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Tell Me Where You've Lived, and I'll Tell You What You Like: Adapting Interfaces to Cultural Preferences*

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Abstract. Adapting user interfaces to cultural preferences has been shown to improve a user's performance, but is oftentimes foregone because of its time-consuming and costly procedure. Moreover, it is usually limited to producing one uniform user interface (UI) for each nation disregarding the intangible nature of cultural backgrounds. To overcome these problems, we exemplify a new approach with our culturally adaptive web application MOCCA, which is able to map information in a cultural user model onto adaptation rules in order to create personalized UIs. Apart from introducing the adaptation flexibility of MOCCA, the paper describes a study with 30 participants in which we compared UI preferences to MOCCA's automatically generated UIs. Results confirm that automatically predicting cultural UI preferences is possible, paving the way for low-cost cultural UI adaptations.

Key words: Cultural User Modeling, Personalization, Localization

1 Introduction

Today, the number of localized software and web applications underline the growing awareness that considering culture in user interface (UI) design is the key to improvements in work efficiency and user satisfaction – and thus, to customer loyalty in global marketplaces [1,2]. The design process is typically done in all conscience of the target nation(s) by conducting ethnographical analyses. However, due to this time-intensive endeavor, the manual localization of UIs has proven to be prohibitively expensive. If software manufacturers are willing to invest this money, another problem remains: the problem of assigning one interface to a whole nation. In today's globalized world, it is highly contradictory to restrict culture to country borders. In fact, although a person's culture is certainly influenced by his or her country of residence, other aspects such as former stays in other countries, the parents' nationality, or religion also strongly impact the dynamic nature of cultural background [3].

In this paper we propose to address this problem by an automated customization of the UI, using a rule base to transform a user's cultural model into a personalized UI. In order to reduce the time needed for the initial information acquisition, we show how a

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small number of initial questions are already enough to predict user preferences and provide a suitable first adaptation of the UI. To illustrate this approach, we have developed MOCCA, an application that can adapt ten different aspects of its UI (not counting language) with 39’366 combination possibilities altogether. In addition to presenting the technical implementation of the flexible interface generation, this paper also evaluates MOCCA’s core functionality: the adaptation rules that are responsible for the resulting UIs.

In the following, we shortly present related work and its limitations before explaining the basics of our approach. Next, we introduce our test application MOCCA, detailing on its adaptation possibilities with visible effects for the user, and the technical processes in the back-end. We then discuss our experiment, following with a discussion of the results and their general implications for other culturally adaptive systems.

2 Related Work

Many studies have shown that localization increases user satisfaction and work efficiency; however, many researchers have acknowledged that it is not sufficient for culturally ambiguous users in our globalizing world [4]. While there have been attempts on cultural user modeling - mostly confined to the area of international e-learning applications [5] - the major problem of groundbreaking research in this area seems to be the classification of culture: How can we define culture in order to derive culturally-based preferences for UIs? Hofstede was one of the first researchers to develop a cultural classification with the five dimensions Masculinity (MAS), Uncertainty Avoidance (UAI), Power Distance (PDI), Individualism (IDV), and Long Term Orientation (LTO) [6]. Although often criticized for theorizing culture as a national concept [7], his classification has been successfully applied to the field of Human-Computer Interaction (HCI) [8]. According to Hofstede, who originally developed the dimensions for international business communication, the dimension *Uncertainty Avoidance*, for example, reveals the extent of which people are willing to deal with uncertain and unstructured situations. In the field of HCI, different studies have demonstrated that it also relates to whether users like a non-linear navigation, or prefer consistent applications [2,4,8]. Likewise, all of Hofstede’s dimensions have been mapped to certain aspects of UIs [9,10,11], and his dimensions have been proven useful for predictive purposes [12]. Apart from the need for an applicable classification of culture, an approach to cultural adaptivity also requires extremely flexible UIs. So far, adaptive systems have been mostly developed for different types of learners [13], disabilities [14,15], or know-how [16,17,18]; however, none of these approaches cater for all the needs of users with different cultural backgrounds, such as a versatile positioning of UI elements, varying degrees of colorfulness, or different levels of guidance.

3 Procedure for Cultural Adaptivity

We propose to overcome the problems of manually localized UIs by automatically adapting them to a user’s cultural background. For first-time users, an application inquires about the user’s current and former residences, as well as about the respective durations. For each of these countries, the application retrieves the dimensions from a cultural user model ontology. Since previous user model ontologies were mostly domain-specific and did not include cultural information, we developed the Cultural User Model Ontology *CUMO* [19], which contains information such as different places of residence, the parents' nationality, languages spoken, or religion. Furthermore, CUMO contains information about Hofstede's five dimensions and their values [6]. However, the scores assigned to a user and his cultural dimensions are not static to everybody residing in the same country, and thus, do not resemble a "national culture", as suggested by Hofstede [6]. Instead, we take into account all places of residence and calculate their influence on the user's dimensions according to the duration of the user's stay at those places [12]:

$$influenceOfCountry_N = \frac{monthlyDurationOfStayInCountryN}{ageInMonths} \quad (1)$$

Retrieving Hofstede's values ($countryScore_H$) for the relevant countries from CUMO, we are able to calculate the user's new dimensions with a weighted average:

$$userDimScore_H = \sum_{i=1}^{N} countryScore_H * influenceOfCountry_i \quad (2)$$

(where *H* is Hofstede's dimension 1 to 5; *N* the number of countries the user has lived in, and $countryScore_i$ is the Hofstede score for the respective country.)

The $userDimScore_H$s are further discretized into low, medium, and high according to their distance to the world average scores stored in CUMO. Each adaptable aspect of the application now has a set of rules that associate the user's classification with a UI directive influencing the application's interface. Thus, after obtaining the user's cultural classification from CUMO, the application can look up the corresponding adaptation rules and apply them.

After these first predictions on the user's preferences, we offer two refinement possibilities: (1) The user can manually provide more information about his cultural background, and (2) the application tracks the user interaction, such as mouse movements and clicks. From both, we are able to derive refining adaptations. For example, if the user hovers the mouse pointer over a certain area without clicking for a certain time, we infer that she needs support on which actions to perform next.

4 MOCCA: A Culturally Adaptive To-Do Tool

We have developed a culturally adaptive web application called MOCCA, which is a web-based to-do list tool that allows users to manage their tasks online. Its goal is to automatically adapt to the cultural preferences of its users. This *user-specific adaptation* is in contrast to the country-specific adaptation of usual localized applications. But how flexible does MOCCA really need to be? What interaction elements need to be adaptable? To answer these question, we looked at the influence of culture on UI perception, compiled a list of general *adaptation guidelines*, and evaluated them in a survey [12]. According to these adaptation guidelines, various UI aspects need to be adaptable to users' cultural backgrounds, the most obvious being date and time formats, language, and the reading direction. These evident aspects are easily changed: the reading direction, for example, 'only' requires to re-align text and elements (such as the navigation)

(a) MOCCA with left-alignment, flat navigation, and color-coded to-dos with high structuring.

(b) MOCCA with right-alignment, high information density, flat navigation, and an adaptive wizard.

Fig. 1. Example interfaces for MOCCA

to the left or to the right. However, it is also said to impact the visual attention on the UI [20]. Thus, elements that cannot be arranged centrally but still need the user's attention should be placed in the lower left corner (for right-to-left readers), or in the lower right corner (for left-to-right readers). Consequently, MOCCA offers full alignment of all interface elements to the left or to the right (as shown in Figures 1(a) and 1(b)).

Cultural differences in perception also necessitate other adaptations that are oftentimes too subtle to be included in conventional localization. For example, in a neural fMRI study Gutchess et al. found that Western cultures attend to individual objects more than people from Asia who usually concentrate on object correlations [21]. Their findings coincide with our adaptation guidelines, which suggest to highly structure objects for users with a high score for the dimension Long Term Orientation. Hence, MOCCA offers different levels of content structuring by spatializing objects and color-coding elements that belong together (see Figure 1).

Even more subtle differences in perception are concealed in Hofstede's interpretation of culture. Many researchers have concentrated on the influence of his cultural dimensions on HCI and found that a low score in the dimension Uncertainty Avoidance, for example, suggests a strong preference for a high information density. High Individualism, in contrast, indicates that the user favors color-coordinated interfaces with fewer gadgets, such as blinking animations, whereas a high Power Distance Index relates to the requirement for a higher level of support [12]. Accordingly, MOCCA has to be able to include an easier navigation with more buttons (Figure 1(a)), or intensify user support with a wizard (1(b)), to name a few.

Summarizing, MOCCA has to be extremely flexible in the composition of different UI elements - more flexible, than required for previous adaptive systems (cf. Related Work). In the following, we therefore discuss how we implemented this flexibility in MOCCA and introduce the most important adaptation rules.

4.1 Technical Details and Adaptation Rules

In order to fulfill the requirements, MOCCA has to be sufficiently flexible to allow the exchange of each UI element with alternative placements. To model the 'space' of possible solutions, the different compositions of UI elements, their dependencies among each other, their types (e.g. navigation or header), and their representations (for different scores in a certain dimension) were modeled in an application-specific *adaptation ontology*, which defines the adaptable parts of the UI.

MOCCA considers nine aspects of the interface, each of which can be adapted to either a low, medium, or high score of the dimension they are associated with (see Table 1). In addition, it can adapt itself to the users reading direction (i.e., left-to-right or right-to-left) resulting in a total of $3^9 * 2 = 39'366$ possible combinations of UI elements. As an example, consider a user with a cultural background of 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' (number 8 in Table 1), resulting in a UI akin to the one shown in Figure 1(b). 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` would result in an interface comparable to Figure 2(d).

In order to place the elements, MOCCA relies on placement information in the adaptation ontology, which includes the preferred precise location, preferred general area (in case of conflict), extent of the element, priority, and association with the cultural dimension for each UI element. All elements have to be dynamically composed into a grid layout. MOCCA first retrieves all possible interface elements from the adaptation ontology. For each UI aspect it then chooses the most appropriate element comparing the user's cultural preference stored in CUMO with the ones of the elements stored in the adaptation ontology. Next, all elements are tentatively placed in their preferred location on a temporary UI grid. In case two elements are associated with the same or overlapping locations, the priority tag in the adaptation ontology decides which element takes precedence and which one needs to be moved. The elements are then placed according to the free locations within their preferred general area. The result of this operation is a non-overlapping two dimensional layout of the culturally appropriate UI elements, which MOCCA then generates as an AJAX UI.

Apart from the dynamic placement of suitable UI elements, MOCCA has further adaptation possibilities with an overall effect on all elements, such as color schemes, languages, or left/right alignment. The choice of these *meta elements* is made on the basis of their categorized instances in the adaptation ontology with the same procedure that has been described for the UI elements.

5 Experiment

We have conducted an experiment on the adaptations in MOCCA comparing a user's interface choices to MOCCA's automatically generated UI. Thus, the experiment evaluated the adaptation rules (our *predictions*).

5.1 Method

Participants. 30 participants (mean = 28.7 y, sd = 3.9 y, 7 female) from the local university campus took part, all had high computer literacy, and university education. The majority had lived in > 2 countries (mean # = 2.5), 22 were non-Swiss nationals, but had lived in Switzerland for at least 9 months (avg. 3.4 y, sd = 4.3 y). Only 3 of 8 Swiss participants had always lived in Switzerland and/or did not have foreign parents.

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

Procedure. Participants were asked to put themselves into the position of a UI designer, and reflect on their own experiences with UIs. They were encouraged to think aloud throughout the test, take their time to choose between the elements, as well as further

Table 1. Adaptable Interface Aspects

No.	Interface aspect:	Effects:	Linked with dimension
1	Information Density	Amount of information visible at first sight, level of hierarchy in the information representation.	Long Term Orientation (LTO)
2	Navigation	Structures the navigation in a range from nested menu items such as in a tree, to a flat navigation.	Power Distance (PDI)
3	Workflow I	Presence and accessibility of functions, e.g. whether buttons are always visible or can be activated on mouse-over.	Power Distance (PDI)
4	Workflow II	Integration of functions with the interface, e.g. whether other items are still accessible or the user is forced to concentrate on the current operation.	Uncertainty Avoidance (UAI)
5	Structure	Different levels of structure for the interface, e.g. grouped information, accentuated affiliations.	Individualism (IDV)
6	Colorfulness	Influences whether the user interface presentation uses many different colors or is rather homogeneously colored.	Individualism (IDV)
7	Brightness & Contrast	Saturation and contrast of colors, e.g. complementary colors.	Masculinity (MAS)
8	Support	Amount of on-site support the user receives, e.g., wizards versus tool tips.	Uncertainty Avoidance (UAI)
9	Help text	Error messages and general help, e.g. strict or friendly instructions.	Power Distance (PDI)
10	Alignment	Alignment of all interface elements to the user's reading direction.	Reading Direction

ask questions for clarification. Throughout the test, we recorded what participants were saying to be able to retrace the train of thought for their choices. The experimenter then explained the application purpose, and its main aspects. The experiment consisted of eight tasks (one for each interface aspect), the participant chose between three interface elements each. Prior to each task, we briefly explained the differences of the three choices, complying to a precise description to keep the explanation consistent and neutral. Participants then had to place the chosen element within an outline of the MOCCA interface. The tasks were presented in the same order, however, we counterbalanced the presentation of the different choices of UI elements between participants. All arrangements of the UI were photographed. Participants also filled out a short questionnaire about age and gender, current and former residences, durations in years and months, and nationality of parents. A small incentive was given for time.

Hypotheses. (1) Hofstede's dimensions can be used as a basis for predicting UI preferences of culturally ambiguous users; (2) certain dimensions (see Table 1) yield a better prediction rate for particular interface aspects than others; (3) the majority of incorrect predictions deviate by only 1 (instead of 2).

Test Design and Analysis. We used a within-subjects design with the following factors and levels: (1) *Cultural Background:* 5 dimensions x 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 UI 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 his cultural background into low, medium, or high for each of the five dimensions. We subsequently simulated MOCCA's adaptations by looking up the corresponding adaptation rule and the resulting UI. 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 UI element assigned to the category low, we noted a deviation of 2 (=the maximum deviation). 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 (Workflow I) were additionally assigned to the dimension Uncertainty Avoidance, and task 8 (Support) to the dimension Power Distance.

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. In fact, most people who had a low PDI 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. After this adjustment, the following section reports on data of 7 tasks performed by 30 participants, adding up to 210 choices altogether.

5.2 Results and Discussion

MOCCA's adaptation rules accurately predicted the users' preferences for all seven tasks at the significance level of at least 5% ($\chi^2 = 44.08, 7.6, 9.89, 15.38, 3.92, 5.61, 3.92$; $p = 3.14e^{-11}, .006, .002, 8.80e^{-5}, .048, .018, .048; d.f = 1$). We achieved an average deviation of .46 over all dimensions and tasks. The number of correct predictions lay between 15 and 27 (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 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 are not so much concerned about the prediction errors with a deviation of 1, the 6.67 % 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 not suitable initial adaptation.

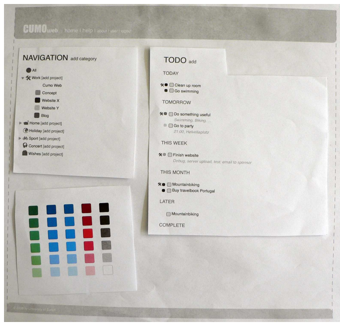
Distribution of Choices. Participants' choices were almost evenly distributed over the three interface options: elements assigned to a low score were chosen 72 times, the ones for a normal score 76 times, and the elements for a high score 62 times. Thus, participants went for the "extremes" in 134 cases out of the 210 choices ($\approx 64\%$). The distribution of the users' scores for each cultural dimension related to this phenomenon.

Prediction of User Interface Aspects. In the following, we describe the most remarkable results for each UI aspect separately (cf. Table 2):

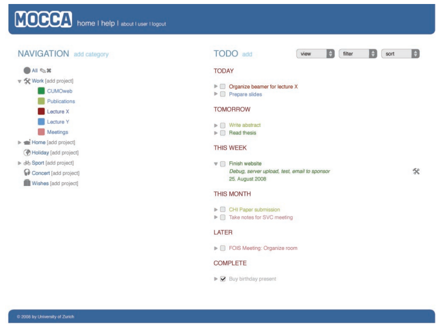
The *information density* proved to be very well-predictable with the dimension Long Term Orientation. For 90 % of all participants we were able to anticipate the correct

Table 2. Summary of the results (in %)

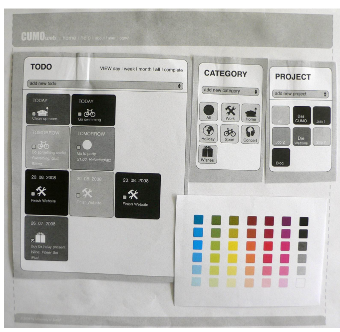
Interface aspect	Tested with dimension:	Correct Predictions	Deviation of 1	Deviation of 2
Information Hierarchy	LTO	90	6.67	3.33
Navigation	PDI	56.67	36.67	6.67
Workflow I	PDI	60	40	0
Workflow II	UAI	66.67	30	3.33
Colorfulness	IDV	50	36.67	13.33
Brightness & Contrast	MAS	53.33	26.67	20
Support	UAI	50	50	0
Average		60.95	32.38	6.67



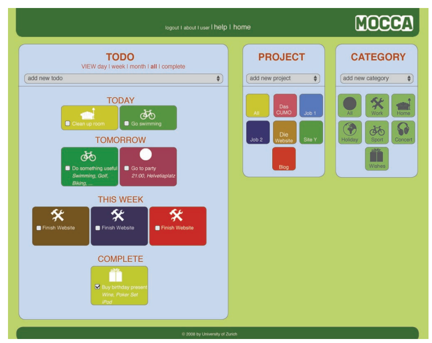
(a) The UI as chosen by Participant 3 (PDI = low, IDV = high, MAS = high, UAI = normal, LTO = low).



(b) MOCCA's UI for Participant 3.



(c) The UI as chosen by Participant 27 (PDI = high, IDV = low, MAS = high, UAI = low, LTO = high).



(d) MOCCA's UI for Participant 27.

Fig. 2. The self-built interface and the interface generated by MOCCA for two different participants

choice. As shown in Figure 2(c), for example, participant 27 chose a UI 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 2(d)). In contrast, participant 3 chose the UI designed for normal Long Term Orientation (Figure 2(a)), which shows less information at first sight by being less encoded with colors and symbols (Figure 2(b)). MOCCA, however, was not able to correctly predict her choice basing its prediction on a low Long Term Orientation with scarce to-dos and unfolding notes (Figure 2(b)). 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 UI design. Altogether, a deviation of 1 occurred in 6.67 % of the cases. For 3.33 % of all participants, MOCCA provided for a low information density (as shown in Figure 2(b)), whereas the participant showed a preference for the opposite, a high information density as in Figure 2(d). We did not find any cases where participants preferred a low information density although predicted to favor the opposite.

We provided three *navigation choices*: (1) A tree navigation as shown in Figure 2(b) allows to nest categories and projects and is bound to a list view of the to-dos in order to be able to sort this list accordingly; (2) a flat navigation bound 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 2(d). We were 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 with 6.67 %.

The accessibility of functions for the task *Workflow I* was accurately predicted for 60 % of the participants. Thus, we were able to anticipate whether participants preferred a "hidden" accessibility of 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 we failed the correct prediction with a deviation of 1; however, none of the participants chose the interface variant deviating from our prediction completely (0 % with a deviation of 2).

Workflow II adhered to a self-dependent handling of procedures: MOCCA's interface can either adapt to a high Uncertainty Avoidance by leading users through a 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. We were able to correctly predict 66.67 %. 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.

Tasks 5 and 6 (*Colorfulness* and *Brightness & Contrast*) were expected to strongly related to each other: Participants who chose a colorful interface (low Individualism) were thought to prefer bright colors (high Masculinity). Likewise, the choice of an interface with matching 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 poor result for these two aspects.

MOCCA provides *support* from short tool-tips (low Uncertainty Avoidance), a more comprehensive help-on-demand after hovering the mouse over different question marks on the UI, 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 tending to the middle variant of support explains why we had 0 % with a deviation of 2, but 50 % with a deviation of 1.

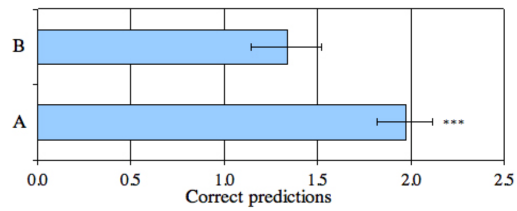


Fig. 3. Predictions based on the initial dimensions (A) result in significantly (***, $p < 1e{-}7$) more correct predictions than using alternative dimensions (B) for three interface aspects.

Suitability of Alternative Dimensions for Prediction. Certain aspects of the UI could not be clearly linked to one dimension only, as their effect on UI performance is partly ambiguous. We therefore replaced the dimensions responsible for triggering the UI elements for three different tasks. Task 3 and 5 (Workflow I and Support) were newly predicted with the dimension Uncertainty Avoidance (instead of LTO and PDI), and task 8 was newly predicted with 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, $p < 1e - 7$) than the same test with alternative dimensions (see Figure 3 where column A refers to the initial dimensions as listed in table 1 and column B is the result for the alternative dimensions). This further reinforces hypothesis 2 in that the dimensions incorporated in our adaptation rules effect the assigned aspects of the UI, and that the result of our prediction cannot be reproduced by randomly choosing alternative dimensions.

6 Conclusion & Future Work

In the age of a global software industry the cultural differences in UI preferences become increasingly important. We have introduced a new approach to convert knowledge about a user's cultural background into predictions of UI preferences. We exemplified our approach in the test application MOCCA, which is able to adapt the user interaction to the user's cultural background. In addition, this paper succinctly discussed the interaction between the application-independent cultural user model ontology, the adaptation rules, and the application-specific adaptation ontology.

In order to substantiate the approach, we conducted an evaluation with 30 participants of different cultural backgrounds, demonstrating a high significance in accurately predicting UI preferences ($\chi^2_{(1,N=30)}, 0.05 < p > 3.14e^{-11}$ across all 7 task). With that, we showed that an automated generation of suitable UIs for different cultural preferences is feasible, providing a basis for future approaches to cultural adaptivity. Our future work includes usability evaluations of MOCCA in different countries in order to assess whether its adaptations actually result in an increased work efficiency. We plan to evaluate both the initial UI, as well as the ongoing adaptations that result from the continuous prediction, detection, and correction of mistakes of the initial adaptation with the help of the user interaction tracking.

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