender does not represent culture, nor does it influence someone's cultural background, but it can create similarities across cultures. Cultural differences, however, are usually more important than gender differences [Nisbett, 2003]. As an example for this, consider the interpretation of color: While females in the Western world often prefer lighter, less contrasting colors, males tend to like strong colors better. Nevertheless, the use of colors should always correspond to their interpretation in a certain culture, because their attributed meaning varies heavily across cultures [Thorell and Smith, 1990]. As a first measurement, user interface designers should therefore adhere to partialities of target cultures, before addressing gender-related preferences. For this reason, we have discarded gender as a predictive variable in our cultural user model. More research is needed, however, to compare the preference prediction with and without this variable. As suggested by [Kamentz and Womser-Hacker, 2003], gender can serve as a control variable for this reason.

Culture can outweigh differences in gender

3.3 Defining Cultural Influences on Human-Computer Interaction

In the context of corporate culture, Green stated that “you do not control culture, at best you shape it” [Green, 1988]. The same is true for culture in general, which is best defined separately for each field it influences. With the variables described above that influence human-computer interaction and perception, we have attempted to find such a definition for this very narrow field. It is important to note that we do not intend to define culture, but rather tried to narrow down its influences on perception and preferences. In the following, the thesis will therefore understand culture as follows:

Definition *The influences of a person’s cultural background on Human-Computer Interaction evolve from current and former residences, the prevalent political orientation and social structure, nationality of both parents, religion, different languages spoken, the level of education, as well as the most familiar form of instruction in education.*

With this, we have attained a tangible definition of cultural aspects that influence human-computer interaction, which can be used for our approach to user modeling as described in the next chapter.

4

An Approach to Cultural Adaptivity

While the previous chapter explained the basics of how culture can be understood, the following sections detail how this understanding can be used for an approach to cultural adaptivity. Specifically, the chapter introduces a reusable framework for the whole approach, subdividing it into the process of:

- acquiring and storing knowledge about the user (Section 4.2),
- defining and storing initial adaptation rules that map this knowledge onto user interface adaptations (Section 4.3),
- implementing a user interface that can transform these adaptation rules (Section 4.3.2),
- refining the initial adaptation rules (Section 4.4).

The chapter closes with a preliminary evaluation of this approach.

4.1 Overview

Essentially, the idea of culturally adaptive user interfaces spans interdisciplinary research fields that underlie the premise of successful Human-Computer Interaction. To reveal the culture-dependent components of software, it is necessary to build a user model based on cultural particularities before the adaptation can be accomplished. The idea is that the computer acquires the user's cultural background by taking into account various cultural influences that affect user interface preferences, as discussed in the previous chapter. This information can be saved in a user model that the computer uses as a personal knowledge base about each user. Each of these user model instances links to a set of rules, which trigger the adaptation of the user interface to best suit the user's needs. To correct unsuitable adaptations, the user should be able to add more information about his or her cultural background to the user model. Likewise, the application connected to the user model should also be able to learn new, and refine existing adaptation rules. If the user model is updated by either the user (manually) or the computer (automatically through observation of the user's interaction with the system), the adaptation rules are automatically updated too, triggering new adaptations of the user interface.

Framework

Figure 4.1 illustrates this adaptive process in more detail: If the user model is employed for the first time, the user needs to initially *provide information* in a short questionnaire provided by an application, and/or a user model editor. This information is *explicitly added* to the user's respective user model instance on the user model server, so that his or her cultural dimensions can be calculated by accessing the cultural user model. Users can also interact with applications and/or devices that are enabled to access the user model server (e.g. an application on a mobile phone, or a computer program). These applications log the user interactions and subsequently

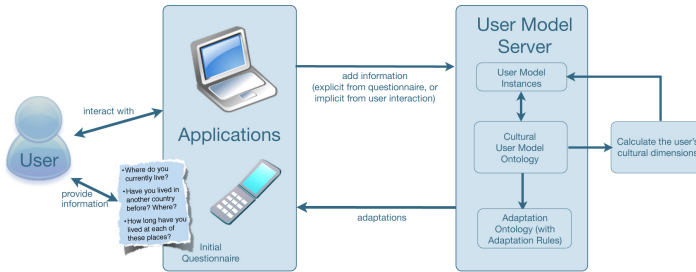


Figure 4.1: The framework for cultural adaptivity

inform the user model server about them. Likewise, users can *explicitly add or modify information* in their personal user model instances. On the server, both interactions and modifications update the user model, which is closely linked to the adaptation rules. This, in turn, triggers adequate adaptations that change the application's user interface.

According to this outline, our requirement for cultural adaptivity is a holistic usability between applications and devices, which could be achieved with a distributed user model. Furthermore, the aim is to limit the initial acquisition process to a minimum but still present users with fairly suitable user interfaces before they decide that they do not like the look & feel ("the first impression counts" [Lindgaard et al., 2006]). Since this will not necessarily result in the best possible user interface, a further requirement is the possibility to refine the adaptations both manually by the user, and automatically by the system.

Requirements

The following section first concentrates on the prerequi-

sites of a distributed user model, which outlines the users' cultural backgrounds.

4.2 Cultural User Modeling

The previous chapter described the viewpoint of cultural anthropologists on the term culture, and investigated the influence of cultural variables on user interface perception and preferences. The analysis led to a collection of cultural variables and aspects of culture that impact interface preferences, and thus, human-computer interaction. Although this collection does not qualify to be a completely comprehensive set of influences on user preferences per se, the cultural variables are a step towards overcoming the stereotypical approach of providing one interface per country.

Intersection between cultural aspects and their influences on HCI

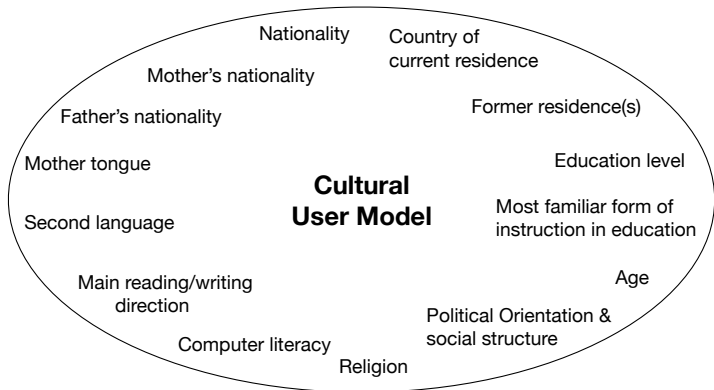


Figure 4.2: The set of cultural variables and aspects that impact user interface preferences, which in combination can be used for modeling the user's cultural background.

Figure 4.2 shows the aspects that we will use to model the user's cultural background for the purpose of predicting preferences. Summarizing the discussion in Chapter 3, we have compiled a list of these aspects and related them to the particular interface aspects that they have been found to influence in previous studies (see Table 4.1). As suggested in Chapter 3, country and nationality have been combined and are both linked to the effects of Hofstede's dimensions on user interfaces. Table 4.1 shows that a person's country and nationality also reveal the most information on possible adaptations of the user interface. Further knowledge about language, age, education, computer literacy, and political orientation/social structure might provide the means to refine or verify this information, but these influences do not necessarily add new knowledge about a user's preferences. In contrast, the user's reading direction, as well as his or her religion, cover extra information, which could refine the prediction of preferences.

Overview of user model aspects

The following sections describe one possible way how this information could be stored in an application-independent ontology, and how it can be filled with knowledge about a user.

4.2.1 A Cultural User Model Ontology

Throughout the history of user modeling, the storage of information about users has mostly been handled by means of application-dependent databases. One of the reasons that only a handful of applications employ user modeling techniques today, however, is the problem that little is known about the user when employing the user model for the first time, as mentioned in the introduction of this thesis. To mitigate this bootstrapping problem [van Kleel and Shrobe, 2007] researchers have suggested employing user models across several applications as an approach to cross-system personalization [Mehta and Nejd1, 2007]. The idea is a user model that ac-

Bootstrapping problem

Cross-system personalization

Table 4.1: The effects of each aspect from the cultural user model on the user interface.

User Model Aspect:	User Interface Adaptations:
Country & Nationality (according to the effects of Hofstede's dimensions on user interfaces)	Variable complexity/information density Different levels of hierarchy in the information presentation Non-linear navigation versus linear navigation with instructions Objects in focus, versus objects embedded in context Different levels of content structuring Different color schemes: colorfulness, brightness & contrast Different levels of support Variable numbers of navigational cues Number of images Representative versus explanatory images
Language	Objects in focus, versus objects embedded in context
Reading/writing direction	Left-to-right alignment, right-to-left alignment, or right-to-left-top-to-bottom alignment of all interface elements Right or left alignment of all elements that require full attention
Age	Objects in focus, versus objects embedded in context Different levels of support Non-linear navigation versus linear navigation with instructions
Education level	Different levels of support Variable numbers of navigational cues
Form of instruction	Non-linear navigation versus linear navigation with instructions Different levels of support
Computer literacy	Different levels of support Variable numbers of navigational cues
Political Orientation/Social structure	Objects in focus, versus objects embedded in context Different levels of hierarchy in the information presentation Variable complexity/information density Number of images Representative versus explanatory images Non-linear navigation versus linear navigation with instructions
Religion	Different numbers of religious symbols, exchangeable for each religion Different color schemes: colorfulness, brightness & contrast

companies the user ‘wherever they go’, no matter which application or device he or she uses. Our framework of cultural adaptivity aims to support this accessible and reusable nature of all user information by different applications.

With the rise of the Semantic Web and its concept of shared taxonomies, researchers have promoted such distributed user models with the help of ontologies (e.g., [Dolog and Nejd, 2003a, Heckmann et al., 2005, Baldoni et al., 2005, Zhou et al., 2005, Abel et al., 2007]). Ontologies provide the means to specify a common and unambiguous understanding of the user modeling domain. Furthermore, they enable the specification of concepts and their dependencies on each other.

Distributed user modeling

Taking advantage of these facts, we have developed an OWL ontology [Reinecke et al., 2007, Reinecke et al., 2010], which is composed of the cultural aspects listed in Figure 4.2. Figure 4.3 shows an overview of some example aspects in the ontology, and how they relate to each other.

In CUMO, the central concept is the `Person` class with its disjoint¹ subclasses `Female` and `Male` (at the moment, these are used as control variables as suggested by [Kamentz and Womser-Hacker, 2003]). Datatype properties connect the class `Person` with Hofstede’s dimensions. According to Hofstede’s cultural score table, these properties have been assigned an integer value. Another datatype property, the `hasYearOf Birth` with the value `year`, represents the user’s age. The information here can be collected either explicitly, or implicitly by inference from the sum of all durations the user has lived at current and former residences.

Description of CUMO

¹In OWL, classes can be separated by disjoining them, in order to allow individuals to only be an instance of one of these classes.

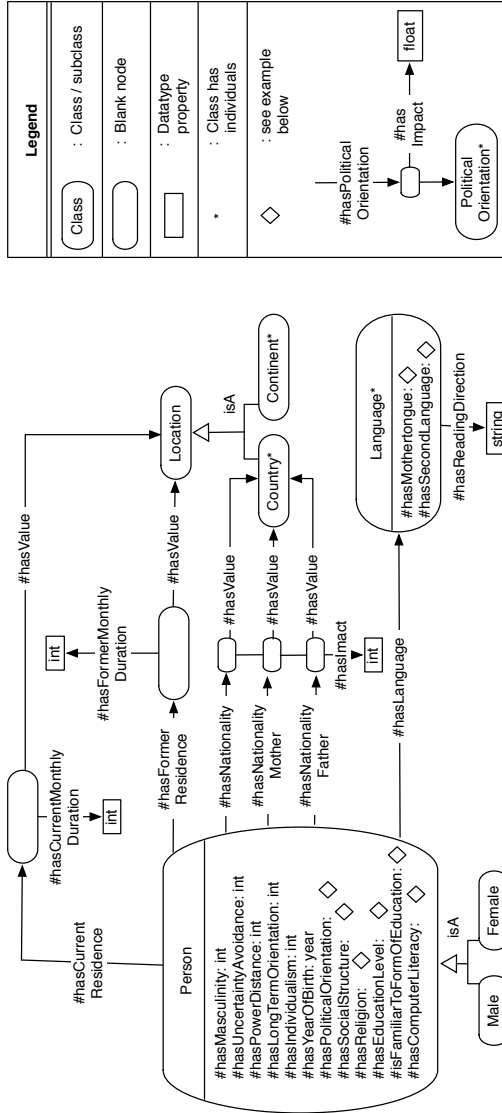


Figure 4.3: The Cultural User Model Ontology CUMO

The `Person` class in CUMO further links to the classes `PoliticalOrientation`, `SocialStructure`, `Religion`, `EducationLevel`, `FamiliarFormOfEducation`, and `ComputerLiteracy`. All of these classes are interconnected through datatype properties modeling the impact on the user's cultural background (see legend in Figure 4.3). This impact factor can be customized by the application, the user (e.g. with the help of a user model editor), or both. Additionally, each of these knowledge classes is connected to all relevant individuals. The class `Religion`, for example, provides instances of different religious beliefs as well as of major philosophies.

Additionally, CUMO has been complemented with the class `Language`, which is subdivided into the disjoint sub-classes `Mothertongue` and `SecondLanguage` (in Figure 4.3, these are connected to the class `Language` via a blank node). Thus, a person's native language cannot also be specified as a second language. As with the other classes within the domain `Person`, both can be assigned an impact factor, and both inherit an integrated language ontology from `Language` as listed in ISO 639 [International Organization for Standardization, 1997]. All languages have been assigned a reading direction.

To model the cultural influence of different places of residence, CUMO comprises the object properties `hasCurrentResidence` and `hasFormerResidence`, all having the range `Location`. The property `hasCurrentResidence` is functional, and can therefore have at most one individual relating to it. `Location` is further subdivided into the sub-classes `Continent` and `Country`, which contain individuals of all continents as well as of all countries listed in ISO 3166 [International Organization for Standardization, 1997]. CUMO contains Hofstede's cultural score table, so that the 80 countries he has investigated (see Appendix A) are assigned five integer values (one for each of the five dimensions). We

have investigated the remaining countries in ISO 3166 for their cultural and geographic proximity to those ones listed in Appendix A. Although this procedure risked generalizing culture, it was a necessary step to be able to approximate the cultural background of people from these remaining countries. The assigned cultural dimensions, however, are only used until MOCCA's learning mechanism has enough information to switch to other knowledge sources (cf. Section 4.4).

In addition, CUMO includes the world averages for each dimension to allow for later comparison. Furthermore, datatype properties of the range integer record the months of residence for each instance of `currentResidence` and `formerResidence`. With the help of the datatype property `hasYearOfBirth`, which provides us with information about the user's age, we can calculate the cultural influence of each of these locations on the user. The algorithm for this calculation is described in the second part of Section 4.2.2.

With CUMO, we have built a re-usable knowledge base, which is the basis for deriving user interface preferences — provided that we know the details of all aspects about every user. The next section elaborates on the problem of acquiring this information in order to fill the user model.

4.2.2 Acquiring Information about the User's Cultural Background

Acquisition process in conventional localization

The acquisition of the user's origin in the conventional approach to localization carries the problem that users have to decide for one country, or are automatically presented a localized web site based on their IP address (cf. Section 2.1).

In our approach, information about users is stored in CUMO, which has the advantage that it can contain a more complex model of the user's cultural background, and that it only has to be acquired once in order to be accessible to an in-

finite number of applications. This knowledge acquisition can be achieved in both static and dynamic ways. Static knowledge acquisition usually stands for information that is explicitly provided by the user, e.g. in an initial registration process. Mostly, this information does not change over time. In contrast, dynamic knowledge acquisition describes the process of learning while a user interacts with the system; it is this dynamic part of user modeling that accounts for the system's intelligence.

Static and dynamic
knowledge acquisition

Naturally, information provided by the user in a static knowledge acquisition process is most accurate. There is, however, one major reason why static knowledge acquisition has only limited capabilities: Users generally avoid filling in long questionnaires. While we could argue that a one-time registration process should be bearable for most people, the benefits of personalized user interfaces are simply unknown to most users. Thus, many of them could restrain from registering. On the one hand, it is therefore crucial to limit the registration process to a minimum. On the other hand, insufficient information about a user risks that the personalized user interface does not adequately cater for the user's preferences, in which case the user might be deferred from using it.

We suggest balancing this conflict by limiting the registration process to three questions about the user's current residence, former residences, and the respective durations he or she has lived in those countries. Hofstede's dimensions can then serve as a predictive measurement of the user's national culture, but it can also cater for some parts of anthropology's place and space discussion [Gupta and Ferguson, 1997], if we calculate the percentage influence of each residence by its duration. This approach assumes that the sum of all durations roughly equates to the user's age. If a Chinese user, for example, has lived in Sweden for 18 years, and in China for 24, we can calculate the influence of Sweden and China according to these durations, and assume his or her age to be 42.

Initial acquisition with
three questions

Referring to our variables through which we define the user's cultural background, this approach covers the current and former residences, age, and (by inference from age) roughly the computer literacy. Because Hofstede's dimension Individualism is automatically included in this approach, we could compensate for the lack of information about the user's political orientation and social structure. To approximate the view of culture in anthropology, we propose to acquire the remaining information about the user's cultural background on a voluntary basis: The more questions the user answers, the more detailed the cultural profile becomes, and the more accurate the predictions of his or her user preferences will be. Hence, in our approach, the user can choose to answer additional information about the parents' nationality, which can have a strong influence on the person's "nationality in their mind", if different from nationality by birth. Additionally, he or she can provide further information about spoken language(s), reading direction, education level, and religion.

The explicit and static knowledge acquisition still risks misjudging the user's preferences and abilities. To limit this risk, it is preferable to add dynamic knowledge acquisition, such as the tracking and later interpretation of the user's interaction with the system, and/or the refinement of adaptation rules according to manual changes of the user interface by other users. Both possibilities are described in Section 4.4.

4.2.3 Calculating the Influence of Different Residencies on Cultural Background

According to the registration process with three initial questions, we have developed an algorithm that calculates the cultural background, and results in the possibility of triggering suitable adaptations. The algorithm traverses the following steps:

- The application enquires about the user's current and former places of residence, as well as about the respective durations.
- This information is passed onto the server, which stores it in the user-specific RDF-based instance of CUMO.
- The application receives the cultural dimensions for each of the user's places of residence from the server.
- The application calculates the percentage influence of each residence with the help of the single durations and the cumulative duration (which is assumed to be the user's age).

$$influenceOfCountry_N = \frac{monthlyDurationOfStayInCountry\ N}{ageInMonths} \quad (4.1)$$

- Each country's influence is consecutively multiplied with all cultural dimension scores, which generates the user's new cultural dimensions. With the help of Hofstede's five dimensions for each country, we can calculate the user's score in each dimension H (where H is one of Hofstede's 5 dimensions; N the number of countries that influences the user, and $countryScore$ is the country's score in the dimensions):

$$userDimScore_H = \sum_{i=1}^N countryScore_H * influenceOfCountry_i \quad (4.2)$$

- The new cultural dimensions are compared to the world averages that are stored in CUMO. In the adaptation rules, the deviation now provides information about which rules are triggered.

After traversing the algorithm, the user will be presented a user interface composed of elements that have been defined by the adaptation rules.

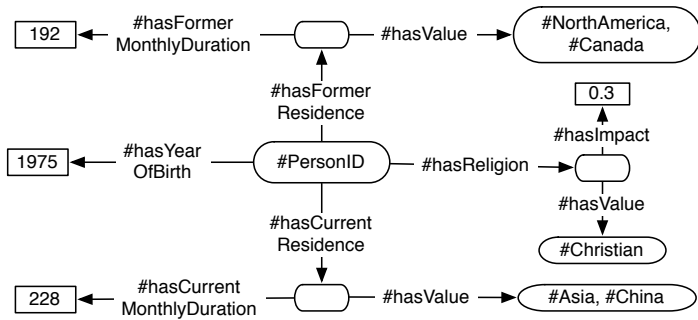


Figure 4.4: An example of a cultural user model instance

Example user
model instance

By following the algorithm described above, the cultural user model is built up as shown in Figure 4.4 for an example person. A user first needs to enter his or her current place of residence, as well as former countries he or she has lived in, if applicable. The data allows us to look up the corresponding cultural dimensions and pass them onto the cultural user model. The accuracy of the assigned values for the dimensions can be verified and improved with the subsequent set of questions. If the user provides information about the duration he or she has lived at current and former residences, we can derive the percentage influence by these countries. In our example, we have ascertained that the user has lived in China for 19 years (228 months) and in Canada for 16 years (192 months). Deriving from these facts, we can assume the user to be 35 years old (i.e. the datatype property `#hasYearOfBirth` can be assigned the value 1975 with

today's year being 2010). Accordingly, we can calculate the influence of both countries on the user's (national) cultural background.

Because of the possibility of refining the user model, further information can be added, such as the user's religion. In this case, the user is Christian and the cultural impact is estimated to be 0.3, or 30 %. The exact number can be assessed by the user, or the system could define a standard. For our example user, the system should factor 30 % of the most obvious religious rules, such as religious colors, into the adaptation process. The next section details the process of mapping this information onto precise user interface adaptations.

4.3 Adaptation Rules for Culturally Adaptive Interfaces

Drawing on the reported influence of Hofstede's cultural dimensions on user interfaces as discussed in Chapter 3, our adaptation rules translate a user's position in the cultural dimensions into changes of the user interface. Adaptation rules are usually dependent on a particular application domain. Table 4.3 lists some example rules for the broad field of user interfaces, which are derived from related work that concentrates on very special areas within this field, such as on the influence of Hofstede's dimensions on the user interface design in mobile applications. For use in a specific application, these rules have to be interpreted to suit the domain.

The table shows the adaptation rules 'extremes' for each of Hofstede's dimensions and user interface aspect; these adaptation rules can be further refined by adding different changes in the user interface that mirror this gradation. The more gradations, however, the higher the complexity of the culturally adaptive software, since each design has to be implemented.

Table 4.2: Adaptation rules as derived from related work on the effect of Hofstede's dimensions on user interface design for users with a high or low score.

	Low score	High score	Reference
PDI	Different access and navigation possibilities; non-linear	linear navigation, few links, minimize navigation possibilities	[Voehringer-Kuhnt, 2002, Hofstede, 1986, Marcus and Gould, 2000, Burgmann et al., 2006]
	Data does not have to be structured	Structured data	[Marcus and Gould, 2000]
	Many functionalities	Reduced choice of functionalities	[Hofstede, 1986]
	Most information at interface level, hierarchy of information less deep	Little information at first level	[Marcus and Gould, 2000, Burgmann et al., 2006]
	Friendly error messages suggesting how to proceed	Strict error messages	[Hofstede, 1986, Marcus and Gould, 2000, Marcus and Gould, 2001]
	Support is only rarely needed	Provide strong support with the help of wizards	[Marcus and Gould, 2000]
	Images show the country's leader or the whole nation	Images show people in their daily activities	[Marcus and Gould, 2000, Gould et al., 2000]
IDV	Traditional colors and images	Use color to encode information	[Marcus and Gould, 2000]
	High image-to-text ratio	High text-to-image ratio	[Gould et al., 2000]
	High multi-modality Colorful interface	Low multi-modality Monotonously colored interface	[Hermeking, 2005] [Barber and Badre, 1998]
MAS	Little saturation, pastel colors	Highly contrasting, bright colors	[Voehringer-Kuhnt, 2002, Dormann and Chisalita, 2002]
	Allow for exploration and different paths to navigate	Restrict navigation possibilities	[Ackerman, 2002]
	Personal presentation of content and friendly communication with the user	Use encouraging words to communicate	[Hofstede, 1986, Dormann and Chisalita, 2002, Callahan, 2005]

UAI	Most information at interface level, complex interfaces	Organize information hierarchically	[Marcus, 2000, Marcus and Gould, 2000, Marcus and Gould, 2001, Zahed et al., 2001, Hodemacher et al., 2005, Cha et al., 2005, Choi et al., 2005, Burgmann et al., 2006]
	Non-linear navigation	Linear navigation paths / show the position of the user	[Marcus, 2000, Marcus and Gould, 2000, Marcus and Gould, 2001, Baumgartner, 2003, Hofstede, 1986, Kamentz et al., 2003, Corbitt et al., 2002, Burgmann et al., 2006]
	Code colors, typography & sound to maximize information	Use redundant cues to reduce ambiguity	[Marcus and Gould, 2000, Marcus and Gould, 2001]
LTO	Reduced information density	Most information at interface level	[Marcus and Gould, 2000, Marcus and Baumgartner, 2004]
	Content highly structured into small units	Content can be arranged around a focal area	[Marcus and Gould, 2000]

Hofstede's dimensions often provide suitable hints about the needs of an 'average user', but these assumptions can become invalid or be contradicted by other information about the user's cultural background. This is why, as previously described, CUMO contains classes representing a more comprehensive cultural background, consisting of information about the user's religion, educational background, or age. Adding this information could result in the verification of many assumptions that have been implicitly made during the initial adaptation process by using Hofstede's dimensions. Knowledge about the user's most familiar form of education, for example, can help us to adjust the level of support. Hofstede's dimensions might contradict the user's needs in some cases, such as if the Power Distance score is high (resulting in high

Adaptation rules for other aspects of the cultural background

support), but the user has a high computer literacy and does not need the support. In such cases, explicit feedback from users about other aspects in CUMO can help to refine adaptations. Table 4.3 exemplifies some adaptation rules for other aspects modeled in CUMO (cf. also Table 4.1), and identifies where contradictions might occur, or where information has priority and other information has to be disregarded. Such prioritizations can be made with the `#hasImpact` datatype property in CUMO.

Theoretically, all information hinting towards a certain adaptation should be taken into account equally. However, if there are contradictions (i.e. a high computer literacy, but young age), the information has to be prioritized. Additionally, all information has to be seen in context: If the user states a high computer literacy, but specifies being mostly used to teacher-centered education, he or she might still need a high support level for new software, but less support for programs and web sites the user already knows.

4.3.1 An Adaptation Ontology

A culturally adaptive user interface has to be sufficiently flexible to cater for all adaptation rules listed in Table 4.3 in all possible combinations, and with their progressions between the extremes ‘low’ and ‘high’, plus all possible combinations of the rules and their assigned user interface elements.

At first, developers have to extract those application rules out of the set listed in Table 4.3 that are applicable to the planned application and its domain. Second, this subset of adaptation rules has to be mapped to the specific elements of the user interface that they influence. Assuming there are eight adaptation rules that are relevant for a certain application, and each cultural dimension is subdivided into *high* and *low* only (as presented in Table 4.3), then the user interface would have $2^8 = 256$ different compositions. One could ar-

Mapping adaptation rules to user interface elements

Table 4.3: Example adaptation rules for other cultural aspects listed in CUMO (excluding Hofstede’s dimensions). Priorities of information are in descending order per adaptation.

Adaptation	Triggered if one of the following pieces of information is known	Explanation
High support	Computer literacy = low Age = high Instruction = teacher-centered Education level = low	A high computer literacy outweighs “contradictory” specifications on age, instruction form, or education level.
Non-linear navigation	Age = low Instruction = student-centered Political orientation = Communism	The younger the person, the more likely he or she is to cope with a non-linear navigation. Age also outweighs the most familiar form of instruction, as well as the political orientation (which is a vague assumption in any case).

gue that it is more time-efficient to design 256 different user interfaces than to develop an adaptive system. However, if we cater for finer gradations in the cultural dimension scores (e.g. classifying users with a score ≤ 30 in one dimension as *low*, users with a score ≥ 70 as *high*, and everyone in-between as *medium*), the number of different possible compositions results in $3^8 = 6561$ user interfaces. Here, and likewise with finer gradations of the cultural dimensions, the development of adaptive software has a clear time advantage.

According to the previous example, the software’s complexity obviously increases exponentially with the number of applicable adaptation rules and with the number of gradations in the cultural dimension scores. To fulfill such complexity, we have developed an adaptation ontology in OWL

Description of the adaptation ontology

for the domain of web applications. The adaptation ontology can be re-used and extended to suit specific user interface designs, and could be easily modified, e.g. for the use in mobile applications. Furthermore, it can be merged with other ontologies that comply with the OWL/RDF standard and can easily exchange information with our cultural user model ontology CUMO.

Defining all adaptable parts of the user interface, the adaptation ontology models the 'space' of possible solutions (i.e. the different compositions of user interface elements), their dependencies among each other, their types (e.g. navigation or header), and their representations (for different scores in a certain dimension). As shown in Figure 4.5, the adaptation ontology's main element is the class *UserInterface*, which defines general layout characteristics such as the colorfulness, color saturation, and alignment of the interface. It also specifies which user interface element is currently used with the datatype property *isUsed*. The user interface is further divided into the disjoint subclasses *Header*, *Content*, and *Footer*. The class *Header* generally describes the top part of a web page, which usually features a logo, a menu and sometimes breadcrumbs showing the exact position within the hierarchy of web pages. The class *Content* can be divided into the disjoint subclasses *Navigation*, which contains several individuals such as a tree navigation, or a flat, non-hierarchical navigation, and *WorkArea*. The latter describes the part of the web page where the content is being presented, and this presentation can be adapted with different levels of information density, guidance, and accessibilities of functions. Additionally, the look & feel of the *Navigation* and *WorkArea* changes according to various characteristics inherited from the classes *Content* and *UserInterface*.

Values of each interface element

To derive those characteristics defined in the adaptation ontology that are suitable for a person's cultural background, all interface elements are connected to the class *CumoValue*

via the object property #hasValue. The class stores the score for one or more of the cultural dimensions in five corresponding sub properties. The user interface element with the score closest to the one stored in the user’s cultural user model instance is later selected by the application and taken for the composition of the user interface. Hence, the adaptation ontology shows which element of the user interface relates to which cultural dimension. The sub properties of the class CumoValue could also be extended with further aspects of a person’s cultural background, such as with religion, assuming that we know which aspect of a user interface is influenced by certain beliefs.

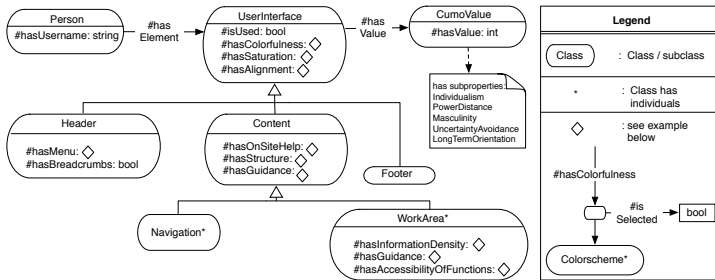


Figure 4.5: The upper layer of the adaptation ontology. The ontology requires the input of a user’s cultural dimension scores in order to compare them with values assigned to each user interface element.

4.3.2 Linking Applications to the Adaptation Ontology

While the adaptation ontology is designed to define possible user interface compositions, the application itself has the responsibility to retrieve and interpret this information. It is therefore strongly interwoven with the cultural user model ontology CUMO, which stores the information about the user’s

cultural background including his or her dimension scores. The retrieval of these scores is a precondition for triggering the corresponding user interface composition: At first, the application has to read out the user's scores, and possibly other information about the user's cultural background. Secondly, it has to look up the corresponding adaptation rules in the adaptation ontology by traversing the user interface elements for ones that correlate with the user's scores. Note that this correlation has to be defined by the application; in our approach, the user interface elements are chosen according to the smallest difference between the user's cultural score of the responsible dimension and the score assigned to the respective user interface element.

After this comparison has been completed, the application can compose the user interface. Since this is subject to implementation details and the technologies used, the exact procedure will differ from application to application. We will therefore exemplify the information extraction process from the ontology, as well as the composition of the user interface with our adaptive web-application MOCCA, which is described in the next chapter.

4.4 Refinement of the Adaptation Rules with Machine Learning

The approach described up to this point enables the triggering of the *initial adaptations* of the user interface. The user registers in an application, and based on the information provided about his or her residencies and the respective durations, receives a personalized user interface. What, though, if the resulting user interface is not the best-suitable one for the current user?

This section describes two methods to refine the initial adaptation rules with the help of machine learning: (1) A recommendation algorithm, which suggests user interface preferences based on the selection of users with a similar cultural background, and (2) a user interaction tracking approach, which allows the observation of possible difficulties in the user's handling of the user interface.

Besides triggering new adaptations (or recommendations) for the current user, both approaches aim to improve the adaptation rules in order to prevent *new* users from leaving the web site. Hence, the following methods are also a way to enhance the user's first impression, during which he or she often already decides whether to leave or to stay [Lindgaard et al., 2006].

4.4.1 Recommending User Interface Preferences

While applications incorporating our approach are able to present users with interfaces adapted to their cultural background, the resulting user interfaces are not always suitable. We therefore propose to allow users to modify their personalized user interface, and for the system to incorporate these modifications by learning new, and refining existing adaptation rules.

The related work outlines different approaches to personalization: On the one side, systems enable the manual rearrangement, or customization, and selection of components of interest in order to personalize the site for one's own interest (e.g. iGoogle², or LiveJournal³). This approach has been widely appreciated for its possibility to tailor the look & feel of a web page, providing users of blogging sites, for instance, with the possibility to express one's identity [MacKinnon and

Manual adaptation of
the interface

²<http://www.google.com/ig>

³www.livejournal.com

Warren, 2006]. However, the downside of manual personalization are, firstly, that users often avoid the effort of manually adapting the user interface to suit their needs (thus, leaving it as per default), secondly, they only personalize their most favorite sites (i.e. ones that are regularly re-visited [Blom and Monk, 2003]), and thirdly, they often do not know how to adapt the user interface for their own benefit [Kobsa, 1993].

On the other hand, the rise of commercial and collaborative platforms on the internet has led to a continuous increase in the number of systems that infer knowledge from (the interaction with) other users in order to derive similar interests. Such recommender systems have been widely applied in both industry (e.g., Amazon [Linden et al., 2003]) and research [Herlocker et al., 1999], but mostly suggest products, such as music, news, or books based on similar interests. Recommender systems make use of learning mechanisms - the most widely applied method probably being *collaborative filtering* [Goldberg et. al, 1992, Hill et. al, 1995]. Automatic collaborative filtering systems collect so-called 'ratings' for items in a certain domain (e.g. books, or movies), and recommend them to other users based on a calculation of their similarity, which is based on homogeneous interests [Herlocker et al., 1999]. Such systems have the advantage that they often recommend items that fit into the user's interest profile, but were unexpected for the user. Their disadvantage, however, lies in the tedious collection of assumptions about the user's interests, which leads to the previously discussed *cold start problem* [van Kleel and Shrobe, 2007] (cf. Section 2.3): The recommendation mechanism needs some time to implicitly or explicitly collect information about the user before it is able to compare the profile to that of other users, and this can delay recommendations immensely.

Conventional collaborative filtering systems are designed to understand similarities between users as a preference for the same products (*item-to-item collaborative filtering*). Some

take into account the user profile based on similarities to comparable entries [M. Balk and I. Jelinek, 2009], but to our knowledge there are no systems that do this on the basis of cultural background. Our approach therefore extends related work in that we recommend the design of different user interface aspects based on preferences by other users of similar cultural background. Thus, we make use of the fact that people of the same cultural background often share similar (design) preferences (note that this will be subject of one of our evaluation in Section 6.2). By being able to immediately assign new users to groups of similar cultural background, this approach also aims to overcome the cold start problem.

Collaborative filtering
in our approach

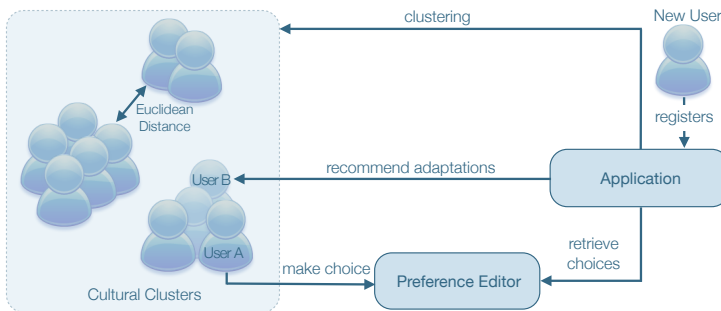


Figure 4.6: Refining the adaptation rules: Users are being clustered by their cultural background in order to recommend user interface preferences to users of the same group

The precondition for being able to calculate such recommendations is the knowledge about the *choices* of similar users. In contrast to the initial adaptation of the user interface, which is passively received, a choice is usually taken actively. The item-to-item collaborative filtering approach employed by Amazon, for example, uses the information about what the

Active choices

customer has bought (i.e. about their active choices), and what he or she has recently looked at in order to model the customer's interest [Linden et al., 2003]. Additionally, it incorporates information about other customer's with similar interest (i.e. with similar buying behavior) in order to perform recommendations.

Deriving choices using
a preference editor

To gain information about the user's active choices in our approach, we propose offering the possibility of manually adapting the user interface. Chapter 5 provides details on a possible implementation of this with the help of a built-in preference editor. The editor gives an overview of alternative design options for the user interface and adapts the user interface upon selection of an option that is different to the initially provided one. Selections are considered as *active choices* once the user has entered the preference editor, no matter whether they have been changed, or left as they were.

The active choices of user's with similar cultural background can be accumulated and, if consistent across the majority of users, recommended to a new user that can be assigned to the same cultural group. Thus, while conventional collaborative filtering algorithms base their recommendations on ratings, we have adapted the approach to estimate the preferences of an active user based on the preferences of other users with similar cultural background. The approach can be applied to culturally adaptive systems as follows:

Ratings = choice
of UI element

- Ratings in conventional collaborative filtering systems are equivalent to the choice of a user interface element in the preference editor. The approach presumes that users have modified certain aspects of the user interface in the preference editor. If not, the system assumes that the user is happy with the current look of the user interface. However, since some users simply might not bother to manually personalize their system, retained elements receive a lower weight than elements that have been actively chosen. The

system encodes actively chosen elements with a weighting of 1, while retained elements receive a lower weighting (assuming that active choices are more reliable). User interface elements (choices) are binary-coded (1 for chosen elements, 0 for others), such that after calculation, the user's estimated preference can range from 0 to 1.

- Similarity between users is not measured by similar ratings, but by cultural background. The system calculates such similarities between users with the Euclidean distance between the five-dimensional cultural vector that represents each user in the normalized feature space. Thus, in our approach, cultural similarity is based on Hofstede's five dimensions that are re-calculated upon registration to include possible former residences in addition to a person's current country of residence. In the future, this cultural background could be extended with additional aspects of culture as suggested in [Reinecke et al., 2010], resulting in more-dimensional vectors (however, this also requires more users if similarities are to be found). Cultural similarity
- According to the similarity of the users' cultural backgrounds, the system subdivides its user population into *cultural clusters* (see the *user clusters* on the left in Figure 4.6), using the partition-based clustering algorithm k-means [Duda, R. O. and Hart, P.E. and Stork, D.G., 2000]. Each user's cultural background serves as one input feature vector for k-means, all of which are subsequently grouped by similarity. K-means also requires the input of a k-value to specify the number of clusters. We randomly selected the number of clusters (k), and iteratively re-run the algorithm with Hofstede's country vectors until there were no further changes in the clusters. Note that conventional collaborative filtering does not require previous clustering. We added it for mainly two reasons: (1) in cases of very few users in the database, the previously defined clusters pre- Cultural clusters

vent someone from being assigned to a cluster with totally differing cultural vectors. Without this, a Canadian user could have a Malaysian user as her nearest neighbor, and thus, his preferences would be included in the recommendations for the Canadian. (2) Clustering allows us to extract the evolving preferences of a defined cultural group over time - a feature that is especially desirable for future work (see Chapter 8).

If a new user registers with the system, he or she will be allocated a cultural cluster according to the minimal Euclidean point-to-centroid distance. Accordingly, some of the initial cluster centroids will change. The system should not derive new recommendations from these changes for users that have already registered in order to avoid imposing new user interfaces on them.

Collaborative filtering to generate recommendations

- After the allocation of users to a cultural cluster, the application is able to generate preference recommendations with the help of collaborative filtering. Retrieving the choices from the preference editor, the system estimates the preferences of an active user based on his or her neighbors within the same cultural cluster. Thus, we have restricted the recommendations calculated by the collaborative filtering algorithm to one cultural cluster per time. The more similar a neighbor (i.e. the closer the cultural vector) to the active user, the more his or her rating (i.e. the choice) influences the estimated preference of the active user. For all adaptation rules that have been determined by the system, it can then perform the following calculation in order to receive a prediction $p_{a,e}$ for an active user a and the element e (adjusted to our purposes from [Herlocker et al., 1999]):

$$p_{a,e} = \frac{\sum_{u=1}^n c_{u,e} * s_{a,u}}{\sum_{u=1}^n s_{a,u}} \quad (4.3)$$

where n is the number of neighbors, $c_{u,e}$ the choice of neigh-

bor u and element e (0 or 1), and $s_{a,u}$ the similarity weight between the active user a and one neighbor u .

Before recommending the adaptations, the system should check whether they had been previously selected or rejected by the active user. Only if this is not the case should the adaptation be offered on the basis of a user-controlled self-adaptation, where the system proposes alternatives but the user decides whether he or she would like to accept them. The exact procedure of how adaptations are recommended in our example application will be described in Chapter 5. The chapter also details the implementation and storage of the user's preferences in an extension of the CUMO ontology with preferences.

4.4.2 User Interaction Tracking

A second option to refine adaptation rules is a form of dynamic knowledge acquisition, which observes the user's behavior and infers mistakes and/or improvement possibilities. For example, if a user moves the mouse pointer for a certain time without clicking, this could indicate that he or she is looking for something, and hence, needs more support. So far, work on inferring user interface adaptations from mouse movements or other user input has proven feasible as a way to classify users into novice or expert [Hurst et al., 2007], or derive user interface constraints for people with motor impairments [Gajos et al., 2008]. Previous studies also demonstrate that one could draw conclusions on certain cultural dimensions from a user's mouse movements and navigation behavior [Kralisch, 2005, Heimgärtner, 2005]; however, these observations did not point towards the possibility of inferring on user interface preferences as envisioned by our adaptation rules.

The prerequisite for applying user interaction tracking is the definition of *inference rules*, which map certain interaction

Inference rules

patterns to adaptations of the user interface. Thus, we have to determine (1) which parts of the user's interaction with the application are feasible and useful to record, (2) what we can conclude from certain interaction patterns (i.e. a classification of users into certain categories), and (3) what information we can derive from interaction patterns that can be stored in CUMO for use by other applications.

As to the feasibility, Schmidt et al. [2007] have shown an approach to semantically annotate and extend a Javascript/AJAX-based web application with an interaction tracking component, which records mouse movements, clicks, or keyboard input. Previous work has also derived different interaction statistics for classifying users into different learner proficiencies with the help of eye tracking [Amershi and Conati, 2007], skill levels [Hurst et al., 2007], or derive special needs, such as the reading speed for people with disabilities [Stephanidis et al., 1997]. So far, however, it is unknown whether user interface interactions could also reveal other user characteristics and preferences.

Theoretically, the inference part of the user modeling process can be handled independently of previous information contained in the user model, in our case of culture. Thus, observations of the user interactions and inferences on further adaptations are not necessarily restricted to the user's cultural background, but can include an upper level of observation: Is the user able to cope with the adaptations? Are there behavioral restraints that might point to a need for correcting those initial adaptations? As mentioned earlier, mouse hovering could indicate the need for more support, but it can also mean that a person is simply reading. Coping well with a user interface is usually characterized by determined mouse movements (forming a straight line at a certain speed), and few errors (e.g. the use of the browser's back button, or opening and closing a dialog without filling it out could indicate errors). Hence, these upper level observations mainly hint at

Discussion of interaction statistics and their meaning

the skill level, which in our case could complement information about the computer literacy in the cultural user model.

In addition, we were curious to find inference possibilities to gain information about other parts of the cultural user model (i.e. knowledge that has not been explicitly acquired in the initial registration process). Specifically, the question of whether it is feasible to use the interaction tracking to gain or verify information on the user's language/reading direction, education level and form of education, political orientation, or religion. While the level of computer literacy can be extracted from interaction statistics, these other aspects in CUMO do not necessarily express themselves in the user's interaction with a user interface. In particular, it seems to be more realistic to estimate someone's political orientation, religion, and the form of education from information about former and current residencies than via deduction from mouse movements. Computer literacy, in fact, often correlates with the education level (see discussion in 3.2). Our approach, therefore, at first relies on deriving the computer literacy only, and leaves the verification of automatically derived assumptions about the education level to the user.

Inferring information about user model aspects other than residences

In addition, the reading direction can be inferred from the user's language (assuming that we can deduce this information from the country of current and former residence). Although there is the possibility to infer the reading direction from the unconscious focus of the eyes with the help of eye tracking [Röse, 2005, Amershi and Conati, 2007], we have refrained from this due to the fact that eye tracking has not yet been proven to be an everyday solution.

From this analysis of previously employed interaction statistics and our own thoughts on possible inferences from the user's interaction, we have compiled a list of interaction statistics. Table 4.4 gives an overview of those interaction statistics that are applicable to our approach, and briefly describes the interpretation of them into inference rules. Note that this

interpretation could possibly also effect the size of buttons, and the distance between user interface elements for older or motor-impaired users, as suggested in [Gajos et al., 2008]. For now, however, we only make inferences on culture-related changes to the interface according to the adaptation rules in Table 4.3. As suggested in [Hurst et al., 2007], our inference rules aim to classify users without the previous establishment of a task model (i.e. the interaction sequences are unknown).

Overview of inferable aspects

The table reveals that the user's interaction with the interface mainly provides hints about the user's familiarity with the software, or the computer literacy in general. Thus, we can derive the need for a different support level, non-linear or linear navigation, the number of functionalities, and different content structuring. These aspects are predominantly affected by the dimensions Power Distance, and Uncertainty Avoidance (cf. Table 4.1 and 4.3), and could therefore complement or correct the information gained in the initial acquisition process.

The implementation details of our approach to user interaction tracking are described in 5.7, where we also present a short evaluation of the classification system of users into low and high computer literacy.

4.4.3 When and How to Adapt

Controllability

Both approaches described in the previous two sections result in changes in the cultural user model ontology and/or adaptation ontology and trigger new adaptations. In the case of existing users, such new adaptations at run-time could confuse users if they include major visual changes of user interfaces. Thus, one of the major challenges of adaptive systems is the *controllability* [Jameson and Schwarzkopf, 2002]. The amount of control necessary for, or preferred by, a user can highly vary [Kay, 2001], and most probably also depends on culture.

Table 4.4: Inference rules derived from interaction statistics for the refinement of adaptations.

Interaction statistic	Interpretation	Inference rule
Average latency between using interface elements [Amershi and Conati, 2007]	If the latency (e.g. the click distance) is significantly higher in comparison to other users, the current user might need more support. A low latency might indicate an experienced user (high computer literacy). Note that without eye tracking we do not know whether the user is temporarily distracted from the user interface.	<code>if (latency = high) then activate wizard</code>
Mouse velocity in pixels/second [Hurst et al., 2007]	A high velocity could indicate an experienced user, a low velocity someone who is searching or conceiving the presented information	<code>if (mouse velocity = low) then limit functionality, increase guidance in dialogs, activate breadcrumbs, provide linear navigation, activate wizard, provide maximum structure and accentuate affiliations</code>
Mouse hovering [Hurst et al., 2007]	Similar to latency, mouse hovering can indicate that the user is searching for something	<code>if (mouse hovering on general UI \geq average) then activate wizard, if (mouse hovering on dialog box \geq average) then increase guidance in dialogs</code>
Number of errors [Stephanidis et al., 1997]	Errors can be wrong input in dialog boxes, clicking on a link and then on the browser's back button (indicating that the user did not find what he or she was looking for), or false clicks (e.g. next to a button)	<code>if (dialog errors \geq average) then increase guidance in dialogs, if (error messages \geq average) then increase guidance in dialogs, activate wizard, limit functionality</code>
Number of help requests	Requesting help firstly indicates that a user is willing to receive help. Whether users are willing to read through the help also strongly depends on the degree of difficulty of an application	<code>if (Help requests \geq 1) then activate wizard</code>
Mouse scrolling	If the user scrolls several times up and down at short intervals, he or she might be searching for information.	<code>if (scrolling behavior = irregular) then activate wizard</code>

Dimensions
of adaptivity

Previous work has described different approaches to the timing of a new adaptation, e.g. to certain intervals [Jameson and Schwarzkopf, 2002]. In combination with this, some studies also focused on how to adapt by analyzing whether users should be made aware of the adaptation, and how this can be best achieved. In [Dieterich et al., 1993], the authors defined different dimensions of adaptivity:

1. User explicitly requests recommendations and then actively chooses or rejects them
2. User explicitly requests recommendations, that are then automatically triggered.
3. The system automatically recommends changes, but lets the user decide whether to accept or reject them
4. The system automatically triggers changes

Whilst you may have a spontaneous favorite reading these four alternatives, user studies point out that the perfect solution does not exist. Jameson and Schwarzkopf [2002], for example, reported on an experiment on preferences for the automatic or controlled updating of information recommendations, and came to the conclusion that each solution depends on a variety of conditions, such as on the individual experience of users, and on the type of application and its adaptations. Thus, the control over the 'when' and 'how' should be either derived from assumptions about the user's preference according to information in the user model, or left to the user.

When and how to
adapt in our approach

Our approach to culturally adaptive systems includes a number of different solutions:

- When the user logs in for the first time, the system automatically triggers changes. At this moment, the user does not know alternative user interfaces yet, and thus, cannot be confused by changes.

- In case of recommendations, an unobtrusive button appears on the user interface, leaving the possibility to ignore it, or to explicitly request recommendations (1 or 2).
- Upon actively requesting the recommendations (derived from the user interaction tracking or based on choices of other users), we activate a recommendation wizard, which allows the reviewing of recommendations, accepting, or declining them (1).
- Within the recommendation wizard, the user has the chance to configure that future recommendations are to be automatically triggered (2).

With this strategy, the user has the choice between *computer-aided adaptation*, where the user initiates adaptation, the system proposes adaptations, and the user decides, and *self-adaptation*, where the system automatically triggers the adaptations [Dieterich et al., 1993].

4.5 Preliminary Evaluation of the Approach

The described approach to cultural adaptivity is based on two major assumptions: Firstly, it predicates that previous studies on the influence of Hofstede's dimensions on user interface perception have been broadly accurate. Secondly, it assumes that an individual's score can be calculated by weighing the score of all relevant countries by his/her length of stay. The validity of these hypotheses therefore mainly determines the suitability of the initial adaptation for a user.

In the following, we present a preliminary survey conducted with the goal of testing both assumptions. Hence, this study also aimed to verify our adaptation rules. We specifically focused on culturally ambiguous users in order to find

out how residences in different countries influence their preferences.

Test design

The study was conducted with the help of an online survey. Based on the adaptation rules, we developed 45 questions covering 22 general user interface and learning preferences (listed in Appendix C). Each question was asked in both a negative and positive form in order to detect outliers and incorrect answers. One of them required a third, paraphrased question for disambiguation. The questions covered all aspects of the adaptation rules, such as the preferred kind and level of navigation support, or the favored form of information presentation. Adaptation rules derived from Hofstede's work on the relation of his dimensions to learning style [Hofstede, 1986] were later generalized to the handling of web sites. All questions were asked in English.

Answers had to be given a rating on a scale from 1=*strongly agree* to 5=*strongly disagree*. Furthermore, the survey consisted of questions about current and former residencies as well as their respective duration (in months), the respondent's age, highest level of education, parents' nationality, languages spoken, religion, and political orientation. For statistical purposes, we also asked about the occupation, English proficiency, computer skills and the frequency of computer use. A pilot version of the survey was tested with four subjects. With the pilot we detected ambiguities in the questions and adapted the survey accordingly. The survey was then released online. Respondents were sent a link to the survey and an explanation of the survey's purpose. An incentive for serious participation in the survey was a subsequent prize-drawing.

Data adjustment

From 46 survey responses, 16 surveys had to be discarded because answers were incomplete, or two questions covering the same preference in opposite directions were answered with the same rating, indicating a careless handling of the survey. All respondents specified a very good or good understanding of English. Also, the frequency of computer usage

was relatively constant for all respondents: 13 % of all participants specified to use the computer four to six days a week, while a vast majority of 87 % uses it daily. Furthermore, most respondents (80 %) were classified as culturally ambiguous because they had lived in multiple different countries (see Tables 4.5 and 4.6). We have analyzed the data in three steps:

Data analysis

- **Algorithm:** The information about current and former residencies was used to determine a subject's dimensional scores (see previous section). Instead of actually adapting an interface, we listed the adaptation rules that would normally have been triggered.
- **Prediction:** Based on the adaptation rules, we calculated the predicted answer for each question (e.g. a high score in one dimension triggered a rule that would predict a high preference for hierarchical arrangement of information).
- **Comparison:** We compared the prediction (laid out on a 5 point scale) with the users' answers. The deviation between the two was noted down as absolute error (AE) for each question.

Results

The analysis of the user's answers showed that on average our prediction was correct for 13 out of 45 questions. In 16 cases we were able to predict the answer with a deviation of 1, in 10 cases with an AE of 2. An AE of 3 (3.5 questions on average) and 4 (0.3 questions on average) occurred very rarely. Figure 4.7 shows the distribution of the mean AE of our predictions. The resulting average deviation of only 1.079 indicates a strong correlation between the user's cultural background and the user preferences.

Table 4.5: The countries that were specified to be current residences.

Country of residence	# of respondents
Austria	2
Belgium	1
China	2
France	1
Germany	2
Norway	1
Rwanda	12
Switzerland	8
United Kingdom	1

Table 4.6: The countries that were specified as former residences for a minimum of one month time.

Australia	Nepal
Bolivia	Norway
Brazil	Reunion Island
Congo	Rwanda
Denmark	Senegal
France	Singapore
Germany	South Africa
Ghana	Spain
Greece	Sweden
Hong Kong	Switzerland
Iceland	Tanzania
India	Togo
Israel	Uganda
Mauritius	United Kingdom
Mexico	USA

This result is further supported by the finding that respondents with similar scores provided similar answers. In particular, preferences of different nationalities were consistent with respect to observations made in previous studies. Respondents, whose scores lay in a similar range to the Chinese dimensions, for example, also showed the same preferences as in the study from Rau and Chen with Chinese subjects [Rau and Chen, 2003]. Likewise, the preferences of respondents whose scores were similar to the dimensions for East Africa showed good consistency with our study about Rwandan preferences [Reinecke, 2005].

An additional aspect is that the vast majority of answers from respondents with similar dimensions lay within two neighboring answer possibilities. A variance of such a low extent can be rated as personal propensities that once more sup-

ports our hypothesis of a smooth transition between cultural and personal preferences. Some questions, however, lead to a high divergence of answer possibilities even though respondents had a similar predicted answer. We will have to further evaluate the reasons for such divergences in the future.

Respondents usually indicated a strong preference for the appearance of the user interface. In particular, respondents with strongly differing scores also answered differently. Another group of questions, however, was answered with the same tendency even though the predictions forecasted differences. This could imply that some interface aspects are understood in a similar way by (web-literate) people from different cultural backgrounds. Whether this finding is only true for people with a high frequency of computer usage, as applicable to all our respondents, has to be subject to further investigation.

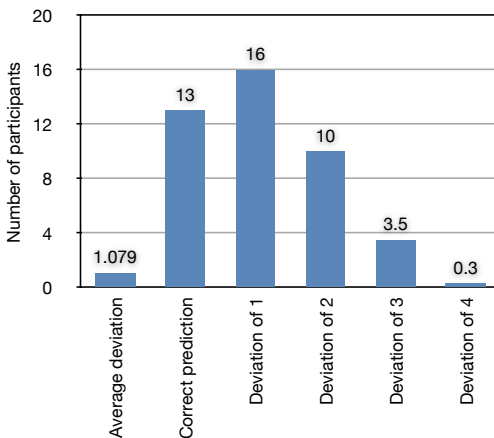


Figure 4.7: The deviation in predicting the user preferences from the actual answers given in the survey.

Improvement of Results. Our AE of 1.079 demonstrates a fairly good prediction of cultural preferences. However, after including other influencing factors on the user's culture (as they are provided in CUMO) into some randomly chosen respondents' profiles, we were able to reduce the AE by approximately 0.3. For example, we included factors such as differing nationality of the parents to the place where the respondent spent most of his lifetime. Whereas our calculation was supported by common sense to estimate how much this differing nationality could have influenced the respondent's cultural background, the algorithm has to be fed with a certain percentage. Our suggestion here is that a refinement made by the user by deciding about this percentage himself seems to be a good way to improve the calculation of his cultural background.

In search of refinement possibilities, we also looked at the adjustment of predictions with machine learning techniques. As previously mentioned, subjects with a similar score for a certain dimension usually provided similar answers for questions covering this dimension. This suggests that an adjustment of the predictions (and, thus, the adaptation rules) by learning about the actual user preferences is likely to improve the prediction for users with similar scores. Following this idea, we have evaluated the survey a second time, grouping respondents with similar dimensions. To predict the answer of one group member we averaged the answers of all the others. This led to an AE of 0.6.

Limitations and Summary of the Preliminary Study

The responses in the preliminary survey verify existing research on mapping Hofstede's cultural dimensions to user interface design. More precisely, the analysis of our survey indicates that our method is suitable for predicting user preferences. With 80 % of respondents being classified as culturally

ambiguous, we were also able to substantiate that our algorithm adequately factors current and former residences into the prediction of the user's preferences, which deviated by 1.079 on average from our anticipated adaptation rules (the maximum deviation was 4).

While our algorithm proved to be suitable to predict the majority of preferences, we did notice an influence of the parents' nationality (if different from the place where the respondent grew up) on the participant's answers. Similarly, we expect other cultural aspects to largely influence choices as well, however, the exact impact of them on user interface preferences are mostly unknown (e.g. it is difficult to determine at what stage in life a person's residence impacts preferences most), and are therefore subject to future work.

An obvious limitation of the study lies in its nature of an online survey: First of all, we were not able to control how thoroughly questions were thought-through. Secondly, textual questions in a survey cannot convey the richness of a user interface. The questions and answers are highly influenced by the person's imagination and interpretation of what is meant, and thus, do not necessarily mirror the participants' real preferences.

To overcome these limitations, the next chapter reports on the development of a culturally adaptive web application, which is the basis for a more extensive evaluation based on a visually perceptible user interface.

5

The Culturally Adaptive System MOCCA

To illustrate and evaluate our approach as described in the previous chapter, we have developed a culturally adaptive web application called MOCCA¹. MOCCA is a web-based to-do list tool akin to applications such as *ta-da list*² or *Remember the milk*³, which help users to access and manage their tasks online. Thus, MOCCA does not provide content itself, but relies on user-generated content. For testing cultural differences in information presentation (as intended by our adaptation rules), this has the advantage that the application does not influence users with culturally-biased content, which could be the case if we had provided a news application, or similar.

The chapter first discusses the requirements for MOCCA and then briefly introduces the most relevant details regarding its implementation and functionalities.

¹MOCCA is an acronym for MOdelling Culture for Cultural Adaptivity

²<http://www.tadalist.com>

³<http://www.rememberthemilk.com>

5.1 Design Requirements and Techniques

MOCCA's goal is to automatically adapt to the cultural preferences of its users. The adaptations can occur at different stages of system use, such as after registration, or after observing the user's mouse interactions and inferring the need for refining adaptations. In both cases, the software's user interface needs to be extremely flexible in the composition of different interface components. Each user interface element should be available in different versions (according to the adaptation rules as listed in Table 4.3), and their placement within the user interface should be as versatile as possible. Thus, MOCCA has to take over parts of the usual design process performed by human designers by calculating the best-possible position of elements for the respective user profile.

We have approached this problem by defining all parts of the user interface in an adaptation ontology (cf. Section 4.3.1), which specifies certain restrictions for each element, such as their interdependence (e.g. element A can only appear on the user interface in combination with element B). It also defines an element's possible placement areas within the user interface, as well as its minimum and maximum size.

Implementation
techniques

In MOCCA, user interface elements are developed as Java Server Pages (JSP), which can be loaded and compiled by an Apache Tomcat server⁴ at runtime. Furthermore, the use of AJAX (Asynchronous Javascript and XML) allowed communication between the browser and server, without the need for a whole page to be reloaded. Design requirements are specified in Cascading Style Sheet (CSS) files, the order of which is predefined in the adaptation ontology. According to this order, certain adaptation rules can overwrite layout and design settings as required for the specific cultural background.

⁴<http://tomcat.apache.org>

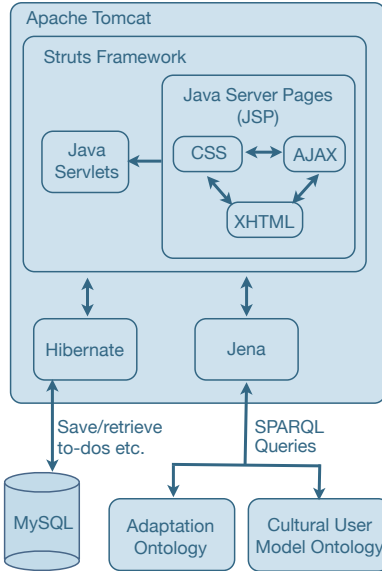


Figure 5.1: Overview of the techniques and scripting languages used in MOCCA.

MOCCA is implemented according to a Model-View-Controller architecture, with the help of the open source framework Struts⁵, which supports the interplay of the above-mentioned techniques (see Figure 5.1 for an overview). Struts also supported MOCCA's internationalization, that is, the adaptation of all software strings to different languages according to a specified locale. So far, MOCCA offers the languages English, German, French, and Thai.

In order to communicate with the adaptation and cultural user model ontology, MOCCA makes use of the open source

⁵<http://struts.apache.org>

framework Jena⁶, which allows it to access and query the ontologies with the help of the query language SPARQL and an OWL API.

Additionally, MOCCA is connected to a MySQL database, which is used to store to-dos, projects, and categories with the help of Hibernate⁷, a framework for relational object mapping.

5.2 Interpretation of the General Adaptation Rules

In Section 4.3 I introduced general adaptation rules, and pointed out that these have to be tailored to suit the specific application domain — in our case to the user interface of a to-do list application. In particular, the adaptation ‘extremes’ (representing the adaptation rule for a low and a high score) have to be extended with a middle variant in order to obtain a subdivision into three score ranges. Hence, all adaptable aspects need to be represented by three versions of MOCCA, keeping in mind that different aspects can be combined (e.g. a low information density with a high structure).

Table 5.1 describes the ten adaptable interface aspects of the general adaptation rules, describing their specific effects when adapted to a low, medium, or high score in our to-do application MOCCA.

Iterative design process

The interpretation of the general adaptation rules was conducted in an iterative design process, which traversed the stages of analysis, design, and implementation multiple times. Time and effort required for the preparative process (analysis and design) were approximately equal to that of the implementation.

⁶<http://jena.sourceforge.net>

⁷<https://www.hibernate.org/>

Table 5.1: Adaptable interface aspects and their effect when classified into low, medium, or high.

Interface aspect:	Linked to	low	medium	high
Information Density	LTO	To-do items provide minimal information at first sight, requiring the user to click before seeing more information	To-do list shows all information at first sight	Complex version that in addition presents color-encoded information with large icons
Navigation	PDI	Tree menu and to-dos in list view, allows nested sorting	Flat navigation and list view, or tree menu and icon-represented to-do list	Flat navigation and icon-represented to-do list
Accessibility of functions	PDI	Functionalities only appear on mouse-over	Functionalities are always accessible but grayed out if not needed	functionalities are always accessible
Guidance	UAI	When users enter a dialog, all other information in the UI remains visible and accessible	Information other than the current dialog is still visible, but inaccessible	Unnecessary information is hidden in order to force users to concentrate on the currently active dialog
Structure	IDV	Maximum structure: Elements are bordered and affiliations between information is accentuated across elements	Elements are separated and color-coded for better distinction	Minimum structure: Different elements of the UI are only structured through alignment
Colorfulness	IDV	Many different colors	A medium number of colors	The UI is homogeneously colored
Saturation	MAS	Pastel colors with little saturation	Medium saturation and contrast	Highly contrasting, bright colors
Image-to-text ratio	IDV	Image icons in the header menu; category, project, and to-do area hold a representative image	Icons in the header menu are composed of both text and image/s	Header menu consists of textual links only; category, project, and to-do area do not show an image
Support	UAI	On-site support with the help of short tooltips	The UI offers questionmark buttons that expand into help bubbles	An adaptive wizard that is always visible
Help text	PDI	Friendly error messages suggesting how to proceed	Neutral error messages suggesting how to proceed	Strict error messages

The design process made use of different sources for inspiration: Firstly, we compared and analyzed variations in the designs of two international webpages: the different national web sites on the 2008 olympic games in Beijing⁸, and the various national versions of the online encyclopedia Wikipedia⁹. While the national versions of the olympic games websites were designed freely, and thus, varied heavily in the representation of content, Wikipedia restricts the localized versions to a certain design, which undoubtedly increases the recognition value. Nevertheless, variations in the design interpretations of the localized versions were recognizable in both web sites, suggesting that the designs were developed by local design teams. We therefore assumed that the websites represented the preferences of the general audience in the respective country.

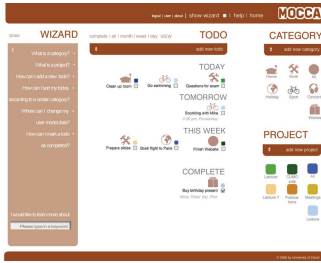
In the next step, we aligned the localized web pages with Hofstede's cultural dimension scores, as well as with our general adaptation rules in order to generate ideas on how MOCCA could incorporate the rules.

Design combinations

The design of the 30 user interface variants (10 adaptable aspects x 3 versions each) was drafted independently at first with the help of gray-scale user interface mock-ups. Subsequently, we analyzed the feasibility of combining the designs with each other. The resulting user interface elements with their different alternatives were again sketched using mock-ups, and the design alternatives were then analyzed for their implementation feasibility. In this process, we also listed all user interface elements, their interdependencies among each other, as well as their size and possible placement on the user interface. This data was later aligned with the adaptation ontology (cf. Section 4.3.1), which was extended with these application-specific requirements.

⁸<http://www.beijing2008.cn/>

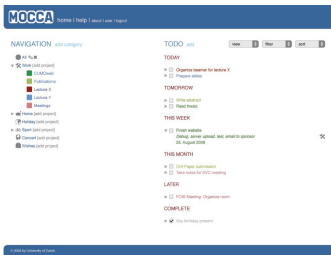
⁹<http://www.wikipedia.org/>.



(a) A version of MOCCA with right-to-left-alignment, high information density, and an adaptive wizard.



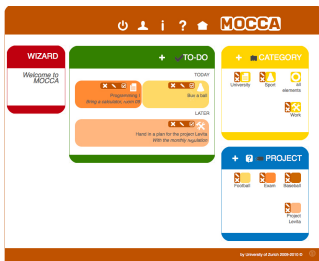
(b) A version with flat button navigation, and color-coded to-dos that indicate the affiliation to a project.



(c) MOCCA with a hierarchical tree navigation, and a to-do list showing only headers at first sight. Functions, such as delete and add, are only accessible on mouse-over, reducing the overall complexity of the interface.



(d) A hierarchical tree navigation, and hierarchical to-do list. The dialog to add a new to-do does not provide extra guidance. Medium support through help buttons.



(e) MOCCA with color-coded content structuring, and strong colors. Functions, such as delete, or add, are always accessible.



(f) A colorful version of MOCCA with right-alignment, and subdivided areas for Categories, Projects, and To-Dos.

Figure 5.2: Example interfaces of MOCCA

5.3 MOCCA's Flexible User Interface

MOCCA considers ten adaptable aspects of the interface, each of which can be individually altered to either a low, medium, or high classification of the dimension they are associated with (see Table 5.1). In addition, MOCCA can adapt itself to the users reading direction (i.e., left-to-right or right-to-left), resulting in a (theoretical) total of $3^{10} * 2 = 118,098$ possible combinations of user interface elements (excluding language). In practice, many of these combinations are very unlikely to occur since some aspects share their dependency on one of the five cultural dimensions. With the help of the preference editor (described later in Section 5.5), users can also freely personalize their user interface, without restrictions from the cultural dimensions. Thereby, the full range of possible combinations might well be used by a given user.

Examples of how
MOCCA adapts
to cultural aspects

As an example for MOCCA's flexibility, consider a user with a high Uncertainty Avoidance and a right-to-left writing direction (e.g., as applicable to some people in Japan). For such a user MOCCA would trigger the rule `if (UAI = high) then show wizard` associated with the interface aspect 'Support', resulting in a user interface akin to the one shown in Figure 5.2a. In the case of a low Uncertainty Avoidance and low Individualism the wizard would not be shown and the rule `if (IDV = low) then color-code to-dos` results in an interface comparable to Figure 5.2b.

Additionally, MOCCA is able to adapt to more subtle aspects of culture that influence perception as discussed in Chapter 3. For example, it incorporates the results of studies indicating that Western cultures pay attention to individual objects more than people from Asia who usually concentrate on object correlations [Gutchess et al., 2006]: The user interface allows different possibilities of content structuring by spatializing objects and color-coding elements that belong together. Different alternatives of this are shown in Figure 5.2b with its

color-coded to-dos, Figure 5.2c, where the to-dos are color-coded, but in a less dominant manner, and Figure 5.2d, which only shows the affiliation to a project with the help of a colored box visible when expanding the to-do.

As culture is constantly changing throughout people's lives, another aspect affecting user interface preferences is a person's age: Older users have a tendency for a less holistic view of their environment, and often need explicit verbal instructions to navigate it [Sjolinder, 1998]. Hence, the demand by older users for clear navigation and navigational cues often coincides with a high Power Distance Index, and vice versa for younger users. MOCCA takes these different needs into account by adapting to a flexible tree navigation for users with a low Power Distance Index (Figures 5.2c and 5.2d), or to a flat navigation with reduced functionality for users with a high score in this dimension (e.g. Figure 5.2a, or Figure 5.2e). In addition, MOCCA responds to a high Power Distance index by increased user support (Wizard in Figures 5.2a, and 5.2e), while a medium Power Distance score triggers small help buttons (in Figure 5.2d these can be seen next to the headlines "Navigation" and "To-Do").

MOCCA can further adapt to a person with a low Individualism score with a colorful interface and a high image-to-text ratio, as shown in Figure 5.2b. Users with a high Individualism score receive an interface with fewer colors (Figures 5.2c and 5.2d). These interfaces only use self-explanatory symbols (e.g. symbolizing the category), but the symbols are kept small and colored grey to avoid being distracted.

More examples of how MOCCA realizes user preferences will be provided in the next two chapters in relation to our user tests.

5.4 Initial Adaptation

At first log-in, MOCCA requires the user to register and inquires about current and former places of residence, as well as about their respective durations (cf. Section 4.2.2 describing the general algorithm). The registration procedure is only necessary if the application cannot access a shared cultural user model that accompanies the user “wherever he or she goes”. If this was the case, users would only have to log-in to a general account once, reducing the hurdle of answering the registration questions. The advantages of such a future scenario will be further discussed in Chapter 8.

Information provided
upon registration

For the time being, MOCCA welcomes the user with a log-in screen. The user provides his current and possible former residences, as well as the durations spent in each of these countries, a user name, and a password. If applicable, he or she can also enter an existing account. By mapping the supplied information to the cultural user model ontology, the application triggers the generation of a personalized user interface. To begin with, this is done on the basis of the initial adaptation rules. If other users have manually changed their user interfaces, MOCCA automatically incorporates these changes into new adaptation rules, and, in that case, bases the adaptations on these new rules. We will describe this procedure in detail in the next two sections.

5.5 Manual Customization

Users appreciate the ability to customize user interfaces because it can improve aesthetics, allows them to express their identity, or simply provides something new [Blom and Monk, 2003]. The motives for customization are manifold, but they all provide an incentive for people to use an application, often because it gives them a feeling of being in control rather

than being exposed to unwanted content and design [Blom and Monk, 2003]. MOCCA allows users to change all of the application's adaptable user interface aspects in a built-in *preference editor*, which is displayed in Figure 5.3.

The preference editor enables users to view and freely combine alternative user interface elements with one another. All adaptable aspects are shown one-by-one, with each allowing the choice between two or three different possibilities. A preview window (not shown in Figure 5.3) further provides an overview of the new user interface based on the user's selections. The alternatives of user interface elements are presented as gray-scale images and contain a short explanation of the differences between them. By clicking on one of the images, the preference editor displays a larger image with a more extensive explanation. User interface elements that are currently in use, or have been selected, are indicated by an activated radio button beneath the image. Clicking on a radio button other than the one activated, will (1) modify a preview image of the new user interface, (2) change the status of the respective element in the cultural user model ontology, and (3), upon acceptance of the user, trigger adaptations of MOCCA's user interface. The choice/s a user makes in the preference editor are interdependent in that the selections made for the first aspects will change the image presented for subsequent aspects. For example, if a user opts for a high information density at the start, subsequent images on the structure of the user interface, or the color will be adapted to depict the high information density as well.

Upon selection, MOCCA saves all changes made in the preference editor as *choices* of new user interface elements. Choices are stored in an extension of CUMO, the *preference ontology*, with the aim of providing this information across different applications. While the users' choices in the preference editor are specific to MOCCA, their manner of storage is ab-

MOCCA's preference editor

Storage of preferences in CUMO

stracted to a degree where other applications can interpret the information for their own domain.

In an extension of CUMO for preferences, a `Person` instance connects to a `Preference-Set`, which we supplemented with a time stamp property. This allows the tracking of changes in the user's preferences over time, for instance to detect how frequently people change the user interface. Each `PreferenceSet` is subdivided into specific `Preferences` of the user interface, which correspond to the ten aspects listed in Table 5.1. In the future, this list can be easily extended, although special attention has to be given to retain preferences as unambiguous units (see discussion in Chapter 8 about the interaction of different applications with CUMO).

Recommender states The preferences in CUMO are further annotated with one of the following states:

- `initial`: The state refers to the initially assigned adaptations as defined by the initial adaptation rules and those changed due to differing preferences within a cultural cluster.
- `chosen`: The state describes those elements that have been actively chosen in the preference editor.
- `deselected`: If a user swaps a formerly active user interface element with another one, the now inactive element is assigned the state `deselected` and the newly chosen element is assigned the state `accepted` or `chosen`.
- `recommended`: The state indicates which elements have been suggested by the recommender mechanism.
- `accepted`: A user interface element receives the state `accepted` if the user agrees to a recommended element and accepts it.
- `rejected`: The state marks user interface as rejected if the user did not accept the specific recommendation.

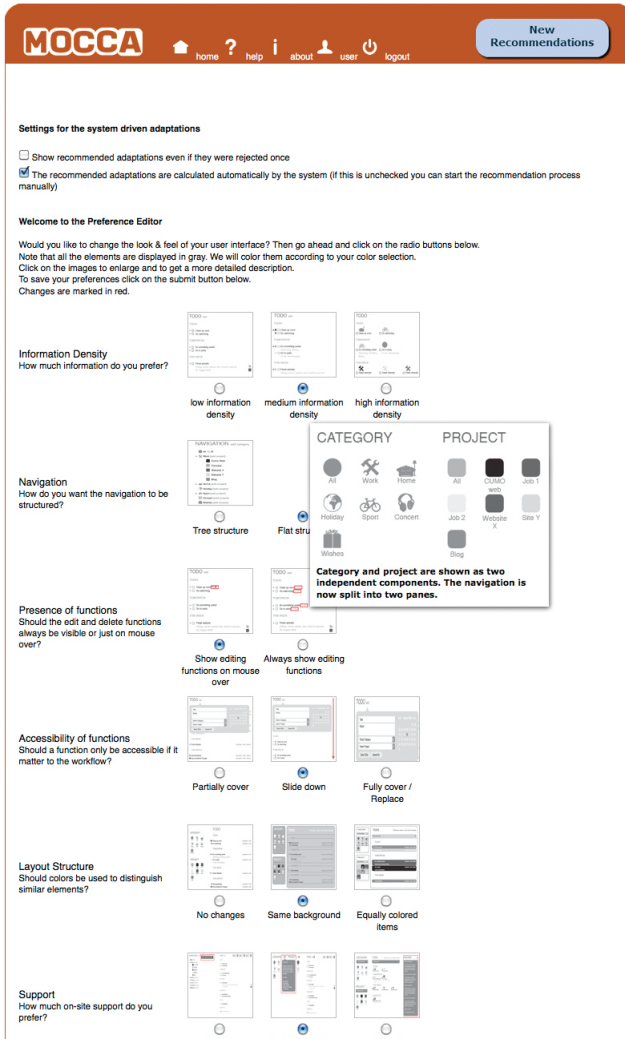


Figure 5.3: MOCCA's built-in preference editor, which allows users to customize their interface. The differences between the user interface variants are described below each image. In addition, red markers on the images point to major differences.

According to these rules, an interface element cannot be assigned the states *initial*, *chosen*, and *accepted* at the same time. An element that has been actively chosen by a user cannot be in the state *recommended*. Likewise, an element cannot be *recommended* and at the same time receive one of the states *initial*, *chosen*, or *accepted*.

User interface elements that have previously been deselected or recommended are not reconsidered for recommendation. Since preferences can change over time, the preference editor also provides the option to deactivate this rule in order to review all elements again (“Settings for the system-driven adaptations” in Figure 5.3).

5.6 Preference Recommender

The choices made by users in MOCCA’s preference editor provide a valuable source of information about the particularities of users’ design preferences. Based on the assumption that people of similar cultural background often share similar preferences, MOCCA uses the choices of all registered users to improve the predictions for new users, and to recommend adaptations to existing users. A procedure for this learning mechanism was proposed in Section 4.4.1. Accordingly, MOCCA was extended with a learning component that (1) clusters users into groups of similar background, and (2) calculates the weighted average of preferences within this group with the help of collaborative filtering. Figure 4.6 presents this process in more detail, and how it is implemented in MOCCA. MOCCA’s users are able to modify the user interface with the help of the preference editor. For *User A* (cf. Figure 4.6), for instance, such manual personalization immediately triggers the corresponding adaptations upon selection. The user’s modifications are saved in the cultural user model ontology. Other users (e.g. *User B*) can now profit from these

Functioning of the
learning component

updated preferences: MOCCA performs collaborative filtering with the weighted similarities (i.e. how similar users are according to the Euclidean distance of their cultural vectors) of other users and their preferences. Subsequently, the system recommends these preferences, unless someone has previously rejected a specific recommendation.

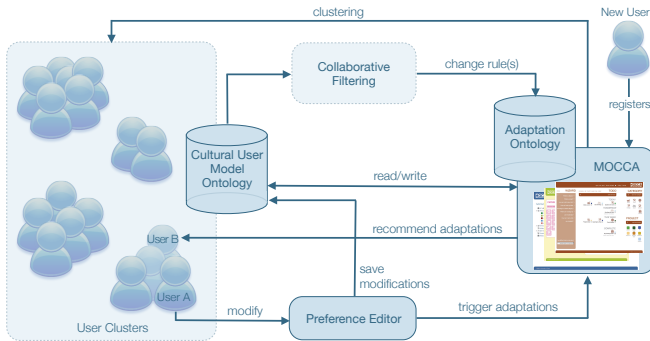


Figure 5.4: MOCCA's recommendation procedure in detail. The aim is to provide new users with a user interface composed of the preferences of other users with a similar cultural background, without the usual cold-start problem of collaborative filtering.

5.7 User Interaction Tracker

The analysis in Section 4.4.2 demonstrates that user interaction tracking is mainly suitable for deriving different levels of

support, a preference for non-linear or linear navigation, the number of functionalities, and different content structuring. We also concluded that such inference could complement or verify the information about the user and his or her cultural dimensions.

In MOCCA's implementation, we decided against changing the user's cultural dimension scores based on the interaction history, since the reciprocal effect is currently only based on assumptions. Instead, we trigger the corresponding rules directly and save the assumptions as a preference in the user model. The user's cultural dimensions remain unchanged in order to avoid conflicts that might occur with other adaptation rules.

AJAX-supported
tracking

In order to record all the interaction statistics listed in Table 4.4, our approach relies on the use of AJAX, a web application technique combining asynchronous communication, JavaScript and XML. In contrast to conventional techniques, AJAX allows interaction tracking of user requests on the client side [Schmidt et al., 2007], such as scrolling, or hovering. As an additional advantage, changes on the user interface can be triggered without reloading the whole page, thus improving the user experience.

We have used parts of the approach introduced in [Amerishi and Conati, 2007], which employs both unsupervised and supervised machine learning in order to find suitable categorizations of interaction statistics. The process is presented in Figure 5.5 for a generic AJAX application:

Procedure

The user's interaction is recorded with the help of JavaScript events that log mouse coordinates, clicks, scrolling, or keyboard input. This *raw data* is retrieved with the help of XMLHttpRequest objects and stored in *log files* on the server in combination with a time stamp. Each user's data is stored in a separate log file, which combines the interaction sequences of different sessions. At frequent intervals, MOCCA analyzes the data in the current user's log file and generates interaction

statistics (e.g. a calculation of his or her overall mouse velocity), which serve as multidimensional *feature vectors*. Feature vectors contain low-level features from the collected data, such as the mean and standard deviation of mouse hovering.

The feature vectors are stored in a combined *interaction statistics file*, which holds the information about all users' interaction statistics. The interaction statistics file allows the comparison between the interaction statistics of different users. Data about the speed of a user's mouse movements, for instance, is meaningless if not compared to other users' speed.

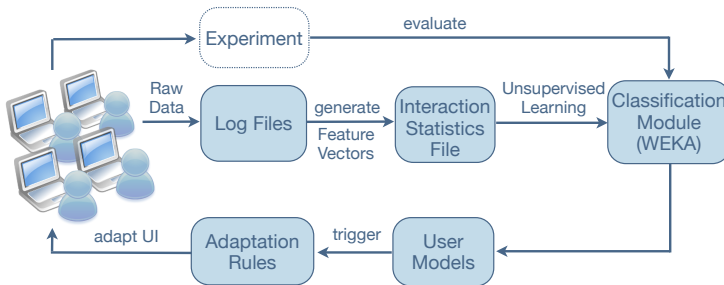


Figure 5.5: The process of interpreting user interaction statistics in order to establish an automatic classification mechanism for new users.

The interaction statistics file can then be processed by a *classification module*. Since the data in the interaction statistics file is unlabeled, we make use of unsupervised machine learning. Precisely, we incorporated the WEKA toolkit [Hall et al., 2009] into MOCCA, and clustered the data with the help of k-means based on their similarity (i.e. the Euclidean distance of data points). The required input for k-means, the number of clusters k , is dependent on the number of different groups we would like to classify users into. For example, if the application offers two adaptation rules, one for users with a low computer literacy, and one for users with a high computer lit-

eracy, respectively, then $k = 2$.

For the allocation of clusters to certain instances in the user model (for example, to a high or low computer literacy), they have to be interpreted in order to provide the application with a mean value of the interaction statistic for each cluster. As suggested by [Amershi and Conati, 2007], this can be done with the help of information gained in an experiment in which one can compare the results of users with a high and a low computer literacy. According to the resulting mean values for each cluster, we can now store the information in the *user model*, before triggering the corresponding *adaptation rule*.

Based on the clusters and their allocation to certain user model instances derived from this (initial) process, a new user can be automatically classified with the help of supervised classification: As the new user interacts with the application, he or she will be automatically allocated to one of the existing clusters with the help of the same k-means clustering algorithm. Over the time, the user's feature vector is updated and thus, the user can also move from one cluster to another.

In order to test the approach and gain mean values for the interaction statistics for two clusters (low and high computer literacy), we carried out a small experiment, which is presented in the following section.

5.7.1 Experiment on the Classification of Interaction Data

The aim of the following experiment was to exemplify the ability to derive data for the classification of users into different clusters; in this example for different categories of computer literacy (beginners versus advanced users).

Participants and Procedure. 8 participants with a medium to high computer literacy took part (4 female, mean age = 33 years, $sd = 15.18$). All participants were from Switzer-

land or Germany, and thus, represented similar cultural backgrounds. We ensured that none of the participants were familiar with MOCCA. We recorded specific user data, such as an estimation of their own computer literacy, the cultural background, age, and gender.

Participants had to perform two tasks with MOCCA's Swiss version, which required them to add a new category, and subsequently add a new to-do, which participants needed to then assign to the new category. The tasks were identical except for the wording of categories and to-dos that had to be added. We expected participants to improve their handling of the application over time, so that the first task was presumed to represent a beginner group, while participants were thought to reach an advanced level by task 2. At the end of each task, participants were asked to rate their performance on a 5-point scale (1 = very easy, 5 = very difficult) in order to compare these subjective results to MOCCA's classification. After the second task, they were additionally asked to rate their perceived benefit of learning from task 1 on a 5-point scale (1 = not at all, 5 = very much).

Task description

Results. Participants needed on average 146.01 seconds when performing task 1 ($sd = 56.97s$), and only 78.84 seconds ($sd = 30.35s$) when performing task 2 (see Table 5.2). All participants were faster with the second task (an average improvement of 67.17s), which confirms our assumption that participants would work more efficiently after a short learning period.

Subjective results of the questionnaire supported this improvement: 6 of 8 participants rated their benefit of having learned from the first task as the maximum (5 on a 5-point scale). For the same question, one participant rated 3 (the middle on a 5-point scale), and the last one rated 2.

The comparison of the two post-test questions demonstrated that 7 of 8 participants found task 2 less difficult compared

to task 1 (one participant found both very easy). 6 participants found task 1 easy (2 on a 5-point scale), one very easy, and difficult (4). Task 2 was perceived as very easy (1) by 6 participants, while the 2 remaining participants stated they found it easy (2).

Likewise, the average click distance (in pixels) and click delay (in milliseconds) was higher for task 1 than for task 2 (see Table 5.2). Contrary to our expectations, the mouse velocity was higher for the ‘beginners’ in task 1, although this is likely the result of explorative movements with the mouse over the user interface.

Table 5.2: Average values for the interaction data logged in our experiment.

		Com- pletion time (s)	Click dis- tance (px)	Click delay (ms)	Mouse velocity (px/s)
Task 1 (Begin- ner)	Mean	146.01	326.96	7958.63	168.17
	Standard deviation	56.97	144.56	3548.14	71.02
Task 2 (Ad- vanced)	Mean	78.84	212.35	6467.67	152.87
	Standard deviation	30.35	116.03	3822.58	70.44

As planned, the average values of our interaction statistics were later used in MOCCA to define classification clusters for computer literacy. The data serves as a verification for our approach, and as a starting point for MOCCA. With the help of the users’ log files and MOCCA’s ability to analyze the common interaction statistics file, the data will be automatically updated over time.

6

Empirical Evaluations of MOCCA's Adaptation Rules and Learning Mechanism

In this chapter, I first report on two summative evaluations of MOCCA's ability to adequately adapt to the user's cultural background. The first study focuses on participants with an international background, whom we refer to as 'culturally ambiguous', because they have been influenced by several countries of residence. We show that the algorithm, which calculates the user's cultural background based on a weighted average of current and former residencies is suitable for predicting user interface preferences. Subsequently, we demonstrate that the results can be replicated with culturally unambiguous users who have only lived in one country. This second evaluation also substantiates our assumption that people from similar cultural backgrounds (in this case, from the same country) share similar preferences, and that this could be used for refining the adaptation rules. Thus, we designed the third

evaluation presented in this chapter to test MOCCA's learning mechanism, or, more precisely, to analyze the extent to which learning from other users' preferences improves the prediction rate.

6.1 Accuracy of the Adaptation Rules for Culturally Ambiguous Users

The first study aims to evaluate whether MOCCA's adaptation rules are suitable for predicting user interface preferences of international users. We designed the experiment in such a way that it would reveal the choices of users if presented different options of interface elements, and that these choices could be subsequently compared to MOCCA's automatically generated, personalized user interface.

Note that we did not ask participants to rank the different options of the interface element, but asked them to decide on one. While ranking the elements would have possibly answered further questions, such as whether some elements are less favored than others, decision-making theory has found that this can influence the outcome of evaluations (see [Jungermann et al., 2010] pp. 263-272).

Method

Participants. 30 participants were recruited from the local university campus (age: 24-37, mean = 28.7, sd = 3.9, 7 female). All participants had a high computer literacy, used the computer several hours a day, and a high education level (university education). The majority of participants had lived in two or more countries in their life (mean = 2.467, sd = 0.89). 22 participants were non-Swiss nationals, but had lived in Switzerland for at least 9 months (mean = 3.4 years, sd = 4.3

years). Of the eight Swiss participants only three had always lived in Switzerland and/or did not have foreign parents. The parents of 28 participants had the same nationality as the participant (some of whom also hold two passports). Two participants had one parent with a differing nationality.

Apparatus. The experiment was carried out using paper-based user interface mock-ups in shades of gray, so that participants were able to choose their preferred layout without the complexity and limitations of a user interface design tool. The gray-scale user interface elements prevented any influence on the participants' preferences by the chosen colors – which is often a decisive aspect of user interface acceptance and preference. Each participant was presented with a paper computer screen and the different user interface elements. Participants were able to see all three user interface representations for each task at once and arrange them freely.

Procedure. Prior to explaining the tasks, we asked participants to put themselves into the position of a user interface designer, who is developing the software for his or her own use. Participants were expected to consider their own experiences and preferences with user interfaces, and were asked to think aloud throughout the test. Additionally, participants were encouraged to take their time to choose between the elements, and furthermore to ask questions for clarification. We then briefly explained the application's purpose, and its main functionalities (e.g. the possibility to create todos, categories and project).

Participants were presented with an outline of the MOCCA interface within which they were asked to place their choice of user interface elements. Participants had to perform eight tasks altogether concerning the following eight interface aspects (see Table 5.1 for a description of the aspects and their

three choices): (1) Information Density, (2) Navigation, (3) Accessibility of functions, (4) Guidance, (5) Structure, (6) Colorfulness, (7) Saturation, and (8) Support.

Choice between
three UI elements

For every task, participants were asked to choose between three interface elements. The tasks were presented in the same order for each participant, because they partly built on one another. The presentation of the different choices of user interface elements was counterbalanced between participants.

We preceded each task with a short explanation, where the main differences between the three choices were pointed out. In order to avoid influencing the users' decisions, we followed a written script that enabled us to keep the explanations both consistent and neutral. Throughout the tasks, participants were encouraged to think-aloud, and these comments were noted down. On completion of each task, we took photos of the arrangement on the user interface outline.

Demographic
questionnaire

The test ended with a small questionnaire soliciting information about the participant's current residence, and possible former countries of residence with durations in years and months. We also recorded the nationality of the participant's father and mother, as well as the participants' age and gender. Participants were given a small incentive for their time.

Test Design and Analysis. We used a within-subjects design with the following factors and levels: (1) *Cultural Background*: 5 dimensions × 3 subdivisions each (low, medium, high). (2) *General User Details*: age, gender, computer literacy, (3) *Interface elements*: eight elements with three options each, (4) *Participants*: 30.

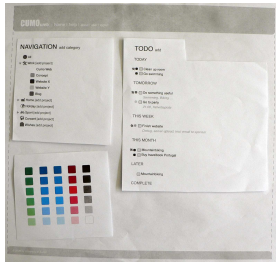
For comparing the choice (= our dependent measures) of a user interface element for each task by the user and the system, we first entered the information from the questionnaire into MOCCA and its user modeling component, receiving a classification of the user's cultural background into low,

medium, or high for each of the five dimensions. Subsequently, we simulated MOCCA's adaptations by looking up the corresponding adaptation rule and the resulting user interface. The participants' choices (with a range of three – *low*, *medium*, *high* – according to the allocation of the interface element representation in the adaptation ontology) were then compared to the adaptation rules. The probability of guessing the participant's choice was $p = 1/3$. An example: if MOCCA calculated the participant's Uncertainty Avoidance Index to be high, but this participant chose the user interface element assigned to the category low, we noted a deviation of 2 (=the maximum deviation). It is important to note that the deviations of 0, 1, or 2 do not represent a certain order, because the difference between the three interface elements is individually perceived. With the calculation of deviations, we therefore make a theoretical prediction that the distances are ordered. Likewise, we assume that we can test the *probability at random* with $p = 1/3$. In reality, this equal distribution of probabilities could be an unfair baseline for comparison, since the distribution of choices across all three elements could be skewed. The result section therefore also details on the distribution of choices.

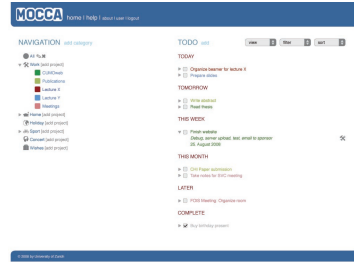
Experimentally, we tested three of our eight interface aspects on two dimensions in order to find out whether other cultural dimensions might be more suitable to predict preferences for certain interface aspects: Task 1 (Information Density) and task 3 (Accessibility of Functions) were additionally assigned to the dimension Uncertainty Avoidance, and task 8 (Support) to the dimension Power Distance.

Hypotheses. Our main hypotheses are: (1) Hofstede's dimensions can be used as a basis for predicting user interface preferences of culturally ambiguous users; (2) certain dimensions (see Table 5.1) yield a better prediction rate for particular interface aspects than others; (3) the majority of incorrect pre-

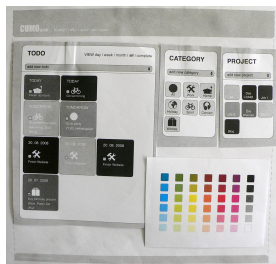
dictions deviate by only 1 (instead of 2, meaning that in the majority of cases, the prediction does not completely oppose the user's choice).



(a) The user interface as chosen by Participant 3 (PDI = low, IDV = high, MAS = high, UAI = normal, LTO = low).



(b) MOCCA's automatically generated user interface for participant 3.



(c) The resulting user interface after participant 27 laid down the elements (PDI = high, IDV = low, MAS = high, UAI = low, LTO = high).



(d) MOCCA's automatically generated user interface for Participant 27.

Figure 6.1: The self-built interface in comparison to the interface generated by MOCCA for two different participants

Adjustment of Data. We excluded task no. 5 from analysis after the majority of participants made a choice contradictory to their oral statements. After inquiring about the reason for their choice afterwards, most participants stated that the design of the version assigned to a low PDI was slightly confusing and they felt that they would have a better overview of their to-dos with the version assigned to a high PDI. In fact, most people who had a low Power Distance Index actually chose the opposite version. Overall, the version for high PDIs was preferred by 14 participants, which was different to the fairly even distribution of choices we achieved testing other interface aspects. We therefore put this aspect aside for a thorough re-design of the user interface aspect taking into account participants' comments. Thus, the following result section reports on data of 7 tasks performed by 30 participants, for a total of 210 choices altogether.

Results and Discussion

The comparison of MOCCA's prediction with the participants' choices showed that the number of choices that were accurately predicted was significantly higher than those predictions that deviated by 1 or 2 from the user's choice for all seven tasks ($p < .05$, see Table 6.1).

The average deviation from the correct prediction over all dimensions and tasks was .46. Out of 30 participants, the number of correct predictions lay between 15 and 27 per task (mean = 18, $sd = 4.23$) with a correct prediction rate of 60.95%. The number of false predictions with a deviation of 1 lay between 2 and 15 (mean = 9.1, $sd = 4.07$), and the false predictions with a deviation of 2 ranged from 0 to 6 (mean = 2, $sd = 2.23$). Table 6.2 shows a summary of the prediction results relating to the percentages of correct predictions, and ones with a deviation of 1 or 2.

While we were not so much concerned about the predic-

tion errors with a deviation of 1, the 6.67 % of cases with a deviation of 2 are indeed critical. In practice, offering such an interface to users with opposing preferences without any alternatives could mean that these users refrain from using the application. It confirms the need for intervention possibilities that allow the user to choose alternatives in case of a less suitable initial adaptation.

Distribution of Choices. Participants' choices were evenly distributed over the three interface options: elements assigned to a low score were chosen 72 times, the ones for a normal score 76 times, and the elements for a high score 62 times (no significant difference according to a $\chi^2_{(2)}$ test). Participants went for the 'extremes' in 134 cases out of the 210 choices ($\approx 64\%$).

Prediction of User Interface Aspects. In the following, I describe the most remarkable results for each user interface aspect separately (refer to Table 6.2):

The *information density* proved to relate very well to the dimension Long Term Orientation. For 90 % of all participants we were able to anticipate the correct choice. As shown in Figure 6.1c, for example, participant 27 chose a user inter-

Table 6.1: Results demonstrate that the correct predictions were not due to random guessing (using an alpha level of .05).

Interface aspect	$\chi^2_{(1)}$	Significance
Information Density	44.08	$p < .001$
Navigation	7.6	$p < .01$
Accessibility of Functions	9.89	$p < .01$
Guidance	15.38	$p < .001$
Colorfulness	3.92	$p < .05$
Brightness	5.61	$p < .05$
Support	3.92	$p < .05$

face with a high information density (color-coded to-dos with symbols) and a low level of hierarchy in information presentation (permanently visible notes). MOCCA was able to correctly predict this choice (Figure 6.1d). In contrast, participant 3 chose the user interface designed for normal Long Term Orientation (Figure 6.1a), which shows less information at first sight by being encoded with fewer colors and symbols (Figure 6.1b). MOCCA, however, was not able to correctly predict her choice basing its prediction on a low Long Term Orientation with to-dos that show notes and other information only on click (Figure 6.1b). Nonetheless, a comparison of the two pictures shows that the deviation of 1 in the cultural dimension had only a small effect on the overall user interface design. Altogether, a deviation of 1 occurred in 6.67 % of the cases. For 3.33 % of all participants, MOCCA provided a low information density (as shown in Figure 6.1b), whereas the participant showed a preference for the opposite, a high information density as in Figure 6.1d. We did not find any cases where participants preferred a low information density when predicted to favor the opposite.

Table 6.2: Summary of the prediction results for culturally ambiguous users (in %).

Interface aspect	Tested with dimension	Correct predictions	Dev. of 1	Dev. of 2
Information Density	LTO	90.00	6.67	3.33
Navigation	PDI	56.67	36.67	6.67
Accessibility of Functions	PDI	60.00	40.00	0
Guidance	UAI	66.67	30.00	3.33
Colorfulness	IDV	50.00	36.67	13.33
Brightness & Contrast	MAS	53.33	26.67	20.00
Support	UAI	50.00	50.00	0
Average		60.95	32.38	6.67

MOCCA provides three *navigation* choices: (1) A tree navigation as shown in Figure 6.1b allowing for the nesting of categories and projects, which is bound to a list view of the to-dos in order to be able to sort this list accordingly; (2) a flat navigation linked to a list view of the to-dos restricts users to clicking on categories or projects, but does not allow nested sorting; and (3) a flat navigation bound to the picture-representation of to-dos, as shown in Figure 6.1d. MOCCA was able to correctly predict the choice for 56.67 % of participants, and had a deviation of 1 in 36.67 % of the cases. A deviation of 2 was rare at only 6.67 % of all cases.

The *accessibility of functions* was accurately predicted for 60 % of the participants. Thus, MOCCA was able to anticipate whether participants preferred 'hidden' functionalities, reaching them only on mouse-over (for a low PDI), or a constant accessibility, with two differing degrees of information density (for a normal and a high PDI). For 40 % of the participants MOCCA failed at correctly predicting this with a deviation of 1; however, none of the participants chose the interface variant deviating from the prediction completely (0 % with a deviation of 2).

Guidance adhered to a self-dependent handling of procedures: MOCCA's interface can either adapt to a high Uncertainty Avoidance by leading users through a given process while obscuring other information (e.g. when adding a new to-do), force the user to concentrate on the current process by making other functionalities inaccessible (although still visible) for a normal Uncertainty Avoidance, or enables more freedom by permanently accessible functionalities. MOCCA was able to correctly predict 66.67 % of the users' choices on guidance. Unlike the choices for other tasks, participants strongly favored the normal version (20 participants were anticipated to choose this version and 17 actually did choose it). In contrast, only 4 participants chose the low version, and 7 chose the interface element assigned to a high Uncertainty

Avoidance.

Choices in tasks 5 and 6 (*Colorfulness* and *Brightness & Contrast*) were expected to highly correlate to one another: Participants who chose a colorful interface (low Individualism) were thought to prefer bright colors (high Masculinity). Likewise, the choice of an interface with homogeneous colors (high Individualism) was expected to implicate the choice of a pastel-colored interface with less contrast (low Masculinity). However, 14 participants chose either low/low, or high/high; hence the predicting accuracy for these two aspects was rather low (50 % and 53.33 % respectively, see Table result summary), especially when seeing that users chose the complete opposite element in 13.33 % of the cases for the task colorfulness, and in 20 % of the cases for the task brightness & contrast.

MOCCA provides *support* via short tool-tips (low Uncertainty Avoidance), a more comprehensive help-on-demand which appear upon hovering the mouse over different question marks on the user interface, to an extensive wizard. To our surprise, all five users who we had expected to choose the wizard because of their high Uncertainty Avoidance score, instead chose the normal version and rejected the wizard. At this point, it might be important to consider the level of computer literacy, as well as the level of difficulty of the application into the design of the adaptation rules. However, although all users had a high computer literacy and had used to-do applications previously, only five participants chose the tool-tip designed for users with a low Uncertainty Avoidance Score. Instead, the majority (20 participants) preferred the more comprehensive help-on-demand. The high number of users who selected the middle variant of support explains why we had 0 % with a deviation of 2, but 50 % with a deviation of 1.

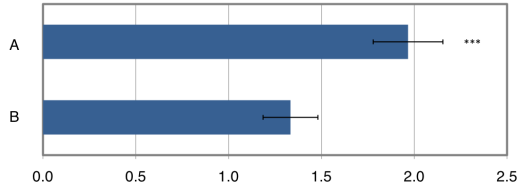


Figure 6.2: Predictions based on the initial dimensions (A) result in significantly more correct predictions than using alternative dimensions (B) for three interface aspects (***, $p < .001$). Error bars show the standard error.

Suitability of Alternative Dimensions for Prediction. Certain aspects of the user interface could not be easily linked to only one dimension, because their affect on user interface performance is ambiguous. We therefore replaced the dimensions responsible for triggering the user interface elements for three different tasks. Task 3 and 5 (Accessibility of Functions and Support) were instead predicted using the dimension Uncertainty Avoidance (instead of LTO and PDI), and task 8 was newly predicted using the Power Distance Index (instead of UAI). The dimensions that were initially linked to certain interface aspects in the adaptation rules were demonstrated to be more suitable for prediction (t-test, $p < .001$) than the same test with alternative dimensions (see Figure 6.2 where column A refers to the initial dimensions as listed in table 5.1 and column B is the result for the alternative dimensions). This further reinforces hypothesis 2 in that the dimensions incorpo-

rated in our adaptation rules affect the assigned aspects of the user interface, and that the result of our prediction cannot be reproduced by randomly choosing alternative dimensions.

Impact of Other Cultural Influences. Participants were chosen based on a high computer literacy in order to avoid a bias due to differences in the knowledge of common user interface functionalities. As expected, participants with strongly differing cultural backgrounds showed noticeable differences in the choice of interface elements. Thus, computer literacy does not seem to play a big role for the user interface aspects tested in our evaluation. Similarly, the high education level of all participants did not influence choices. We anticipated higher education levels to result in a more limited spread of choices, which were instead uniformly distributed according to subjects' dimensions. Last, we looked at the influence of the parents' nationality. As cultural differences appear to develop early in life [Fernald and Morikawa, 1993], we expected the parents' nationality to have a strong impact on the participants' dimensions towards the parents' cultural background. After adding Hofstede's dimensions for the parents' nationality with an estimated impact of 25 % to the participants' dimensions, the score of seven participants (out of 30) changed in a way that it would trigger a different adaptation of the user interface. The number of correct predictions, however, decreased for six of the seven participants with the new adaptation, resulting in an overall lower rate of correct predictions (mean before = 5.1, mean after = 3.4). Hence, the parents' nationality did not prove to support the prediction accuracy in our case, however, this is an interesting result, which needs to be studied further in the future.

Summary of Results

Support of
Hypothesis 1

As stated in Hypothesis 1, the calculation of cultural dimensions based on Hofstede's country scores and the influences of other countries of residence proved to be a good predictor of user interface preferences ($\chi^2_{(1, N=30)}, p < .01$ across all seven tasks). Consequently, MOCCA's design of user interface aspects and their corresponding three nuances also proved to be correctly assigned to the dimensions and their categories with an overall agreement of predictions and choices of 60 %, 33 % with a deviation of 1, and 6.67 % with a deviation of 2.

Support of
Hypothesis 2

Hypothesis 2 relates to our test of using alternative dimensions for predicting the user interface preferences rather than those specified in table 5.1. Results demonstrated a highly significant advantage when using the initially specified dimensions for prediction (t-test, $p < .001$) as opposed to alternative dimensions. This further reinforces our hypothesis that the dimensions incorporated in the adaptation rules affect the assigned aspects of the user interface and that the result of our prediction cannot be reproduced by randomly choosing alternative dimensions.

Support of
Hypothesis 3

We further hypothesized that prediction errors mostly occur with a deviation of 1, and thus, that MOCCA is able to reduce those cases to a minimum, where it triggers the completely opposite user interface element. We were able to prove this hypothesis with only 6.67 % of the predictions deviating by 2 from the correct prediction.

6.2 Accuracy of the Adaptation Rules for Users Influenced by Only One Country of Residence

The first study has already shown that MOCCA, to a large extent, is able to correctly predict preferences of international users. This follow-up study was designed to verify MOCCA's performance for users who have lived in only a single country. Apart from the validation of the adaptation rules, it also aimed to find out whether preferences for users of the same country are indeed similar, as previous work suggests. If this is the case, a learning mechanism could be used to modify the adaptation rules for certain users by learning from the design preferences of people with similar cultural background.

Method

Participants. The experiment was conducted in three different countries with a total of 75 participants: 30 participants from Thammasat University in Bangkok in Thailand (mean = 20.7 y, sd = 1.5 y, 21 female), 21 participants from the National University of Rwanda (mean = 25.6 y, sd = 5.12 y, 4 female), and 24 participants from the University of Zurich in Switzerland (mean = 26.5 y, sd = y, 8 female). Figure 6.3 shows an overview of the Hofstede scores for each of the three countries. In order to minimize variation in the cultural background within countries, only students at university level were invited to take part in the study, thus ensuring a high education level amongst all participants. All participants also reported a high computer literacy, and were in addition required to speak English.

Apparatus and Procedure. The experiment used the same paper based user interface mock-ups, and followed the same procedure as described in the previous study (Section 6.1).

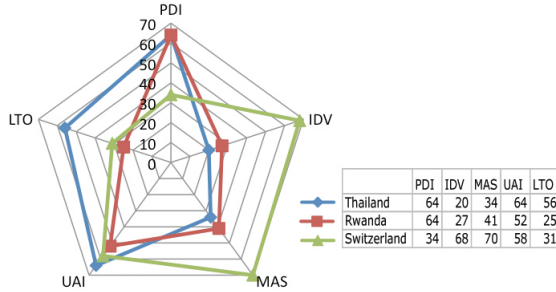


Figure 6.3: Test country dimensions according to Hofstede for Thailand, Rwanda, and Switzerland

Hypotheses. Our main hypotheses are: (1) that our initial adaptation rules are better in predicting the user's choices than a random assignment of user interface elements, and (2) that a significant majority of users from the same (national) culture choose the same user interface elements.

Test Design and Analysis. The experiment was a within-subjects design with the following factors and levels:

- *Cultural Background:* 3 countries (30 Thai, 21 Rwandans, 25 Swiss)
- *Interface aspects:* 8 aspects (tasks) with 3 choices each (see Table 5.1).

The dependent measures were the choices of an interface element for each task by dimension low, medium, or high by the user and the system MOCCA. For analysis, we followed the same procedure as in the previous study: Participants' information from the questionnaire was entered into MOCCA's user modeling component, which automatically classifies the user into low, medium, or high for each of the five dimensions, and triggers the corresponding adaptation rules. The

participants' choices were then compared to these adaptation rules, again resulting in a range of deviations between 0 and 2 for each task and each participant. The total number of tasks amounted to 240 for Thailand, 168 for Rwanda, and 192 for Switzerland (the differences resulting from the differing numbers of participants), adding up to 600 choices altogether.

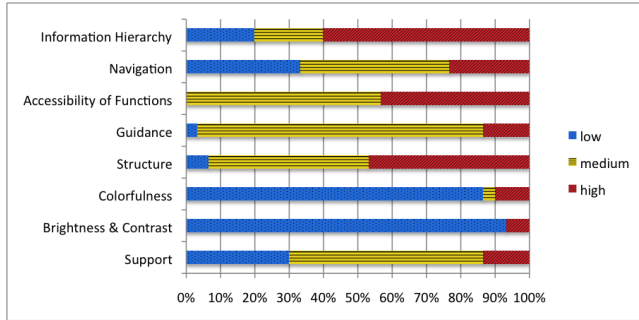
Since the three choices of user interface elements did not represent a certain order, we analyzed the relationship between participants' preferences and MOCCA's predictions with Pearson's chi-square test for categorical data (with one degree of freedom). We also used chi-square tests to investigate the distribution of participants' choices for each interface aspect and country in order to note whether a significant majority had chosen the same element (3 countries \times 3 possible choices contingency table, 4 degrees of freedom). Additionally, the distribution of choices between two countries was analyzed with a chi-square test, and a 2×3 contingency table (2 degrees of freedom). For cell counts with an expected frequency below 5, we applied Fisher's Exact test.

Results

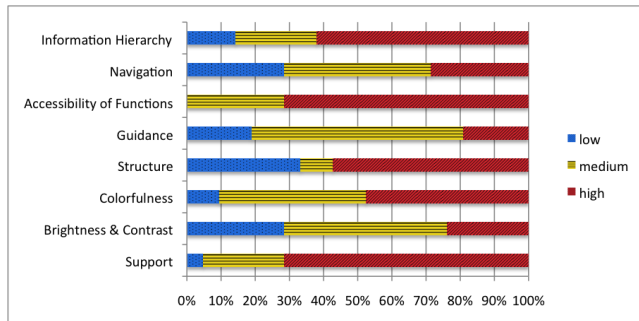
The initial adaptation rules resulted in an overall prediction accuracy of 47.3 % across all tasks and participants. Hence, with the probability of guessing the users' choice being $p = 1/3$, or 33.33 %, the initial adaptation rules are better in predicting the user's choices than a random assignment of user interface elements. Hypothesis 1 is therefore supported. For 41.4 % of the time MOCCA predicted the wrong element with a deviation of 1, and in 11.3 % of all cases the user chose the complete opposite element (deviation of 2).

The main choices in each country are summarized in Table 6.3, and marked with an asterisk (*) if they matched our predictions. Additionally, the distribution of the choices are visualized separately for each country in Figure 6.4.

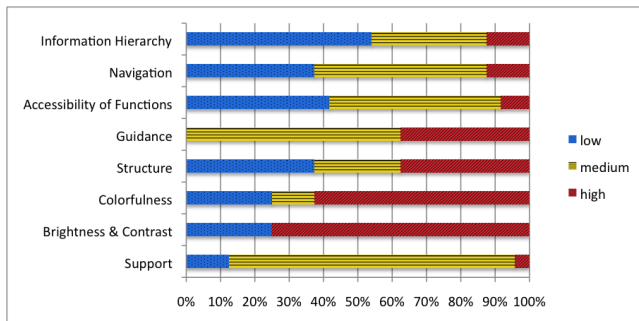
Support of
Hypothesis 1



(a) Thailand

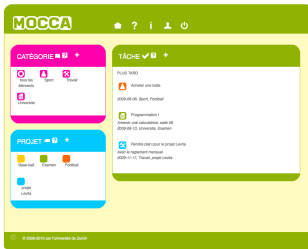


(b) Rwanda



(c) Switzerland

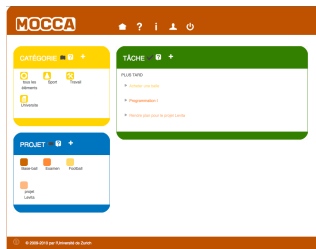
Figure 6.4: The distribution of choices made in all three countries by participants in our evaluation.



(a) The initial user interface for Thailand with a list-view of to-dos, a flat navigation, and many different, but light colors .



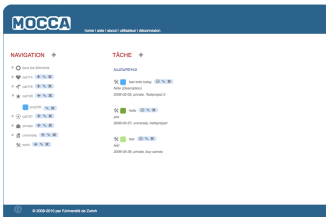
(b) The user interface for Thailand after learning new rules.



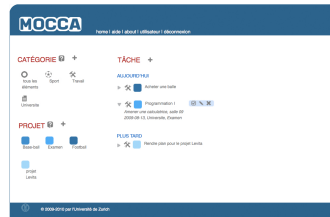
(c) The user interface for Rwandans before learning, with a flat navigation, and a list-view of to-dos.



(d) After learning: Rwandans preferred a higher information density, a hierarchical navigation, and a wizard for maximum support.



(e) The Swiss interface with a hierarchical navigation, a medium information density, and minimal color.



(f) The final interface for Swiss users with a low information density and structure, and the preferred flat navigation.

Figure 6.5: MOCCA's user interfaces for Thailand, Rwanda, and Switzerland before and after refinement of adaptation rules.

Support of
Hypothesis 2

Within countries, a significant majority of participants chose the same element in 6 of 8 tasks ($p < .05$), supporting Hypothesis 2. We will later show that contrasting these relatively homogeneous choices within countries, participants' preferences significantly differed between countries. Beforehand, we present the most noteworthy results per country. For an overview of the user interfaces as they were initially predicted for the three countries, and the resulting adaptations after taking into account the majority preferences, please refer to Figure 6.5.

Thailand. MOCCA correctly predicted 60.8 % of the Thai participants' preferences with 146 correctly predicted tasks out of the 240, 37.1 % with a deviation of 1, and 2.1 % with a deviation of 2. At the task level, the number of correct predictions lay between 6 (20 % correct) and 28 (93.3 % correct) (mean = 18.13 correct predictions, $sd = 7.59$). The average deviation across all tasks and participants was .41.

For 6 tasks, a significant majority of the Thai participants chose the same user interface element (cf. Table 6.3). Figures 6.5a and 6.5b show MOCCA's user interface before and after taking into account the majority choices of Thai. The picture demonstrates a strong preference for an icon-based to-do list (60 %, 6 of 9 male participants) and the flat navigation with buttons (preferred by 70 %), giving the whole user interface a playful look with a high *information density*. MOCCA's adaptation rules, in contrast, had predicted a medium complexity.

MOCCA accurately predicted the choices for the *accessibility of functions* ($\chi^2 = 7.59, p = .006, df = 1$), as well as for *guidance* ($\chi^2 = 34.375, p < .001, df = 1$), where participants preferred all information to be still visible and accessible while being led through a certain procedure (e.g. adding a to-do would still show all other to-dos and functionalities). The finding also correlates with the Thai preference for high information density. Only one participant opted for the mini-

malist version where all unnecessary information is hidden.

The choice between different levels of *structure* revealed that participants clearly rejected the low structure version (which corresponds to high individualism) with the plain, white background, with only 2 participants choosing this version. Instead, all other participants opted for colored background areas that help structure the interface (14 chose medium, 14 low). Initially, we had expected the male participants to be more likely to choose the low, unstructured version, however, all favored either a medium structure (5 participants), or the high structure (4 participants). Females and males made similar comments about the advantages of the highly structured version with its colors that emphasize affiliations between projects and to-dos.

MOCCA correctly predicted the preference of 86 % of our Thai participants for a very colorful interface ($\chi^2 = 39.08, p < .001, df = 1$). Participants who chose a medium number of colors (1 chose medium) or even the plainest coloring (3 chose high), however, were all male. In addition, participants preferred low *saturation* of the colors (light, pastel colors), and this was correctly predicted for 93.3 % of participants ($\chi^2 = 49.39, p < .001, df = 1$). Only two (male) participants favored highly contrasting, darker colors. The result of this task was especially compelling when looking at the color scheme that was most often chosen and that was the only one containing the color pink (some of the other color schemes contained rose, but none had this specific pink). Interestingly, most Thai men chose this color scheme as well.

The last task measuring the preferred type of *support* resulted in 56.6 % correct predictions of a preference for help bubbles ($\chi^2 = 5.61, p = .018, df = 1$).

Hypothesis 1 was supported for 5 of 8 tasks, where our adaptation rules proved to be a suitable predictor of user preferences. In the two other cases, the majority of participants

chose what we had predicted, but a similar sized second group chose one of the neighboring versions (deviation of 1).

Rwanda. The choices of our Rwandan participants contradicted our adaptation rules in 6 of 8 tasks, resulting in a low prediction accuracy of 24.4 %, 59.5 % with a deviation of 1, and 16.1 % with a deviation of 2. The number of correct predictions ranged from 2 (9 % correct) to 10 (47.6 % correct) depending on the task (mean = 5.13, sd= 3.04). Thus, Hypothesis 1 was not supported for Rwandan users. The deviation across all tasks and participants averages .92.

A significant majority of Rwandan participants, however, chose the same interface element in 6 of 8 tasks (supporting Hypothesis 2), which resulted in the most complex interface (chosen by 62 %, see Figure 6.5d). In contrast to our adaptation rules, 42.9 % additionally opted for a combination of the icon-represented to-do list with the tree menu, which allows for more freedom in sorting to-dos, but which we thought was the more complicated version. The choices contradicted our adaptation rules, which had provided for the flat navigation and a list-view of to-dos (see Figure 6.5c).

Similarly, the prediction of a preference for *accessible functions* that are grayed out if not needed was also incorrect. Instead, a majority of test participants (71.4 %) wanted all functionalities always visible. This finding corresponds with the choice for a high information density during the first task. For *guidance*, only 19 % participants chose the stand-alone dialog with no other information as it was initially predicted by our adaptation rules. Instead, 61.9 % favored the dialog which overlays the to-do list so that other information is still visible, but inaccessible.

A significant majority (57.1 %) opted for the maximum structure (corresponding to a low individualism) with bordered elements and clear affiliations between elements, and

this was correctly predicted ($\chi^2 = 5.54, p < .05, df = 1$). However, a second group with 33.3 % of users chose the opposite version, which represents minimum structure, and, with its plain white background, is also the least colorful. This preference for few colors was also evident in the subsequent task: Contrasting our adaptation rules which had predicted the choice of a *colorful* interface according to the Rwandan's low score in Individualism, 47.6 % actually chose few colors, followed by 42.9 % who preferred a medium number of colors. For the saturation, participants' choices were almost equally distributed across the three possibilities, with 47.6 % of participants favoring a medium saturation.

The last task on *support* was convincing in that a significant majority of 71.4 % chose the maximum possible support with the wizard, in agreement with our adaptation rules ($\chi^2 = 14.026, p < .001$). The second most popular option was a medium support level with 23.8 % opting for it. The result was especially interesting as all participants studied computer-related subjects.

For Rwanda, we observed many choices that contradicted our adaptation rules, which meant that we were only able to correctly predict ($p < .05$) the choices for 2 tasks (structure and support). Thus, Hypothesis 1 was not supported.

Switzerland. In Hofstede's studies, Switzerland was one of the countries that was not evaluated with regards to their Long Term Orientation. We have therefore adopted the German classification of a low Long Term Orientation (score 31), since it is likely that our Swiss German participants would have been allocated to this category.

We were able to correctly predict 56.8 % of the choices taken by Swiss participants, 27.6 % with a deviation of 1, and 15.6 % with a deviation of 2. Correct predictions per task varied between 9 and 20 (37.5-83.3 %, mean = 13.63, sd=4.14), with an average deviation of .59 across all tasks and partic-

ipants. Our adaptation rules therefore proved to be significantly correct ($p < .05$) for 5 tasks, partly supporting Hypothesis 1. Hypothesis 2 was verified with Swiss participants significantly agreeing on one element for 7 out of 8 tasks (Table 6.3).

Our adaptation rules anticipated Swiss participants to prefer a low *information density*, which proved to be correct in 54.2 % of the cases ($\chi^2 = 4.86, p < .05, df = 1$), with a significant tendency towards little information at first sight. Figure 7.1b shows MOCCA's user interface when adapted to a low information density. A close to significant majority ($p < .1$) of Swiss preferred the flat navigation in combination with a list-view of to-dos. Since MOCCA's adaptation rules provided the tree navigation for Swiss, which was only chosen by 9 participants, the correct predictions did not prove to be significant.

A majority of 62.5 % preferred medium guidance, which does not hide additional information, but prohibits access until the current dialog has been finished. Our adaptation rules proved to be able to accurately predict this preference ($\chi^2 = 9.45, p < .01, df = 1$).

Choices for *structure* were almost evenly distributed, and no one choice stood out as the most preferred one. However, most chose a high, or low structure. Additionally, the distribution of choices was the same for males and females.

Swiss also like few, but intense *colors*: 62.5 % of participants preferred a homogeneously colored interface, in agreement with our adaptation rules ($\chi^2 = 9.45, p < .01, df = 1$). *Saturation* was also correctly predicted ($\chi^2 = 19.148, p < .001, df = 1$), with 75 % of participants opting for high saturation of the color.

For the last task, *support*, a significant majority of 83.8 % of the Swiss participants favored the help bubbles, whereas MOCCA's adaptation rules had suggested a preference for tool-tips only.

The choices of Swiss participants were partly surprising,

because we had expected Swiss users to use computers rather confidently without the need for much support, and with a preference for the flexibility offered by MOCCA's tree navigation. However, MOCCA's resulting user interface after accounting for the majority choices (Figure 7.1b) still looks clearly different in comparison to the version for Rwanda and Thailand (Figures 6.5d and 6.5b), mainly due to a low information density and fewer colors.

Country Comparison: Rwanda, Switzerland, Thailand

Our results demonstrate that the distribution of choices between all three countries was significantly different for 7 out of 8 tasks (see column 'Between all three countries' in Table 6.4). This suggests that preferences indeed differ between countries. Only task 2, asking for a preferred navigation, showed similar frequency distributions for all three countries.

Following up this finding, we investigated the distribution of choices between countries to verify whether differences and similarities in Hofstede's dimension scores can anticipate the relation of choices between countries.

For example, according to Hofstede's dimensions, Thailand and Rwanda received similar scores for Power Distance, Individualism, Masculinity, and Uncertainty Avoidance (see Figure 6.3). In contrast, Switzerland received quite divergent scores for these dimensions. We therefore expected the preferences of Rwandans and Thai to be similar for all task but the first one on information density, which is linked to the dimension Long Term Orientation.

Contrary to these expectations, results demonstrated that the choices of Rwandans and Thai were significantly different distributed for task 3, and tasks 5 to 8 (see the right column in Table 6.4). Comparing these results to the majority choices in Table 6.3, we can see that Thai and Rwandan users indeed showed different preferences for these tasks.

Table 6.3: Majority choices for all three test countries (* = as predicted, significance of χ^2 -test with $df = 2$).

Interface aspect:	Switzerland		
	Thailand	Rwanda	Switzerland
Information Density	high, $p < .01$	high, $p < .05$	low*, $p < .05$
Navigation	medium*, n.s.	medium*, n.s.	medium, $p < .1$
Accessibility of functions	medium*, $p < .001$	high, $p < .001$	medium, $p < .05$
Guidance	medium*, $p < .001$	medium, $p < .05$	medium*, $p < .001$
Structure	low & med. *, n.s.	low*, $p < .05$	low & high*, n.s.
Colorfulness	low*, $p < .001$	high, $p < .001$	high*, $p < .01$
Saturation	low*, $p < .001$	medium*, n.s.	high*, $p < .001$
Support	medium*, $p < .05$	high*, $p < .001$	medium, $p < .001$

Table 6.4: Differences in the distribution of choices between countries, and between Rwanda and Thailand, who share mostly similar dimensions.

Task	Dimension	Between all three countries		Between Rwanda and Thailand	
		Between all three countries	Between Rwanda and Thailand	Between all three countries	Between Rwanda and Thailand
Information Density	LTO	$\chi^2_{(4)} = 16.92, p < .01$	not significant	not significant	not significant
Navigation	PDI	not significant	not significant	$\chi^2_{(2)} = 3.94, p < .05$	not significant
Accessibility of functions	PDI	$\chi^2_{(4)} = 34.71, p < .001$	$\chi^2_{(4)} = 11.67, p < .05$	not significant	not significant
Guidance	UAI	$\chi^2_{(4)} = 13.30, p < .01$	$\chi^2_{(4)} = 41.71, p < .001$	$\chi^2_{(2)} = 10.68, p < .01$	$\chi^2_{(2)} = 30.09, p < .001$
Structure	IDV	$\chi^2_{(4)} = 60.21, p < .001$	$\chi^2_{(4)} = 34.44, p < .001$	$\chi^2_{(2)} = 24.70, p < .001$	$\chi^2_{(2)} = 18.39, p < .001$
Colorfulness	IDV	$\chi^2_{(4)} = 16.92, p < .01$	$\chi^2_{(4)} = 11.67, p < .05$	$\chi^2_{(2)} = 10.68, p < .01$	$\chi^2_{(2)} = 30.09, p < .001$
Saturation	MAS	$\chi^2_{(4)} = 34.44, p < .001$	$\chi^2_{(4)} = 11.67, p < .05$	$\chi^2_{(2)} = 24.70, p < .001$	$\chi^2_{(2)} = 18.39, p < .001$
Support	UAI	$\chi^2_{(4)} = 16.92, p < .01$	$\chi^2_{(4)} = 11.67, p < .05$	$\chi^2_{(2)} = 10.68, p < .01$	$\chi^2_{(2)} = 30.09, p < .001$

Furthermore, task 1 on the preferred information density, was among those tasks where we did not find a significantly different distribution between the choices of Rwandans and Thai. This was in contrast to the disparate scores both these countries received for the dimension Long Term Orientation. However, the preferences of Rwandan and Swiss subjects, who have a similar score in this dimension, proved to be significantly different from one another ($\chi^2 = 13.05, p < .001$). Specifically, a significant majority of Swiss participants ($p < .05$) chose a low information density, while most Rwandans ($p < .05$) chose the opposite variant, namely the highest possible information density (as did Thai participants).

The results suggest that the distance between country's scores in Hofstede's dimensions does not correlate with the users' choices; or, in other words, the dimensions are not equally suitable for predicting user interface preference for different countries. This is also mirrored by the fact that Thai participants' choices were much better predictable than those of Rwandans: Although their cultural scores are very similar, the choices of our Rwandan participants did not correspond well with our adaptation rules, whereas Thai choices did.

As with the task on information density, the choices on structure did not show any clear tendencies that could be attributed to cultural background either. However, the distribution of choices on structure between all three countries was significantly different (see Table 6.4). It is interesting to note that both Thailand and Rwanda are classified into 'low Individualism', and both countries showed the expected tendency towards the corresponding maximum structure. However, Swiss participants, who were classified into 'high Individualism', chose this version as many times as they chose a minimum structure. Further research is needed to determine other influences on users' choices on this aspect.

Another exciting outcome was the result of the two tasks on colorfulness and saturation. Thai showed a strong prefer-

ence for many different, but light colors, and almost without exception, chose the color scheme containing pink. In contrast, Swiss participants showed a significant preference for saturated, and highly contrasting colors, but chose only a few colors for their user interface. Rwandans were not as decisive about the saturation, but the majority of users preferred few colors on their interface. For these two tasks, the choices of our participants were remarkably similar to what we had predicted. In addition, the preferences were in line with the common knowledge that Thai seem to like very colorful interfaces, whereas Swiss represent the Western taste for few colors.

In summary, participants of different countries sometimes chose the same (e.g. for navigation and guidance), although their previous cultural classification differed. Within countries, however, the distribution of users' preferences were significantly skewed towards one choice in the majority of cases. Such cases emphasize the need for learning new, and refining existing adaptation rules. Moreover, the variance in answers in spite of similar dimensions show that MOCCA should learn independently from the initial classification, basing its refined adaptation rules on the user's choices.

Cultural Adaptivity Versus a Universal Interface

According to the previous evaluation, MOCCA's initial adaptation rules correctly predicted 47.3 % of the participants' choices across all tasks and countries. Compared to the baseline of 33.33 % if randomly assigning interface elements to our participants, this represents a significant improvement. However, as we had pointed out in the "Test Design and Analysis" section of the first evaluation of this chapter, the assumption of an equal distribution of choices is somewhat artificial, because the majority of participants across all countries might favor one specific interface element, thus, resulting in

a skewed distribution of choices. Hence, the comparison of our prediction results to a probability at random might lead to false conclusions about the actual power of our adaptation rules.

We have therefore additionally simulated a scenario, where we replaced MOCCA's adaptation rules with the most popular choices. Specifically, we investigated the question whether one user interface that resembles these most popular choices would outperform our culturally adaptive system MOCCA.

As a first step, we normalized our combined population consisting of Thai, Swiss, and Rwandan participants in order to avoid a bias due to different group sizes. Subsequently, we added all choices of our participants and re-analyzed the prediction accuracy for each task with their majority choice across all countries. On average, this procedure lowered the prediction accuracy to 42.8 % from the previous 47.3 %, emphasizing that cultural adaptivity is better suitable to predict users' choices compared to a uniform interface. The result is even more compelling seeing that we assumed to know participants' choices in advance, which would usually not be the case. Interestingly, the correct prediction rate did improve for Thailand (from 60.8 to 65.8) and Rwanda (from 24.4 to 27.9), but it notably dropped for our Swiss participants from a previous 60 % of correct predictions, to a mere 34.6 %. The improvement for Rwanda and Thailand resulted from fairly similar choices made by the participants of both countries, whereas the taste of our Swiss participants often differed to them. The result indicates that there is a strong trade-off between the suitability of a single user interface for certain cultures, and this further stresses the importance of different interfaces for different (national) cultures.

6.3 Evaluation of the Automatic Refinement of the Adaptation Rules

The last experiment showed that participants from the same national culture tend to choose the same user interface element. Our adaptation rules that were derived from related studies, however, often failed to accurately predict these trends. We therefore designed a new study to evaluate whether MOCCA's learning component is able to learn from the preferences of users, as it was described in Section 4.4. We used the participants' choices from the last study to simulate a real-use scenario in which users register to MOCCA, receive a personalized interface according the initial adaptation rules, and subsequently use the preference editor to modify parts of the user interface.

Participants' choices from the previous study were added to the preference editor, which automatically saved them in the user-related instance of the cultural user model ontology. With this information, MOCCA carried out the following procedure: (1) All users were allocated to suitable cultural clusters according to their minimal Euclidean distance to a cluster centroid, (2) MOCCA retrieved all changes made to the preference editor per cluster, (3) for each cluster and each user within that cluster, the system calculated the choices for all 8 interface aspects, and (4) triggered the newly recommended adaptations. Subsequently, we were able to compare the resulting interface with the choices made by our test participants. Again, the deviations were retrieved by noting down the difference between the user's choice and MOCCA's recommendation.

Due to the homogeneity of our participants within one country (i.e. all participants had the same cultural dimensions, and thus received a similarity of 1), the similarity

weighting between users did not impact the results; an experiment with more diverse participants is left for future work.

MOCCA recommended the following changes for the adaptation rules:

- *Thailand*: Instead of a medium information density, use high.
- *Rwanda*: Information density was instead recommended as high, rather than low. The accessibility of functionalities changed to high (from medium), and guidance from low to medium. The colorfulness moved from medium to high (for a homogeneously colored interface.)
- *Switzerland*: Instead of a tree navigation, the recommender suggested the flat navigation (medium). The accessibility of functions changed from low to medium (on mouse-over).

The recommendations corresponded to the preferences of the majority of users per country, as they were calculated in our previous experiment. Therefore, the number of accurately predicted choices increased for all three countries (see Figure 6.6). In the case of Thailand, MOCCA's recommendations resulted in 65.8 % correct predictions (as opposed to 60.8 % before). The number of accurate predictions per user ranged from 3 to 8 ($mean = 5.27$, $sd = 1.08$), thereby increasing from an average of 4.87 tasks that were correctly predicted by MOCCA's initial adaptation rules (Figure 6.6). The improvement resulted from only one change in the adaptation rules.

In contrast, the adaptation rules for Rwanda were changed in 4 cases out of 8, resulting in 54.2 % of accurately predicted preferences (an increase from 24.4 %). Accurate predictions ranged between 2 and 6 per user ($mean = 4.33$, $sd = 1.11$). Thus, for the average user, we were able to correct more than 50 % of the user interface preferences correctly. Additionally, the deviation of 1 decreased from 59.5 % to 34.5 %.

For the Swiss participants, MOCCA now achieved a prediction accuracy of 60.4 % with accurate predictions per user

ranging from 3 to 8 ($mean = 4.83$, $sd = 1.34$). Compared to the average correct prediction of 4.54 (Figure 6.6(a)), this was the smallest increase in prediction accuracy of all three countries.

Altogether, MOCCA's prediction accuracy increased from 47.3 % to 61 %. The number of times MOCCA predicted with a deviation of 1 dropped from 41.4 % to 30.5 %, and for a deviation of 2 from 11.3 % to 8.6 %.

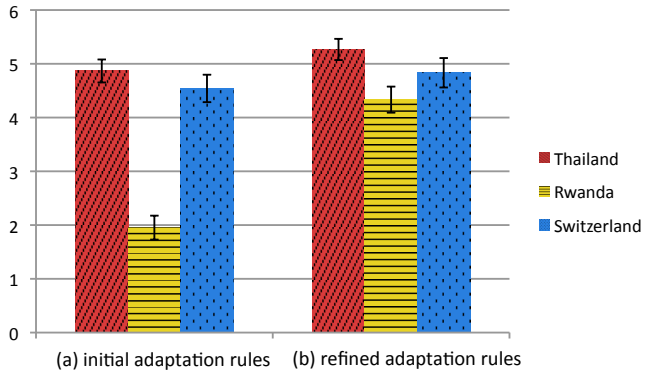


Figure 6.6: The average number of correct predictions per task (the y-axis represents the number of tasks) and per user measured with MOCCA's initial adaptation rules (a), and with the refined adaptation rules (b). Error bars show the standard errors.

Based on the findings from the second study presented in this chapter (Section 6.2), MOCCA demonstrated to be able to significantly improve the suitable interface adaptations when learning within homogeneous cultural groups. It has to be noted that this increase in prediction accuracy resulted from only a relatively small number of users and the information about their manual adaptations in the preference editor. We

expect that the precision increases with more users; however, this will be subject to future work. Similarly, we expect that culturally ambiguous users would highly profit from MOCCA's learning component, increasing the prediction accuracy of our first experiment in this Chapter, where MOCCA proved to be able to anticipate the majority of preferences of culturally ambiguous users.

Since the test participants were of similar age, and had a similar education level, future work should concern other preference-influencing differences, which could provide more information for increasing the prediction accuracy.

6.4 Summary of the Evaluations

In order to evaluate the adaptation rules of our culturally adaptive system MOCCA, we asked 105 participants (30 with international backgrounds, 30 Thai, 21 Rwandans, and 24 Swiss) to choose their preferred elements for different aspects of the user interface. For each participant, these choices were then compared to MOCCA's automatically generated interface.

MOCCA correctly predicted 60.95 % of the choices of the culturally ambiguous participants (as opposed to 33.3 % that could have been achieved by random prediction), 56.8 % of Swiss preferences, 60.8 % of Thai preferences, but only 24.4 % of the choices of Rwandan participants. The choices made by the Swiss, Thai, and Rwandan participants, however, emphasized that people of similar cultural background share similar preferences. We therefore evaluated how much improvement could be achieved via employing MOCCA's learning mechanism. From the previous prediction accuracy of 47.3 % across all three countries, MOCCA now produced an average increase in correct predictions by 29 %. For Thailand, we achieved 65.8 % correct predictions, for Rwanda 54.2 %, and for Switzerland 60.4 %.

The findings presented in this chapter demonstrate that it is feasible to anticipate a majority of user interface preferences by learning from choices of users with similar origin. However, 60 to 70 % of correct predictions appear to be the threshold where our prediction accuracy converges, even after learning. Our assumption is that an even higher prediction accuracy could be achieved by incorporating more user characteristics, such as gender, or computer literacy. Regardless, the last evaluation suffered from a problem known to most recommender systems: not enough users. An exciting question for the future will be to see whether the number of correct predictions increases if MOCCA was able to learn from more users and their choices in the preference editor. Another interesting question in this regard is how MOCCA performs under the influence from ratings of culturally ambiguous users.

For now, MOCCA has proven to successfully anticipate the majority of user preferences, and hence, the evaluation results support our hypothesis that cultural adaptivity improves user satisfaction by adapting to the user's cultural background. What is still to be tested, is whether users also prefer their adapted version when working with MOCCA. I will therefore describe an additional evaluation in the next chapter, where MOCCA's personalized versions are tested against a US version in order to investigate possible improvements in work efficiency and user satisfaction.

7

Evaluating the Benefit of Cultural Adaptivity

Although research has previously shown a prevailing preference for local or localized web sites, and industry examples such as Google's struggle to gain market share in South Korea seem to support this, we cannot be sure that our approach to cultural adaptivity increases performance, or the general user satisfaction. More specifically, three questions remain to be answered:

- Can MOCCA personalize the look of its interface in a way that users prefer it over a non-localized version?
- Is a culturally adapted version of MOCCA perceived as more attractive by users compared to a non-localized (e.g. US) version?
- Can a culturally adapted version increase work efficiency?

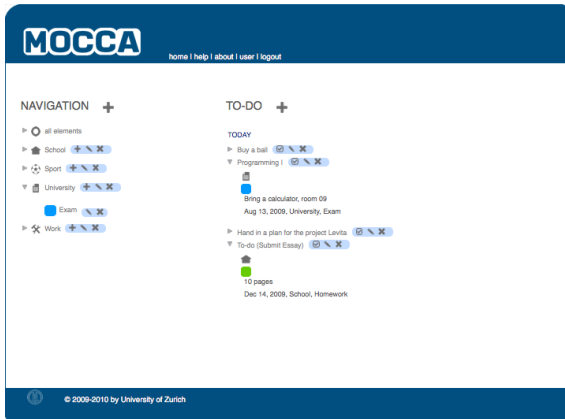
In this chapter, we evaluate these questions with the help of culturally ambiguous participants using MOCCA in a controlled usability study.

7.1 Experiment on Performance and User Satisfaction

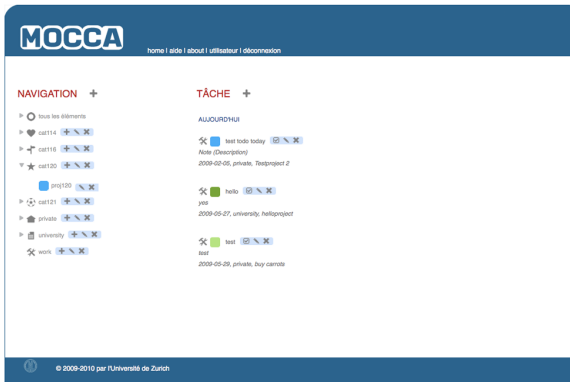
First hypothesis We hypothesize the benefit of cultural adaptivity to be twofold: Firstly, we expect that adapting the interface to a user's 'culture' (i.e. his or her current and former residencies) improves performance. If the interface's complexity, its guidance through different dialogs, or its overall support is adapted to the users' needs, it is likely that users will complete tasks and find information in less time and with fewer errors compared to non-adapted systems.

Second hypothesis Secondly, we assume that cultural adaptivity increases the aesthetic perception of the interface in comparison to non-adapted interfaces. It has previously been suggested that aesthetics might be even more important than the perceived usability [Norman, 2004], purely because it is what users become aware of first. In fact, users have been found to rapidly judge the aesthetics of web pages, often very reliably within 50 milliseconds [Lindgaard et al., 2006]. In [Tractinsky et al., 2006] these results were validated by demonstrating that aesthetic judgements after 500 ms highly correlated with the average attractiveness ratings after an exposure of 10 s. However, we know that what someone perceives as beautiful often differs along cultural values. Is cultural adaptivity able to anticipate this divergent perception of beauty?

Moreover, it might not be enough to meet the taste of a person with regards to aesthetics, since 'beautiful' does not mean that users automatically perceive something as usable [Lindgaard and Dudek, 2003]. Cultural adaptivity therefore has to generate interfaces that cater for both the user's aesthetic taste, and usability requirements based on his or her individual cultural background.



(a) MOCCA's US interface with a hierarchical navigation, which requires to click on the categories in order to see subordinated projects. Similarly, the to-do list on the right only shows the most important information at first sight. On click, users can expand the information to receive more details.



(b) The Swiss version of MOCCA offers the same hierarchical navigation as the US version, where projects can be nested to belong to certain categories. The do-do list showed a medium information density with all information about the to-dos shown at first sight.

Figure 7.1: MOCCA's US interface as it was used to represent the benchmark version in the experiment, and MOCCA's Swiss version in comparison (in French).

US version as
a benchmark

In order to evaluate the benefit of cultural adaptivity, our experiment was aimed to compare the usability and user satisfaction of MOCCA with a personalized version according to a weighted average of the user's current and former residences, compared to MOCCA's US version (see Figure 7.1a). Although none of MOCCA's user interface versions constitute a 'null version', the latter has been defined as a benchmark for comparison, since the large majority of software and web sites are still provided by US companies and designers. Thus, the following study explores the question, which user interface international users prefer, if comparing the US interface to the culturally adapted interface of MOCCA.

Method

Participants. We recruited 41 international participants from a variety of different cultural backgrounds to avoid restricting the results to only a few national cultures. Participants were between 20 and 38 years old ($mean = 26$, 25 female), all of whom had been living in Switzerland for between 1 and 276 months ($mean = 36$ months). Our participants represented 25 different nationalities. We allowed up to 4 people of the same nationality to take part in the study (on average, single nationalities were represented 1.56 times, $sd = .96$). Their former countries of residence, as well as the durations spent in each of these countries, however, were very diverse, with participants having lived in 2-5 different countries previously ($mean = 3.1$, $sd = .97$). Table 7.1 provides an overview of the countries that influenced the cultural background of our participants throughout their lives.

Note that for all participants, conventionally localized web sites would provide the Swiss version of their user interfaces (because all of them were living in Switzerland at the time of the user test), which only differs in few aspects to the US version due to a similar cultural classification of both countries (see Figures 7.1a and 6.5e).

Table 7.1: Overview of the countries where participants spent most of their lives (on the left), and those ones where they had spent additional time (on the right).

Major country	# of participants	Additional countries	# of participants
China	3	Australia	1
Sri Lanka	1	Austria	1
Switzerland	4	Bahrain	1
India	4	Bangladesh	1
Israel	1	Brazil	1
Czech Republic	1	Bulgaria	1
Estonia	1	Canada	2
Romania	2	Chile	1
Spain	1	Denmark	1
Colombia	1	Finland	1
Poland	3	France	3
Lithuania	1	Germany	9
Russia	2	Hong Kong	1
Germany	1	India	2
Chile	2	Ireland	3
Croatia	1	Mexico	1
Hong Kong	2	New Zealand	1
Japan	2	Philippines	1
Canada	2	Romania	1
UK	1	Russia	1
Latvia	1	Saudi Arabia	1
Pakistan	1	Spain	1
Iran	1	Sweden	1
Mexico	1	Taiwan	1
Colombia	1	Thailand	1
		UK	3
		USA	6

In order to balance the education level (and thus, keep this aspect of culture homogeneous), participants had to be students or have completed university (16 had received their Master's, 13 held a Bachelor's degree, and 11 were currently enrolled in Bachelor studies). Participants' study backgrounds

were in a variety of fields, ranging from biology to the humanities. However, in order to ensure that they had as little biasing exposure to the experiment as possible, we excluded participants who had taken courses in human-computer interaction, or culture-related topics. This also limited the risk that participants could have consciously or unconsciously anticipated the experiment's objective, or known which version of MOCCA was their personalized one. In addition to this, we controlled for computer literacy. All but one participant were using computers daily (one participant stated she uses the computer a couple of times per week). Participants were given a small financial incentive for their time.

Demographic
questionnaire

Procedure. On arrival, participants received both verbal and written explanations about the test procedure, followed by a short questionnaire soliciting information about their cultural background (current and former countries of residence, the durations, their own and their parents' nationality, first and second languages, education level, and religion). In addition, we recorded the frequency of computer usage, age, and gender. Participants were then given a short introduction to MOCCA's purpose and functions, as well as an explanation of its structure of Categories, Projects, and To-Dos. The explanation followed a written script in order to keep it consistent for all participants. Explanations as well as the questionnaire were provided in English.

Two subtests

The test procedure consisted of two subtests testing the US version of MOCCA (our benchmark) against a personalized version, which MOCCA generated after entering the user's current and former countries of residence into its registration mask. In order to conceal the US version, this log-in process was performed by the test conductor who either entered the participant's details, or logged in as a new US participant. We also switched off MOCCA's ability to adapt the language and

reading direction, since this could have revealed the user interface version. Instead, all participants were presented both versions in English and left-to-right alignment.

Each subtest consisted of three equal tasks, which only differed in their wording. Since the tasks partly built on one another, their order remained the same. The first task asked users to create a new category in MOCCA, and subsequently assign this category to a new project. The second one referred to a new to-do, which had to be created following specific instructions, and this had to be placed in the previously constructed project of Task 1. The third task required participants to search for an already existing to-do and its due date by filtering the information on the screen to only show to-dos related to a certain project. The user interface versions (UI versions US or adapted) were counterbalanced across participants.

Three tasks per subtest

Participants were asked to read through the first set of tasks, which they subsequently had to perform with one version of MOCCA. After each version participants completed the same questionnaire seeking their subjective impression on usability and aesthetics. On completion of the second version and its questionnaire, users were additionally asked to rate the two UI versions in three questions on a 7-item scale, and write down reasons for their preferences. The whole procedure took between 30-60 minutes.

Post-version questionnaires

Apparatus. We conducted the experiment on an Apple MacBook Pro (2 GHz Intel Core Duo, 2GB RAM) with a built-in 15" LCD display running at the native 1280 x 800 resolution. Participants had the option of using a keyboard with a Swiss German or US English layout. All participants used an external mouse.

Design and Analysis. The experiment was a within-subjects design with UI version (US, adapted) as the main experimental factor.

Objective measures

Throughout the test, we video-recorded participants to extract the following objective performance measures: time needed for each of the three tasks, number and type of errors, the number of clicks, as well as the number of help requests in MOCCA (see Table 7.2). For later comparisons with these objective results, we also noted participants' verbal reactions. Errors were counted if the participant opened a dialog window that did not lead her to fulfill the tasks; further clicks within the 'wrong' dialog did count towards the number of clicks, but not towards the number of errors. In addition, the reported seconds participants needed for each task is the net time, excluding any periods of time spent on explanations or reading.

Table 7.2: Summary of evaluation measurements used in the experiment.

Usability	<ul style="list-style-type: none"> ● Performance analysis (task completion time, number and type of errors, number of clicks needed to accomplish a task, and number of help requests) ● 8-item usability scale on a 7-point Likert scale on effort expectancy, and attitude toward using the system [Venkatesh et al., 2003]
Aesthetics	<ul style="list-style-type: none"> ● 10-item perceived website aesthetic scale on a 7-point Likert scale [Lavie and Tractinsky, 2004] ● 14-item aesthetic scale with contrary adjectives on a 7-point Likert scale [Hassenzahl et al., 2003, Hassenzahl, 2004]
Overall preferences	<ul style="list-style-type: none"> ● 3-items on a 7-point Likert scale on a direct overall, aesthetics, and work efficiency comparison

For the comparisons of time, number of errors, and number of clicks between the two UI versions, we used the non-parametric Wilcoxon signed-rank test for paired samples, since our data was not normally distributed according to Shapiro-Wilk tests ($p < .05$ for all variables). We applied one-tailed

significance for testing our directional hypothesis that the adapted version is superior over the US version. All p-values were corrected for multiple hypothesis testing using the Benjamini-Hochberg correction [Y. Benjamini and Y. Hochberg, 1995]. The correction also accounted for the paired samples that were not significantly different.

The non-parametric Friedman's two-way analysis of variance by ranks for related samples was used to check whether the overall distribution of timing data was the same over all three tasks.

Subjective assessments were made for usability and aesthetics with the help of a post-version questionnaire and 7-point Likert scales, where 1 was "I don't agree at all", and 7 was "I completely agree". The comparison of both questionnaires later provided us with an indirect measure of preferences.

Subjective measures

For the aspect of usability, the Unified Theory of Acceptance and Use of Technology (UTAUT) [Venkatesh et al., 2003], which in contrast to many other usability tests had been previously validated cross-culturally by [Oshlyansky et al., 2007], was used to collect information about effort expectancy (describing the degree of ease associated with the use of a system), and the attitude toward using the system (describing the user's overall affective reaction to using MOCCA). Initially, we had also included the 4-item scale on self-efficacy (describing the user's perceived competence in mastering the tasks with MOCCA), however, inconsistencies in the answers led us to discard this part of UTAUT.

We additionally used the aesthetics scale of [Lavie and Tractinsky, 2004], which subdivides an overall impression of aesthetics into classical, and expressive aesthetics. Classical aesthetics are usually referred to as the more traditional notion of design, with factors such as clean, or symmetrical representation of a user interface. In contrast, items included in the expressive aesthetics scale (e.g. fascinating, original) aim

at capturing the originality or creativity of the design.

We complemented the aesthetic dimensions with Hassenzahl's AttrakDiff [Hassenzahl et al., 2000, Hassenzahl et al., 2003], which directly contrasts the perceived pragmatic quality (i.e. the handling of a product, with variables such as complicated-simple, unpredictable-predictable) with the perceived attractiveness (e.g., quality criteria, such as unpleasant-pleasant, ugly-attractive). Hassenzahl's scale uses bi-polar contrasting adjectives as anchors of the scale. We also used this direct comparison of perceived usability with perceived aesthetic quality to investigate a possible *halo effect*, which describes the correlation between two attributes, such as if something is perceived as beautiful it is automatically found to be more usable [Tractinsky et al., 2000]. Such relations were analyzed with Pearson's correlation with a two-tailed test (because we did not have a directional hypothesis that helped us to anticipate whether the relationship between usability and aesthetics would be positive or negative).

Table 7.3: Average subjective Likert scale measures on a 7-point scale.

Likert scale	Rating for US version	Cronbach's alpha	Rating for adapted version	Cronbach's alpha
Effort expectancy	5.77	.830	6.2	.914
Attitude toward using the system	5.01	.915	5.2	.911
Classical Aesthetics	5.52	.851	5.63	.776
Expressive Aesthetics	4.02	.880	4.39	.878
Pragmatic Quality	5.3	.842	5.59	.744
Attractiveness	5.15	.934	5.52	.932

For all Likert scale items, we tested their internal consistency using Cronbach's alpha [Cronbach, 1951] in order to check for overall reliability, but also to find questions that

had been answered in a quite different and inconsistent way. All scales showed high reliability and construct validity with Cronbach alpha scores greater than .744¹ (see Table 7.3); we therefore computed the averages of participants' responses.

The Likert scale data proved to have significant normal distributions according to Kolmogorov-Smirnov tests on the differences between our dependent scores. Thus, for comparisons of Likert scale data by UI version (US versus adapted), we used dependent *t*-tests² and one-tailed significance in order to test our directional hypothesis. All *p*-values were again corrected for multiple hypothesis testing with the Benjamini-Hochberg correction [Y. Benjamini and Y. Hochberg, 1995].

Possible interaction effects of the UI version on aesthetics and user experience were analyzed with a repeated-measure ANOVA with the dimension (e.g. classical, expressive) and UI version (US, adapted) as within-subject factors.

The experiment ended with three questions on the participants' overall preferences, which directly compared the two UI versions on a 7-point scale (1=the first version, 4=neutral, 7=the second version; later converted to 1=US version, 4= neutral, 7=adapted version). Participants had to answer which version they liked best, which one they found more aesthetically appealing, and which one they could work with more effectively. Correlations between these overall answers and the previously recorded perceived usability and aesthetics were again investigated with the help of a Pearson correlation and a two-tailed test. Furthermore, we tested whether a significant majority preferred one version over the other with the chi-square goodness of fit test, entering the preferred ver-

¹Cronbachs alpha reliability coefficient ranges between 0 and 1; the closer it is to 1.0 the greater the internal consistency of the items in the scale. For high reliability, it is often suggested to use a cut-off of .7 [Nunally and Bernstein, 1994].

²We therefore assumed that the data can be treated interval. Non-parametric tests did not change the results.

sion as a categorical variable with the three levels preferred-Adapted, preferredUS, and neutral.

7.1.1 Results

An overview of our results on the objective performance measures is provided in Table 7.4, and the subjective results are presented in Table 7.5.

Performance. The distribution of timing data was significantly different for all three tasks and UI versions (Friedman's two-way ANOVA, $\chi^2_{(5)} = 42.03, p < .001$). We used post-hoc Wilcoxon tests to follow up this finding.

The overall difference in time needed to complete all three tasks proved a notable advantage for the adapted version ($Z = -2.002, p < .05, r = -.22$) with participants taking 276.46 seconds on average to complete all tasks with the US version ($sd = 129.9$), versus 215.39 seconds ($sd = 98.6$) with the adapted version. This equals an average performance improvement of 22 %.

On average, participants needed 92.37 seconds to complete Task 1 with the adapted version ($sd = 61.2$), but 120.98 seconds ($sd = 75.05$) with the US version, indicating an improved efficiency when working with a culturally adapted interface ($Z = -1.87, p < .05, r = -.21$).

Task 2 was also on average performed faster with the adapted version ($m = 71.29$ seconds, $sd = 25.4$) than with the US version ($m = 83.51$ seconds, $sd = 53.79$), though not significantly.

Task 3 asked participants to find a given to-do and write down its due date. The task was typically completed in less time than the other two, with the fastest participant accomplishing it within 11 seconds using the adapted version. In general, the completion took significantly more time with the US version ($m = 71.09$ seconds, $sd = 44.08$) than with the

Table 7.4: Summary of the objective results on performance (+ indicates the better version, - worse, and = means that we found no significant difference between the two versions with $\alpha \geq .1$). P-values have been adjusted for lower significance (thus higher p-values), using Benjamini-Hochberg adjustment for multiple hypothesis testing, including the paired sample that was not significantly different.

Measures	Task	US version	adapted version	p-value
Task completion time	All	-	+	$p < .05$
	1	-	+	$p < .05$
	2	=	=	n. s.
	3	-	+	$p < .05$
Number of clicks	All	-	+	$p < .001$
	1	-	+	$p < .05$
	2	-	+	$p < .05$
	3	-	+	$p < .01$
Error rate	All	-	+	$p < .001$
	1	-	+	$p < .01$
	2	-	+	$p < .05$
	3	-	+	$p < .01$

adapted version ($m = 51.73$ seconds, $sd = 29.2$), $Z = -2.12$, $p < .05$, $r = -.23$.

The time needed for each task was also mirrored in the number of clicks, proving a significant advantage for the adapted version ($Z = -3.40$, $p < .001$, $r = -.38$). For task 1, participants needed on average 13.9 clicks ($sd = 6.86$), whereas the adapted interface significantly lowered this number to 11.68 ($sd = 4.38$), $Z = -2.06$, $p < .05$, $r = -.23$. The same trend was observed for tasks 2 and 3: Task 2 was accomplished with 9.32 clicks on average for the adapted version ($sd = 2.1$) versus 11.59 clicks ($sd = 6.12$) for the US version (significantly more with $Z = -2.11$, $p < .05$, $r = -.23$). Task 3 could be accomplished with only one click (achieved by 1 participant using the US version, and 12 participants using the

adapted version). However, on average, participants needed 5.27 clicks ($sd = 3.76$) to accomplish the task with the US version, but only 2.85 clicks ($sd = 2.14$) in the adapted version ($Z = -3.39, p < .01, r = -.37$).

Table 7.5: Summary of the subjective results on the US version versus the adapted version of MOCCA (+ indicates the better version, - worse, +/- and -/= describes a trend observed at a confidence level of $\alpha < .1$, and = means that we found no significant difference between the two versions with $\alpha \geq .1$). P-values have been corrected with the Benjamini-Hochberg adjustment for multiple hypothesis testing, including the paired samples that were not significantly different.

Measures		US version	adapted version	p-value
Usability	Effort expectancy	-	+	$p < .05$
	Attitude toward using the system	=	=	n. s.
Aesthetics	Classical aesthetics	=	=	n. s.
	Expressive aesthetics	-	+	$p < .05$
User Experience	Pragmatic quality	-/=	+/=	$p < .1$
	Attractiveness	-	+	$p < .05$
Overall preferences	Overall preferred	-	+	-
	Aesthetically preferred	-	+	-
	Work efficiency preferred	-	+	-

Naturally, participants made the most errors during task 1 when still getting to know the user interface. With an average error rate of 1.27 ($sd = 1.42$), however, the US version caused significantly more errors for this task than the adapted version ($m = .51, sd = 1.08; Z = -2.8, p < .01, r = -.31$). Two participants also requested the system's help whilst using the US version. Both of them were using this version first, therefore this cannot be rated negatively (although there were no help requests whilst using the adapted version).

Task 2 also showed a lower error rate for the adapted version ($m = .02$, $sd = .16$), than for the US version ($m = .24$, $sd = .62$; $Z = -2.12$, $p < .05$, $r = -.23$), and this advantage for the adapted version was also shown for task 3 (adapted version: $m = .20$, $sd = .56$, versus $m = .88$, $sd = 1.25$ for the US version; $Z = -3.07$, $p < .01$, $r = -.34$).

Usability. Subjective usability results are shown in Figure 7.2. The effort expectancy (e.g. “My interaction with MOCCA is clear and understandable”, “I find MOCCA easy to use”) was perceived significantly higher for the adapted version ($m = 6.2$, $sd = .77$) than for the US version ($m = 5.77$, $sd = .88$; $t_{(40)} = -2.46$, $p < .05$). We did not find significant differences in the attitude toward using the system (e.g. “Working with MOCCA is fun”, “MOCCA makes organizing to-dos more interesting”) between the two versions, although the adapted version was again rated slightly better.

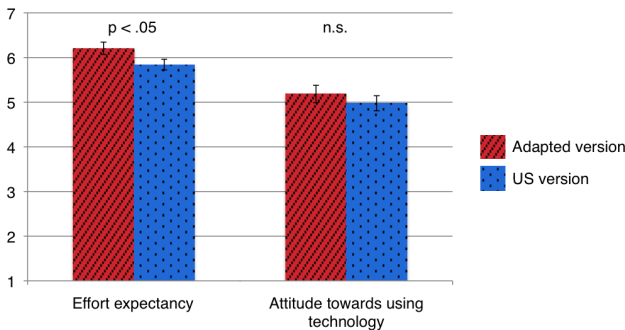


Figure 7.2: Average evaluation scores of UTAUT’s effort expectancy and attitude toward using the system for MOCCA’s US version and the adapted user interface. Error bars represent the standard error.

Aesthetics. The results for classical aesthetics did not prove a strong tendency towards one UI version, with similar average ratings for both (5.52 for the US version, and a slightly higher 5.63 for the adapted version). Thus, both versions seem to satisfy participants' traditional aesthetics sensibility.

The expressive aesthetics received an overall lower rating than the classical aesthetics, but the adapted version was judged significantly better ($m = 4.39, sd = 1.25$) than the US version ($m = 4.02, sd = 1.35; t_{(40)} = -2.17, p < .05$).

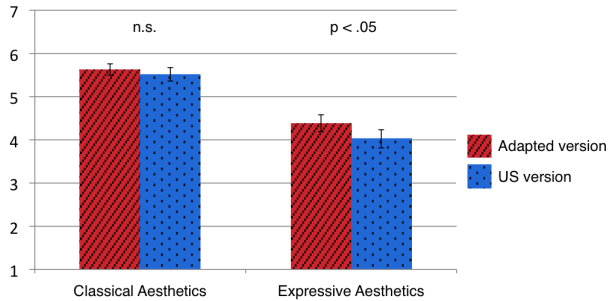


Figure 7.3: Average evaluation scores of classical and expressive aesthetics for MOCCA's US version and the adapted user interface. Users especially favored the expressive aesthetics of the adapted version over the US version, showing that they found the design more original and creative. Error bars represent the standard error.

The average scores for the two aesthetic factors as a function of the factor UI version are shown in Figure 7.3.

To investigate the interaction between UI version and aesthetic factors, we ran a 2x2 repeated-measures ANOVA, which showed a significant effect for the aesthetic factors classical and expressive ($F_{(1,40)} = 95.33, p < .001$), but not for the UI version.

An analysis of the interaction between UI version and aesthetic scale further indicated that the effect of the UI version on aesthetics is slightly modulated by the aesthetics dimension, with a statistical significance at the 90 % level ($F_{(1,40)} = 3.28, p = .078$).

User Experience. The user experience measures were meant to combine participants' impressions on usability and aesthetics, and the results (see Figure 7.4) verified the above-mentioned tendencies towards a preference for the adapted version. The pragmatic scale, evaluating the perceived ease of handling of MOCCA, resulted in an average rating of 5.3 ($sd = .92$) for the US version, and an average of 5.59 ($sd = .66$) for the adapted version, showing a slight tendency towards an improved perceived handling of the adapted version ($t_{(40)} = -1.799, p = .06$).

The attractiveness, often considered as an equal contributor to the overall observed usability [Tractinsky et al., 2000], scored significantly higher for the adapted version ($m = 5.52, sd = .82$) than for the US version ($m = 5.15, sd = 1$), $t_{(40)} = -2.76, p = .05$.

In addition, Pearson's correlation was significant between the pragmatic quality and attractiveness for both versions (US: $\rho_{(41)} = .79, p < .001$, adapted: $\rho_{(41)} = .62, p < .001$), indicating a possible halo effect between the perceived aesthetics and the perceived ease of handling. We found a significant effect for the UI version ($F_{(1,40)} = 6.35, p < .05$), but not for the user experience measures.

Overall Preferences and Qualitative Feedback. Comparing the two versions at the end, the majority of participants preferred the adapted version, and this preference was especially strong for the questions "Which version did you like best?", and "Which version did you find more aesthetically appealing?" (see Figure 7.5). The distribution of answers to all three

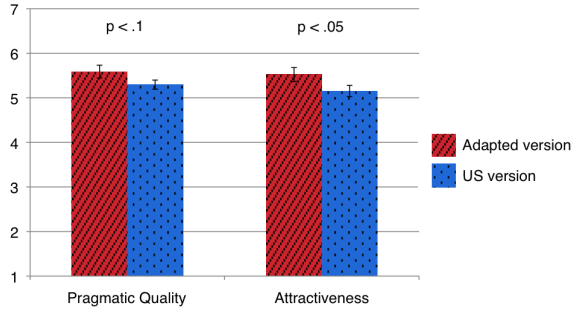


Figure 7.4: Average evaluation scores for the pragmatic quality and attractiveness with UI version as a factor. Error bars represent the standard error.

questions was skewed towards the adapted version:

For the first question, 51 % of the participants rated on the extreme ends of the scale (i.e. 1=US version, or 7=adapted version), with 34 % of the participants strongly favoring the adapted version, versus 17 % who preferred the US version. On the 7-point scale, this resulted in an average rating of 4.76 ($sd = 2.34$).

In order to include the tendencies towards one version, we subdivided the scale into two parts (i.e. 1-3 and 5-7). Combining the choices of each sub-scale, 66 % of the participants preferred the adapted version ($m = 1.7$ on a sub-scale of 1-3, $sd = .82$), 29 % preferred the US version ($m = 1.42$, $sd = .51$), and 5 % were neutral. This advantage for the adapted version was highly significant ($\chi^2_{(2)} = 23.17, p < .001$).

The second question on which version participants found more attractive showed a similar trend: 29 % of the participants favored the adapted version and marked the 7 on the scale, versus 12 % who were clearly in favor of the US ver-

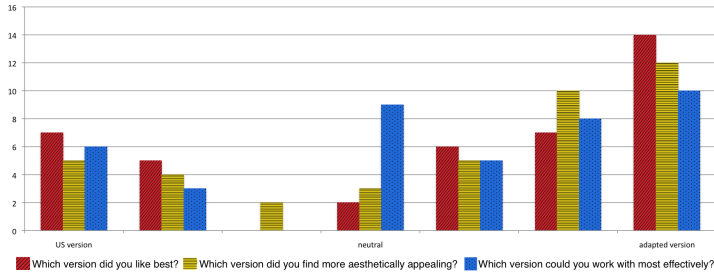


Figure 7.5: Participants' overall preferences on three 7-point Likert scales.

sion (marking 1). The average rating was 4.88 ($sd = 2.15$). On the two sub-scales, 66 % of the participants found the adapted version more aesthetically appealing (85 % of them were the same participants who had also chosen the adapted version as the overall preferred one). In contrast, 27 % preferred the aesthetics of the US version, and 7 % were neutral. The results show that the majority of participants classified the attractiveness of the adapted version much higher ($\chi^2_{(2)} = 21.85, p < .001$).

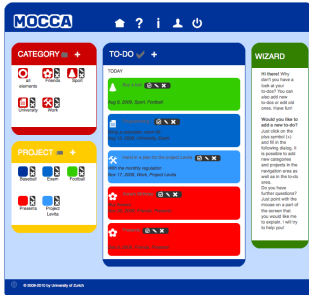
Participants did not show such clear preferences towards the version they could work with most effectively: 24 % highly preferred the adapted version (i.e. rated with 7), while 15 % opted for the US version (rated with 1). However, a relatively high proportion at 22 % were neutral towards both versions. Nevertheless, the distribution of answers was skewed towards the adapted version, with an average rating of 4.66 ($sd = 2.09$). Combining the answers on each end of the scale, 56 % perceived the work efficiency as better with the adapted version, versus 22 % with the US version, and this preference was significant ($\chi^2_{(2)} = 9.56, p < .01$).

Interestingly, the objective performance results partly con-

tradict the subjective feelings of those participants who had stated that they could work better with the US version, because the timing data was not significantly different to the time needed for the adapted version across all three tasks (US: 80.0s, $sd=52.27s$; adapted: 74.4s, $sd=33.25s$). In contrast, participants who thought they could work more efficiently with the adapted version, did need less time with this version for all three tasks (US: 95.8s, $sd=67.5$; adapted: 74.12s, $sd=51.22$; $Z = -2, p < .05, r = -.22$).

Table 7.6: Overview of keywords in participant's written responses to the question why they preferred one version over the other.

	Comment	US version	adapted version
Usability	easier to use	3	8
	guidance through dialogs	-	1
	clear	4	6
	practical	-	1
	overview of to-dos	1	3
	simplicity	10	1
	support	-	2
	flat/hierarchical navigation	2	1
	intuitive	-	1
	structure/organization of the UI	1	7
	more predictable	-	1
Total		21	32
Aesthetics	icons	1	5
	motivating	-	1
	appealing	2	5
	colors	1	13
	creative	-	2
	inviting	-	1
	pleasure / fun	-	2
	formal/informal	4	2
Total		8	31



(a) A brightly colored version of MOCCA with a flat button navigation. The participant who received this interface was from Mexico, and had shortly lived in Bulgaria.



(b) A version with the to-dos in list view, so that to-dos have to be expanded to show more information. The interface was generated for a participant from Poland, who had also lived in Ireland and Germany.



(c) MOCCA with pastel colors, as it was triggered for a participant with Russian, Romanian, and Swiss background. Functions, such as delete, or add, are always accessible and add to the information density.



(d) A version without the colored borders that define the different areas of the interface. It was personalized for an Indian participant, who had lived in France and the US for a rather long time, which reduced the complexity of the 'pure' Indian version.

Figure 7.6: Example interfaces of MOCCA as they were generated for different participants.

Participants' responses to the question, which version they liked best, correlated slightly higher with their opinion on which version they could work with most efficiently ($\rho_{(41)} = .875, p < .001$), than with their aesthetic preferences ($\rho_{(41)} = .558, p < .001$). This could imply that the perceived work efficiency is the crucial factor when being forced to decide between two user interfaces. We therefore analyzed whether participants' written explanations for their preferences confirm this idea. Specifically, we used participants' written comments on the positive aspects of each version to find possible explanations for their choice for one version or the other. The positive keywords mentioned during this final explanation part are listed in Table 7.6. Altogether, usability-related aspects were mentioned 53 times, whereas the aesthetics of the user interface was referred to 31 times. Thus, most participants seemed to base their comparison not on high-level features, such as the number or kind of colors, or the complexity of the user interface, but focused on practical handling aspects. The comments therefore further substantiate the assumption that work efficiency and effectiveness could be the more important factors.

A positive aspect of the US version that was mentioned most often was its simplicity (mentioned 10 times). Four participants who had acknowledged this found the colors of the adapted version nicer, however, for them, the simplicity of the US version seemed to be the decisive factor leading to an overall preference for the US version. Again, this finding further verified that participants' overall preferences were mainly based on aspects of usability.

For the adapted version, its ease of use was positively acknowledged the most (8 times). Those participants whose adapted version included a clear subdivision of categories, projects, and to-dos with the help of colored borders (as shown in Figures 7.6a or 7.6c) approved of this structure (mentioned 7 times). Only 1 participant acknowledged the increased guid-

ance through dialogs in her adapted version, and 2 participants gave more support (i.e. help bubbles or a wizard) as reasons for their preference for the adapted version. Altogether, the usability of the adapted version was positively commented on 32 times, versus 21 comments for the US version, a result that is consistent with the overall majority preference for the adapted version.

Aesthetic aspects were positively acknowledged for the US version by 8 participants, and by 31 participants for the adapted version. Most participants commented on the colors, which were preferred by 13 in the adapted version. It has to be noted that MOCCA's US interface uses very few, monotonous colors due to the US individualism score of 91, which is the highest of all countries that Hofstede compared. The average participant in our test received a score of 48, $sd = 18.04$, and only 17 participants were presented with an equally monotonous color scheme as the US version (although mostly consisting of a different color selection because of the influence of the Masculinity score on the saturation of colors). Most participants were therefore presented with more colorful interfaces. 54.5 % of these participants mentioned the colors as a positive aspect, showing that this is one of the most striking characteristics in MOCCA. This also emphasizes the importance of changing the color schemes when adapting to different cultural backgrounds.

Interestingly, 4 participants found the look of the US version very formal, and said it seemed to be designed for work purposes. Two of them also compared it to the adapted version, which they thought looks as if it was designed for leisure activities. The comments make it clear that preferences often depend on the context of web sites. Since MOCCA's purpose is to support users' planning activities, some of our participants might have found the design of the US version more appropriate. It is even more surprising, that the majority still preferred the adapted interface.

Furthermore, participants' comments were helpful to interpret why some users with divergent opinions on their aesthetics and work efficiency preferences, had a very specific tendency towards one version when asked for their favorite user interface. For example, one participant with a Japanese background preferred the color and layout of the adapted version, and he liked that the divisions (category, project, to-do) are explicitly shown on the screen: "The [US version] is better to understand, though the [adapted version] is better in design". In the overall comparison ("Which version did you like best?"), however, he marked the second box on a 1 (= US version) to 7 (= adapted version) scale. For the question on which version offered him the best work efficiency, he even ticked the first point, indicating the highest preference for the US version. One explanation for his contradictory answers might be that he used the adapted version first, and thus, he probably included his work efficiency improvements into the final judgements. In general, however, we were not able to prove a correlation between the first version the participant used, and his or her final overall preference: 14 participants who had used the adapted version first, and thus, experienced an equally steep learning curve at the start, still preferred this in the overall preference rating (only 6 did so for the US version). Of those participants, who had preferred the adapted version in the end, 13 participants had used the US variant first, versus 6 who later preferred the US one.

Surprisingly, we observed the opposite effect (an overall preference for the adapted version, but a strong preference for the aesthetics of the US version) in only one case, where a participant with Indian background stated that he liked the US version for its simplicity, but found the adapted version more appealing, more creative, and more innovative. For him, the simplicity seemed to be more appropriate for a to-do application, which is why he preferred the look of the US version. Again, this corresponds to previous findings indicating that

preferences depend on the domain.

Two participants also justified their preference for the US version by saying that it reminded them of the social network site Facebook, which uses similar colors.

Although 21 participants rated their overall preference on the 'extreme' ends of the scale (7 voted 1, i.e. the US version, and 14 voted 7, i.e. the adapted version), only 5 of them affirmed that they would refrain from using MOCCA if presented the other version, all of whom referred to "ugly colors" as the main reason.

Possible Influences on the Users' Preferences

As our results showed a marked preference for the adapted version by most participants, we have to exclude the possibility that the US version we presented is simply unattractive, or flawed in some other respect. One argument against this, are the results of our previous experiments, as discussed in the last chapter: Earlier on in MOCCA's design cycle, we had analyzed the user's choices if designing their personal MOCCA user interface following a modular principle in a paper prototype session. Results showed that Swiss participants mostly chose a similar layout to MOCCA's US version tested here, while participants with more divergent cultural backgrounds to the US dimensions (Thais and Rwandans) chose much more complex, and more colorful designs.

Similarly for this evaluation, we expected participants with a cultural background closer to the US ('Westerners') to be less decisive in their preference for the adapted version, than those participants who had lived in Asian or Latin American countries for most of their lives. The latter are considered to be collectivist countries (thus, receiving a low score in the dimension Individualism), who have been found to prefer colorful interfaces, where color is also used to show affiliations between information, and structure the interface (cf. the

adaptation rules in Table 5.1). Hence, MOCCA's user interfaces generated for Asians and Latin Americans were much more colorful, than most of those ones generated for Westerners.

To analyze whether Westerners chose the US version over their personalized interface more often than Latin American and Asian users, we subdivided the user population into two groups according to the country where they had spent most of their lives. This resulted in 19 people who were assigned to the Asian and Latin American cluster, and 22 participants to the Western cluster.

The answers for participants' overall preferences revealed that within both groups a significant majority of users preferred the adapted version over the US interface (Easterners: $\chi^2_{(1)} = 12.96, p < .001$, Westerners: $\chi^2_{(1)} = 23.04, p < .001$). However, this number was lower for Westerners (68 %, compared to 74 % of the Latin American and Asian participants), supporting our assumption that Westerners, who are closer to the US culture than Easterners, were less decisive in their preference for the adapted version.

We also found a significant relationship between the perceived pragmatic quality and the perceived attractiveness for both groups as shown in Table 7.7. The observation suggests that the better participants rated the pragmatic quality of MOCCA's interfaces, the better they classified their attractiveness. The correlation between the two variables is not significantly different for Westerners and Easterners (using Fisher's *r*-to-*z*-transformation), suggesting that the finding is independent of cultural affiliation.

Furthermore, we had assumed that the (usually more colorful) adapted versions would be mostly rejected by male participants. Instead, of the 12 participants who preferred the US version, only 3 were male. Two participants, who preferred the US version, had received a personalized interface in

our evaluation that was fairly close to the US interface at first sight due to similar cultural dimensions: the only visible differences were an expanded to-do list, and an increased support with question mark bubbles which opened upon click. The color scheme, and the hierarchical navigation, however, were equivalent to the US version. The remaining 10 participants were of divergent cultural backgrounds, which resulted in mostly colorful interfaces with a flat navigation, an emphasis on the structure and affiliation between to-dos and the categories/projects they belonged to. These participants gave either a preference for few colors, or the simplicity of the US version as a reason for their preference.

Table 7.7: Correlations between perceived pragmatic quality and perceived attractiveness for Westerners, and Latin American/Asian participants (analyzed with Spearman's correlation and a two-tailed test, * $p < .05$, ** $p < .01$, *** $p < .001$).

	Westerners	Easterners (Asians and Latin Americans)
US version	$\rho_{(22)} = .82^{***}$	$\rho_{(19)} = .79^{***}$
Adapted version	$\rho_{(22)} = .70^{***}$	$\rho_{(19)} = .49^*$

7.1.2 Discussion

Our participants were significantly faster with the adapted version, needed fewer clicks to complete tasks, and made fewer errors. The results were supported by their perceived effort expectancy, which was significantly better for the adapted version.

While we were not able to find a difference for the ratings of classical aesthetics between both versions, this suggests that MOCCA's interface design satisfies traditional de-

sign perceptions (symmetric, clean, pleasant) no matter which version is shown. In contrast, the expressive aesthetics, which stand for more original and creative design, were rated significantly higher for the adapted version. An advantage for the attractiveness (describing the user experience) of the adapted version, supported this result.

Participants' answers in a direct comparison of the two versions were particularly strong: 56 % thought they could work more efficiently with the adapted version, 66 % found the adapted version more aesthetically appealing, and 66 % opted for the adapted version in an overall comparison. These answers to the last three questions asked for a direct comparison between the two versions, and this may have lead many participants to subconsciously perceive the 7-point scale as a dichotomous choice. In a real-life situation, participants would indeed have to decide between one version or the other (in case there is an alternative to a certain web page); thus, our results suggest that the adapted version of MOCCA would outperform competing non-adapted web sites.

Moreover, our results indicate that cultural adaptivity also has an advantage over localized web sites. Conventional approaches to localization would have (more or less automatically) presented users with the Swiss version, because this is where all our participants lived at the time of the experiment. MOCCA's Swiss version (localized), however, is very similar to the US version (non-localized); it is therefore likely that the majority of our participants would also favor the adapted interface over the Swiss variant.

Our findings demonstrate that the perceived work efficiency outweighs the perceived aesthetics when participants have to decide between a non-adapted, and an adapted user interface. In particular, users' responses to why they chose one version over the other suggested that usability was a more crucial factor in their decision than aspects related to the attractiveness. The finding contradicts the assumption of Ben-

Bassat et al. [2006], who had speculated that in lab experiments participants give aesthetics a stronger weighting than usability-related aspects, because a less usable system does not carry any consequences. However, our results of the subjective ratings of perceived usability and aesthetics indicate that the ratings on these two factors significantly relate to one another. This relationship was also strong if analyzing the ratings for Westerners and Easterners (Asians and Latin Americans) separately, suggesting that a halo effect between pragmatic quality and attractiveness is culturally independent. Tractinsky [1997] had previously observed a similar relationship between perceived aesthetics and a priori perceived usability, when doing a study with Japanese and Israeli subjects. While he assumed a possible cultural difference in the magnitude of the relationship (with Israelis perceiving the two factors as more related than Japanese participants), our findings did not support this when dividing participants into Westerners and Easterners.

7.2 Limitations

Our results showed a strong preference for the culturally personalized version of MOCCA, if providing participants with a choice between this and the US version. Due to our experimental design which aimed to prove this superiority for a broad range of cultures (i.e. culturally ambiguous users), we are able to say that cultural adaptivity is able to outperform non-adapted version of the same web site; however, we cannot claim that one of MOCCA's personalized sites is the best suitable for a user. Instead, it is well possible that our participants preferred the adapted version, but would have also said so if they were presented the adapted interface of another participant. To rule out this possibility, future large-scale studies

are needed, where participants can be presented with several different versions.

Future experiments should also evaluate the users' perception of the adapted version versus a non-adapted interface at different stages of usage. So far, our study strongly indicates an advantage for the culturally personalized interface, and a closer look at participants' responses suggested that the perceived usability was the determining factor for this preference. However, the first impression of web pages usually influences the perceived aesthetics, rather than assumptions on whether the site will be easy to use. Our study was not designed to answer the question which factor would be more pivotal to leaving a web site for the competition, but rather whether users were more inclined to do so when using MOCCA's non-adapted version – which our results did suggest. Evaluating this finding in detail will be an interesting goal in the future.

7.3 Summary of the Evaluation

Support of
Hypothesis 1

The results of this experiment substantiate the idea that preferences differ, and that culturally adapted user interfaces could have a competitive advantage over non-adapted user interfaces. By automatically generating user interfaces on the basis of a weighted average of the user's duration of stay at current and former residences, we have demonstrated that users' performance significantly increased by 22.09 %. This supports our first Hypothesis. The result was verified by users' perceived usability, showing that they considered the adapted version to be significantly easier to use.

Support of
Hypothesis 2

Users were also more satisfied with the personalized user interface when asked about their perception of the attractiveness, which is line with our Hypothesis 2.

In an overall comparison of the two interface, all of the above-mentioned results were again emphasized: A remarkable majority of 66 % favored MOCCA's culturally adapted interface, 66 % also found it more aesthetically appealing, and 56 % though they could work more efficiently with this version.

In conclusion, we were able to prove a significant benefit for culturally adapted interfaces over providing users with a web page's 'standard' version. With that, our approach has substantiated our hypothesis that it is very valuable for attracting culturally diverse customers, and improving their user experience.

8

Limitations & Future Work

As with most novel approaches, our research on cultural adaptivity has opened up possibilities for new and exciting future directions. First of all, the results of our user tests supported the idea, however, a broader range of participants, and applications is needed to further investigate details. Future evaluations should, for example, verify the generalizability of our approach for other domains. In our past experiments, we used a to-do application in order to avoid influencing users with possibly culturally-biased content. To-do applications are used for organizational tasks, which are usually seen as less fun than, for instance, using a social networking site to connect with friends. Accordingly, one can assume that visual preferences might differ if using a work-related interface compared to other types of applications that are oriented towards a hedonic experience. The comments made by our participants during our last experiment confirmed this assumption with some users saying that a well-ordered, “clean” looking version of MOCCA (the US version) seems more appropriate for work. It will be interesting to see how our model performs

Generalizability to other domains

when predicting user preferences in other domains, such as when testing online forums, or users' own home pages.

Diversity of
participants

Our experiments also showed that some people's preferences were more predictable by our adaptation rules than others. In future evaluations, larger numbers of participants are needed to analyze which factors lead users to "deviate from the crowd". One limitation of our studies was also that all participants had a high education level, and mostly also a high level of computer literacy. In this regard, it would be interesting to see how the prediction accuracy rate behaves, and whether it can be even further improved if taking into account more aspects that influence culture, such as the education level, or even personality-related aspects.

Comparison to
other approaches

Additionally, an important future work direction is to compare our calculation of the user's cultural background (taking a weighted average of Hofstede's dimensions for all countries of current and former residence) to other methods. The main criticism of Hofstede's work is usually that it confines culture to national borders (hence, the term "national culture"), following the disapproval that he collected his data at different branches of the international company IBM. People have argued that his cultural dimensions cannot be generalized because it resembles a corporate culture. Other people have applied his dimensions in different domains (often due to a lack of alternative definitions), and have found the variables to be more or less explanatory and of predictive value (cf. Chapter 2). Our collaboration with cultural anthropology was characterized by many discussions on this issue, with neither side being convinced of the generalizability of Hofstede's cultural dimensions. And although our experiments have demonstrated that they are suitable for predicting preferences in a majority of cases, it would be exciting to see whether other models, or a combination of Hofstede with refining variables, would result in more accurate results.

In this case, however, research has to find new ways to

unobtrusively acquire this information. One idea is a kind of application-independent “cultural passport”, which holds information that a user has previously entered (e.g. following a questionnaire). Assumably, only few user’s would accept be willing to spend time to answer a number of questions without being able to foresee the benefits of personalization (this is why our approach uses Hofstede and limits the number of questions to a minimum, cf. Section 4.2.2). A universal personal user model could increase user acceptance, if users are only required to enter information once, and if they had been previously made aware of the advantages.

Another issues that we did not address in this thesis is the retainment of recognition value. While our prototype is able to provide fully personalized sites, companies might be afraid of applying this method since changing user interfaces could not be recognized as associated to their brand. In MOCCA, we have therefore tried to retain the recognition value with the help of a logo at the top of the page, and enframing the site with a header and a footer. However, the effects of different user interface looks on brand recognition has to be investigated in the future. We could imagine that companies might want to reduce the adaptation possibilities, so that at least the main colors remain constant to the company’s branding, and this would be very well possible with our approach. Before such reductions can be made, further studies should investigate which adaptation rules are most important for increasing the users’ satisfaction; if color is one of the main factors determining users’ satisfaction with a site (as suggested by the results of Lindgaard in [Lindgaard, 2007]), then excluding the automatic adaptation of colors will impair the success of cultural adaptivity.

Recognition value

Likewise, there are many more opportunities for further exploring the acceptance of adaptive user interfaces from the user’s side. One reason why our aim was to achieve a suitable initial adaptation was that previous research has raised

doubts that such continuous adaptations confuse users (cf. Chapter 2). More research is needed to find out whether this risks fully disqualifies the implicit information acquisition with ongoing adaptations, or how changes in the user interface can be adequately introduced to the user.

9

Conclusion

Localized user interfaces usually provide one adapted view per country, and the adaptations are mostly restricted to modifications of the most visible user interface aspects, such as the exchange of date/time formats, language, or images. Other presentation characteristics (e.g. color, information density, text-to-image ratios) have been mainly ignored, although they are highly important for visually perceived aesthetics. Likewise, workflows and the access to functionalities are normally offered in a standardized way, hindering an international usability.

Counteracting these problems, this dissertation proposed a new approach: Culturally adaptive user interfaces. The idea was to design intelligent systems that can automatically adapt to a person's cultural background. Accordingly, we hypothesized that cultural adaptivity improves the overall usability, and specifically, increases work efficiency and user satisfaction in comparison to localized, or non-adapted user interfaces.

In support of this thesis, we developed a user model, which represents the various facets of users' cultural backgrounds beyond equalizing culture with one country. The aspects that

Support of the hypotheses

influence a user's culture were then aligned with culturally-specific perceptions and user interface preferences. To cater for individual differences in cultural background without having to design innumerable user interfaces, our approach requires a modular and highly flexible interface. We have demonstrated the feasibility of implementing such flexibility with our culturally adaptive software MOCCA, which can personalize its user interface to various user preferences with more than 115'000 possible combinations of interface components. This, and the results of our experiments, fully support our three hypotheses:

Hypothesis I: Cultural adaptivity improves both work efficiency and user satisfaction compared to non-adapted user interfaces.

Cultural adaptivity improves work efficiency and user satisfaction in comparison to non-adapted user interfaces. The results of our evaluations demonstrated that participants were on average 22 % faster with the adapted version, and that a significantly higher number of participants preferred the personalized user interface to the benchmark (US) version.

Hypothesis II: It is possible to develop adaptive user interfaces that do not restrict the adaptations to a finite number of countries, and that this method reduces the process of localization to a fraction of the time needed.

The implementation of our prototype proved that a modular approach to localization (i.e. composing the user interface of different components) is more time-efficient than sep-

arately designing one user interface per country. In addition, we have detached the conventional localization process from designing for specific target countries; Cultural adaptivity does not rely on time-consuming and costly ethnographic analyses, but provides personalized user interfaces for users from any country, and even for culturally ambiguous people.

Hypothesis III: The knowledge about the user's cultural background can be used to provide a fairly suitable initial adaptation, thereby limiting the risk of losing users to the competition.

Our experiments showed that the approach provides suitable user interfaces right after registration, which reduces the risk that users will turn to the competition. Our experiments demonstrated that we can predict user preferences in up to 65.8 % (as opposed to 33 % of a random prediction).

According to these results, cultural adaptivity has demonstrated to bridge the gap between the cost-efficient development of localized applications and international usability.

Building up on a variety of research fields, such as culture and international usability, user modeling, and intelligent user interfaces, one of the main contributions of this thesis is its interdisciplinary: While these areas have so far produced mainly isolated research, cultural adaptivity combines existing results into a holistic approach.

Contributions

Moreover, cultural adaptivity of user interfaces extends existing research. As a basis of our approach, we advanced research on international usability and culture. Our work towards a definition of cultural influences on human-computer interaction and perception incorporates the understanding of the term in cultural anthropology. We aligned these influ-

ences with research findings on perception and preferences, and compiled re-usable guidelines for adapting user interfaces to different aspects of cultural background. The guidelines were later converted into adaptation rules and evaluated in a preliminary survey of our approach [Reinecke and Bernstein, 2008]. Based on our method to calculate the user's "culture" by including the influences of different countries of residence, we demonstrated that the user's cultural background provides a good source of information to predict user interface preferences. We were also able to show which preferences seem to be personal ones, rather than dependent on culture.

We have contributed to research on distributed user modeling by providing the first cultural user model ontology, which is based on cultural aspects that influence user interface preferences. In combination with its extension, the preference ontology, it can serve as an application-independent knowledge base for consistent storage of information about the user's preferences. Applications accessing this knowledge are able to adapt to the user without first having to explicitly or implicitly acquire the information, and users benefit from this by being presented personalized user interfaces whichever (web) application they access.

Furthermore, we have contributed to research on adaptive user interfaces with our prototype MOCCA. We have developed the first application that is able to automatically adapt to diverse cultural backgrounds beyond language, or date and time formats. Based on a modular composition of interface elements, MOCCA is flexible enough to modify all of those visual interface aspects that have been previously shown to be dependent on cultural preferences. MOCCA is also the first recommender system that suggests design and layout preferences based on the preferences of users with a similar cultural background. Our evaluations have shown that MOCCA's initial adaptation rules are suitable to predict a majority of user

preferences, but that such a recommender/learning mechanism even enhances these predictions. Hence, we were able to demonstrate that recommendations are not only possible on the basis of music, or reading preferences, but that we can also learn user interface preferences, and that culture is an adequate similarity measure for such a learning approach.

In a final evaluation, we have further shown that the holistic adaptation of user interfaces to cultural background improves user performance and their overall satisfaction. Users seemed to comprehend the application better if presented a culturally personalized version of the interface, with the result that they were significantly faster, made fewer errors, and needed fewer clicks. Our culturally ambiguous participants also found the adapted version more aesthetically appealing compared to the standard US version, indicating that cultural adaptivity has the potential to improve emotional ties and consequently, increase customer loyalty.

Overall, cultural adaptivity has proven to be a feasible way of addressing the problems of localization with a more holistic adaptation of layout and design to a more comprehensive interpretation of cultural background. Rather than the conventional “one size fits all” approach, culturally adaptive user interfaces cater for individual preferences. We believe that this is a major step towards making users happier – the key to success.

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Part I

Appendix

A

Hofstede's Dimensions

Table A.1: Hofstede's cultural dimensions according to [Hofstede, 2003].

Country	PDI	IDV	MAS	UAI	LTO
Argentina	49	46	56	86	
Australia	36	90	61	51	31
Austria	11	55	79	70	
Bangladesh	80	20	55	60	40
Belgium	65	75	54	94	
Brazil	69	38	49	76	65
Bulgaria	70	30	40	85	
Canada	39	80	52	48	23
Chile	63	23	28	86	
China	80	20	66	30	118
Colombia	67	13	64	80	
Costa Rica	35	15	21	86	
Czech Republic	57	58	57	74	13
Denmark	18	74	16	23	
Ecuador	78	8	63	67	
Egypt	80	38	52	68	
El Salvador	66	19	40	94	
Ethiopia	64	27	41	52	25
Estonia	40	60	30	60	
Finland	33	63	26	59	
France	68	71	43	86	
Germany	35	67	66	65	31
Ghana	77	20	46	54	16

Greece	60	35	57	112	
Guatemala	95	6	37	101	
Hong Kong	68	25	57	29	96
Hungary	46	80	88	82	50
India	77	48	56	40	61
Indonesia	78	14	46	48	
Iran	58	41	43	59	
Iraq	80	38	52	68	
Ireland	28	70	68	35	
Israel	13	54	47	81	
Italy	50	76	70	75	
Jamaica	45	39	68	13	
Japan	54	46	95	92	80
Lebanon	80	38	52	68	
Libya	80	38	52	68	
Luxembourg	40	60	50	70	
Kenya	64	57	41	52	25
Kuwait	80	38	52	68	
Malaysia	104	26	50	36	
Malta	56	59	47	96	
Mexico	81	30	69	82	
Morocco	70	46	53	68	
Netherlands	38	80	14	53	44
New Zealand	22	79	58	49	30
Nigeria	77	20	46	54	16
Norway	31	69	8	50	20
Pakistan	55	14	50	70	
Panama	95	11	44	86	
Peru	64	16	42	87	
Philippines	94	32	64	44	19
Poland	68	60	64	93	32
Portugal	63	27	31	104	
Romania	90	30	42	90	
Russia	93	39	36	95	
Saudi Arabia	80	38	25	68	
Sierra Leone	77	20	46	54	16
Singapore	74	20	48	8	48
Slovakia	104	52	110	51	38
South Africa	49	65	63	49	
South Korea	60	18	39	85	75
Spain	57	51	42	86	
Surinam	85	47	37	92	
Sweden	31	71	5	29	33

Switzerland	34	68	70	58	
Taiwan	58	17	45	69	87
Tanzania	64	28	41	52	25
Thailand	64	20	34	64	56
Trinidad	47	16	58	55	
Turkey	66	37	45	85	
United Arab Emirates	80	38	52	68	
United Kingdom	35	89	66	35	25
United States	40	91	62	46	29
Uruguay	61	36	38	100	
Venezuela	81	12	73	76	
Vietnam	70	20	40	30	80
Zambia	64	27	40	52	25
WorldAverage	61	42	50	66	43

B

World Overview of Hofstede's Cultural Classification

The cultural scores are classified into low, medium, and high according to the approach described in Chapter 4. In the figures below, low is depicted by the lightest color, and high by the darkest color respectively. Countries that have not been assigned a score are represented in gray.

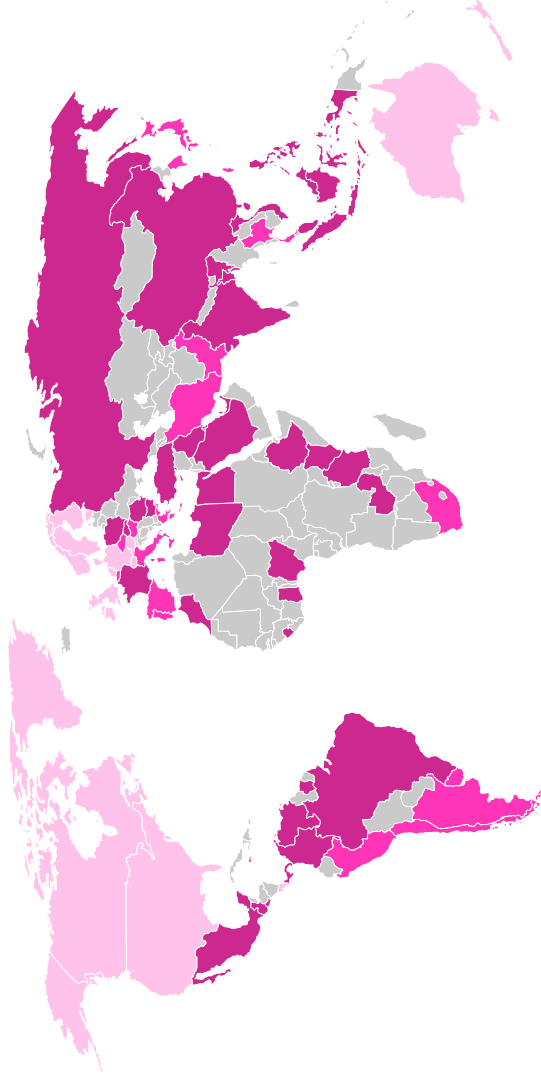


Figure B.1: Power Distance

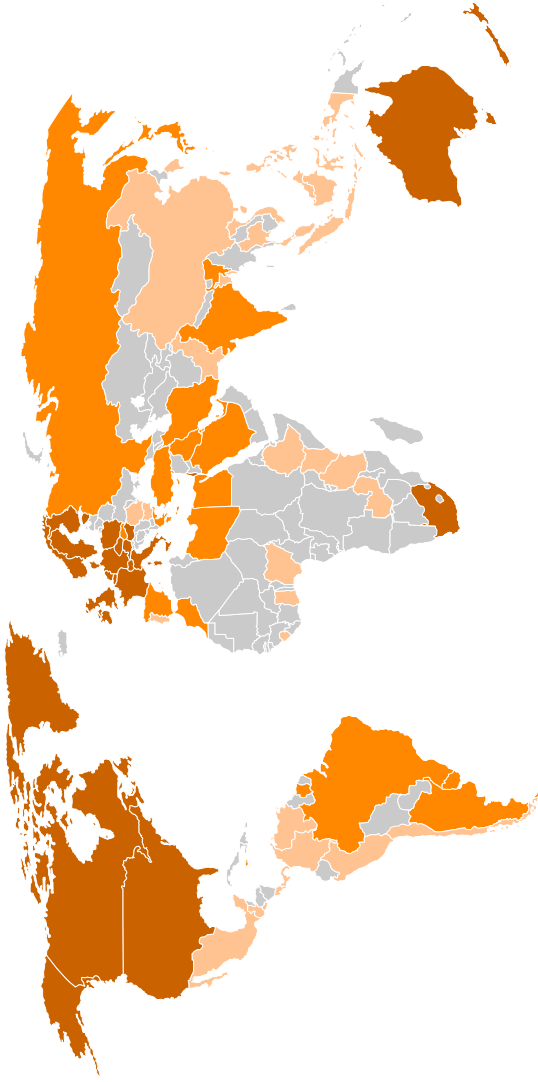


Figure B.2: Individualism

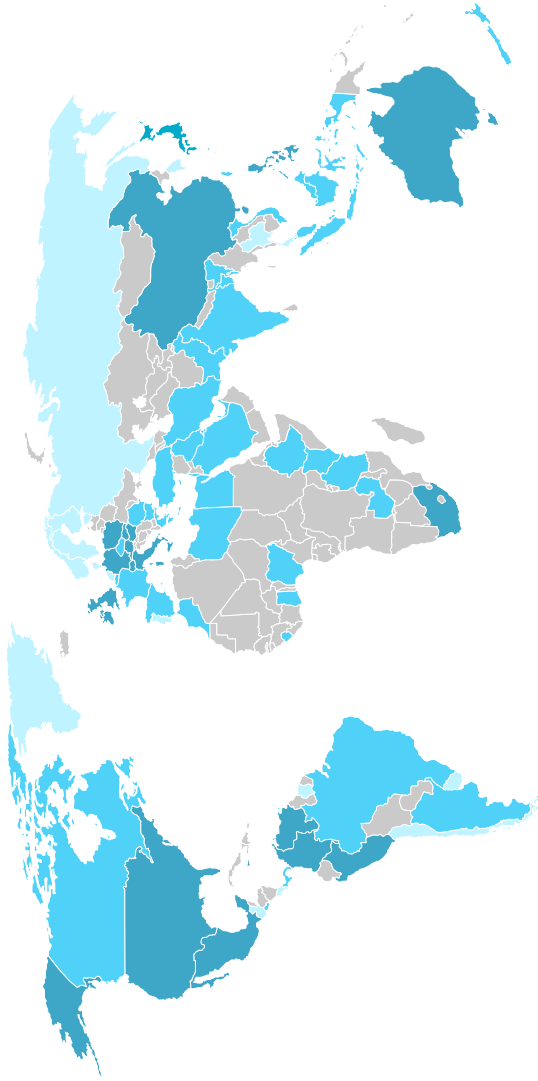


Figure B.3: Masculinity

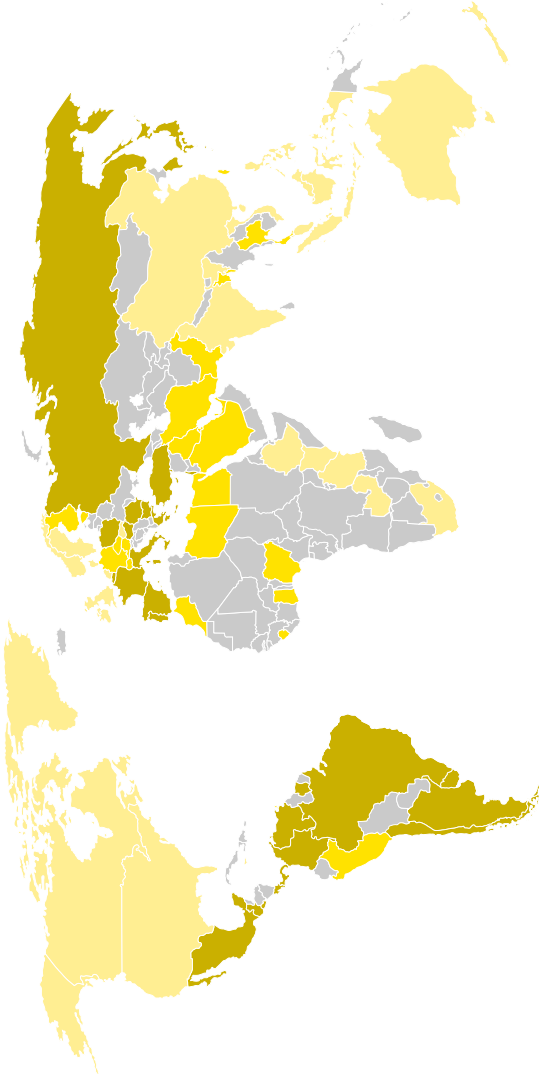


Figure B.4: Uncertainty Avoidance

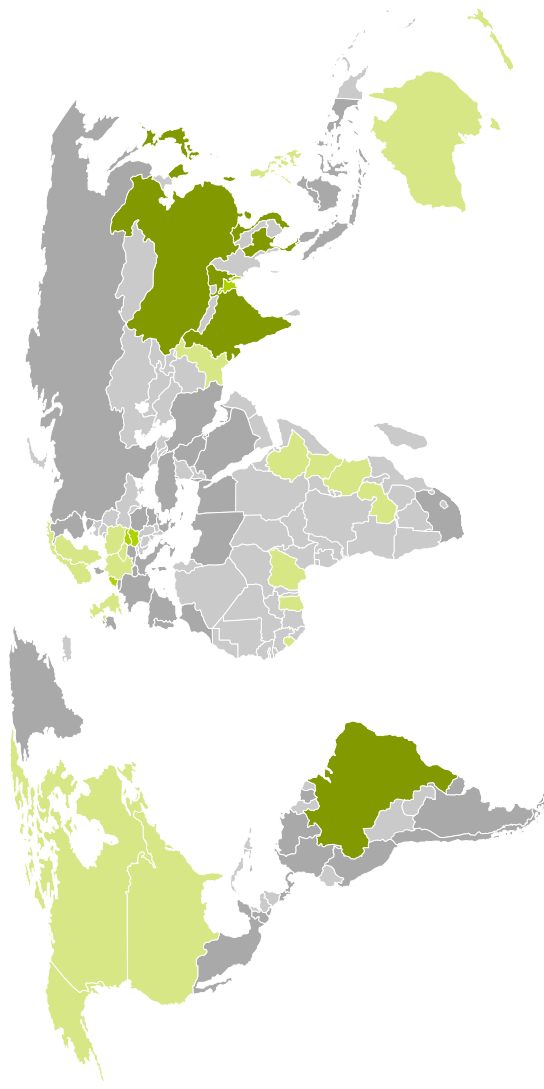


Figure B.5: Long Term Orientation

C

Preliminary Online Survey

All questions included an answer possibility on a rating scale from 1=*strongly agree* to 5=*strongly disagree*. The abbreviations in brackets behind each question indicate the cultural dimension the question relates to. These were not included in the online survey.

1. I like so-called "wizards" in software applications that guide you through a particular task. (PDI)
2. I like hyperlinks and a non-linear structure that lets me explore a software or website. (PDI)
3. I normally organize my files hierarchically in folders. (PDI)
4. I prefer interfaces with meaningful and/or traditional colors. (IDV)
5. I like programs that do not provide too many unnecessary functionalities. (PDI)
6. I prefer to find out how to do something with an application rather than being guided by a wizard. (PDI)
7. I like navigational cues that do not leave too many choices on where to go next. (PDI)
8. Interfaces should always use meaningful colors. (IDV)
9. I prefer images that are mostly used to support a textual description to purely decorative images. (IDV)

10. I like colorful interfaces. (IDV)
11. I rarely organize my files in folder hierarchies with subfolders. (PDI)
12. I prefer simple error messages that tell me what I have done wrong, to error messages that tell me what I can do better. (PDI)
13. I like websites that show pictures of important people. (PDI)
14. I like it when a program offers many functionalities that I can try out, even if they go far beyond of what I need. (PDI)
15. In my opinion, error messages should always give you supporting instructions on what to do next. (PDI)
16. I prefer websites that show pictures of people like "you and me" to websites that show pictures of a leader. (PDI)
17. A webpage should always show my position within the whole website. (UAI)
18. I prefer plain-colored interfaces to colorful interfaces. (IDV)
19. A website should have lots of pictures to look at. (IDV)
20. I like learning new things off by heart. (PDI)
21. I like it if the learning matter is being taught in a humorous way. (PDI)
22. I prefer younger teachers to older ones. (PDI)
23. I enjoy learning facts. (IDV)
24. I prefer to study by myself over studying in a group. (IDV)
25. In my view, teachers should always be impartial and not show their opinion. (IDV)
26. I prefer to choose myself, which information I need to learn to pass an exam. (UAI)
27. I like to learn in a group. (IDV)
28. I like learning by doing better than theoretical studies. (PDI)
29. With serious teachers I often make better progress in learning. (PDI)
30. I like competitions where I can compare myself to other students. (MAS)
31. I think, older teachers are better than young teachers, because they have more wisdom and experience of life. (PDI)
32. I prefer non-formal learning material to formally-written text. (UAI)
33. It is enough if I theoretically learn something, I do not need to deepen my knowledge with practical experience. (LTO)
34. Teachers should tell their students what to learn next and which steps to follow. (UAI)
35. I like the possibility to pose questions and discuss a topic. (PDI)

36. I enjoy teamwork. (IDV)
37. I like to be able to explore a topic that I want to learn about by choosing my own material and my own order of how I work with it. (UAI)
38. Learning material should always be written in a very academic and formal language. (UAI)
39. I like learning situations where I do not have to work towards fixed objectives. (UAI)
40. Practical work definitively deepens knowledge. (LTO)
41. Teachers should have a clear opinion on matters they are teaching. (IDV)
42. In a learning situation, the objectives should always be clearly stated. (UAI)
43. In my opinion, the teacher should always suggest learning material that he wants me to learn. (UAI)
44. Learning achievements should always be comparable to other students with a score. (MAS)
45. Discussions with other learners have little or no advantage over learning by myself. (PDI)

D

Questionnaire for the Evaluation of the Benefit of Cultural Adaptivity

The following pages show the questionnaire as it was used for the final evaluation of MOCCA.



EVALUATION

Have you ever found a web site completely unappealing? Have you maybe even left a web site because you found it too confusing?

With this evaluation we are trying to evaluate two different versions of our to-do list application MOCCA. We will try to answer several questions, such as whether one user interface is enough for everybody, or whether we need different versions in order to cater for individual preferences.

Please note that **we do not assess you as a person**. The evaluation is only about your personal opinion of our web application.

The data you provide will be treated as **strictly confidential**.

General completion information

In the following evaluation, you will be asked to judge certain aspects of MOCCA. These aspects are always presented as shown in the two examples below:

Example no. 1

The web application ...								
is bad.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	is good.

The first example asks to judge the web application. The user rates the application as good, but thinks that there is room for improvement. The further you mark a box to one side, the more you agree with the statement on that side.

Example no. 2

I find the web application has an original design.								
I don't agree at all.	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.

In the second example, the user disagrees with the statement. In his or her opinion, the web application is not original at all.

Please fill in the questionnaire with care and provide an answer to all questions.



General Information

Which country do you currently live in?

Have you lived in other countries for more than 4 weeks before? yes no

If yes, please name the countries and the number of years/months you have lived there.
1. years / months
2. years / months
3. years / months
4. years / months

What is your nationality?

What is your parents' nationality? (If not the same) Mother: Father:

What is your native language (i.e. the first language you learnt as a child)?

Is this the language you currently speak most of the time (i.e. your primary language)? yes no, it is

What is your second language?

How old are you? years

What is your gender? m/f

Please indicate which degree of education you have obtained?
Primary school High school Bachelor degree Master degree Doctor / PhD

How often do you use a computer?
daily a couple of times per week about once a week less than once a week never

What, if any, is your religion (e.g. Catholic, Hindu)?



1st version of MOCCA

You would like to make notes of all your to-dos with the help of MOCCA, so that you don't forget them.

Please go through the following tasks:

1. Imagine that a new semester has started at school.
 - a. On MOCCA's working area, create a new category which you should call "School".
 - b. Create a new project "Homework" and assign it to the category "School".

2. You have to submit an essay.
 - a. To make sure you remember this, create a to-do with the name "Submit essay".
 - b. Add "10 pages" as a note.
 - c. Place this in the project you previously made called "Homework".
 - d. Specify the due date with 14. December 2009.

3. You would like to find out how much time you have left before you need to hand in your project plan for the "Levita project" at work.
 - a. Go to the navigation pane on the left and filter your to-dos to show only those related to the Levita project.
 - b. Look at the to-do list on the right and write down the due date for the project plan here:

due date: _____

4. Click on "logout".



1st version of MOCCA

<i>My interaction with MOCCA is clear and understandable.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>It is easy for me to become skilled at using MOCCA.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>I find MOCCA easy to use.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>Learning to operate MOCCA is easy for me.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>Using MOCCA is a good idea.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA makes organizing to-dos more interesting.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>Working with MOCCA is fun.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>I like working with MOCCA.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>I could complete a task using MOCCA...</i>									
<i>...if there was no one around to tell me what to do as I went along.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>...if I could call someone for help if I got stuck.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>...if I had a lot of time to complete a task.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>...if I had just the built-in help facility for assistance.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.



<i>MOCCA has a clean design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has a pleasant design..</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has a clear design..</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has a symmetric design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has an aesthetic design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has an original design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has a sophisticated design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has a fascinating design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has a creative design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA uses special effects.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.



<i>I found MOCCA's user interface...</i>								
...technical.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...human.
...complicated.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...simple.
...impractical.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...practical.
...awkward.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...straightforward.
...unpredictable.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...predictable.
...confusing.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...clear.
...unmanageable.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...manageable.
...unpleasant.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...pleasant.
...ugly.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	... attractive.
...disagreeable.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...likeable.
...rejecting.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...inviting.
...bad.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...good.
...repelling.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...appealing.
...discouraging.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...motivating.



2nd version of MOCCA

You would like to make notes of all your to-dos with the help of MOCCA, so that you don't forget them.

Please go through the following tasks:

2. You remember that you need to buy flowers for your friend's Birthday.
 - a. Create a new category called "Friends".
 - b. Create a new project "Presents" and assign it to the category "Friends".

3. You would like to remember your friend's Birthday.
 - a. Create a to-do named "Anna's Birthday".
 - b. Add "buy flowers" as a note.
 - c. Place this in the project "Presents".
 - d. Specify the due date with 30. November 2009.

4. You would like to find out when you have the exam for "Programming I" at university.
 - a. Go to the navigation pane on the left and filter your to-dos to show only those related to university exams.
 - b. Look at the to-do list on the right and write down the due date for the "Programming I" exam here:

due date: _____

5. Click on "logout".



2nd version of MOCCA

<i>My interaction with MOCCA is clear and understandable.</i>								
I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>It is easy for me to become skilled at using MOCCA.</i>								
I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>I find MOCCA easy to use.</i>								
I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>Learning to operate MOCCA is easy for me.</i>								
I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>Using MOCCA is a good idea.</i>								
I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA makes organizing to-dos more interesting.</i>								
I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>Working with MOCCA is fun.</i>								
I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>I like working with MOCCA.</i>								
I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>I could complete a task using MOCCA...</i>								
<i>...if there was no one around to tell me what to do as I went along.</i>								
I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>...if I could call someone for help if I got stuck.</i>								
I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>...if I had a lot of time to complete a task.</i>								
I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>...if I had just the built-in help facility for assistance.</i>								
I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.



<i>MOCCA has a clean design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has a pleasant design..</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has a clear design..</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has a symmetric design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has an aesthetic design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has an original design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has a sophisticated design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has a fascinating design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA has a creative design.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.
<i>MOCCA uses special effects.</i>	I don't agree at all.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	I completely agree.



<i>I found MOCCA's user interface...</i>								
...technical.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...human.
...complicated.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...simple.
...impractical.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...practical.
...awkward.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...straightforward.
...unpredictable.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...predictable.
...confusing.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...clear.
...unmanageable.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...manageable.
...unpleasant.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...pleasant.
...ugly.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	... attractive.
...disagreeable.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...likeable.
...rejecting.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...inviting.
...bad.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...good.
...repelling.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...appealing.
...discouraging.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	...motivating.



Comparison of the two MOCCA versions

<i>Which version of MOCCA did you like best?</i>								
The 1 st version.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	The 2 nd version.
<i>Which version of MOCCA did you find more aesthetically appealing?</i>								
The 1 st version.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	The 2 nd version.
<i>Which version of MOCCA can you work with most effectively?</i>								
The 1 st version.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	The 2 nd version.

What did you especially like about the **1st version** of MOCCA?

What did you especially like about the **2nd version** of MOCCA?

Why did you prefer one version over the other?



Many thanks for your participation!

