Cultural Differences in Human Computer Interaction: Results from Two Online Surveys*

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Abstract
This paper describes a method to obtain quantitatively discriminating cultural interaction indicators and their values for cross-cultural Human Computer Interaction (HCI) design as preparatory work for cross-cultural adaptive navigation and multi-media systems. The method has been implemented in a tool for cross-cultural HCI analysis. Two online studies temporally displaced by one year using this tool, regarding cultural adaptability exemplified by use cases of navigation systems, revealed differences in interaction behaviour that depend on the cultural background of the users. The results will be presented and discussed to demonstrate the difficulties, but also the importance to get the cultural differences in HCI to clear the way for cultural adaptability.

1 Determining Cultural Differences in HCI as First Step to Cultural Adaptability

To be able to adapt navigation systems manually (adaptation) or automatically (adaptability) to the cultural needs of the user, the first step is to investigate what must be adapted, i.e. to find out the differences in the cultural needs of the users and hence the cultural differences in HCI on all levels of HCI localization (surface, functionality, and interaction). This is still one of the largest explanation gaps in cross-cultural HCI design, which has to be bridged today. Here areas like presentation of information (e. g. colours, time and date format, icons, font size) and language (e. g. font, direction of writing, naming) or dialog design (e. g. menu struc-

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ture and complexity, dialog form, layout, widget positions) as well as interaction design (e. g. navigation concept, system structure, interaction path, interaction speed) are concerned (cf. [Röse et al. 01], [Heimgärtner 05]). A common approach for this is to perform qualitative and personal studies. Although this process is quite controllable, it is very expensive and time consuming. Furthermore, it is very difficult to find enough test persons to get a sample size, which enables valid application of enhanced methods of statistics. Therefore, many users have been asked online to do certain use cases to get data for studying cultural differences in HCI.

2 Method for Getting Cultural Differences in HCI

This section describes the background of conducting two online studies to get cultural differences in HCI: after finding potential cultural variables in HCI as well as meaningful uses cases, the test tasks, the test tool and the test setting have been developed, followed by the start of the surveys.

2.1 Finding Potential Cultural Variables in HCI

Hall [Hall 76] found differences in communication speed between cultures, which also imply differences in information speed ("duration of information presentation"), information density ("number of parallel pieces of information during information presentation") and information frequency ("number of information presentations per time unit"). Using this method of literature research and analytical reasoning, more than one hundred potentially culturally sensitive variables have been identified, implemented into the "Intercultural Interaction Analysis" tool (IIA tool) and applied by measuring the interaction behaviour of the test persons with a personal computer system in relation to the culture (cf. [Heimgärtner 05]). E. g., one of the variables is measuring the acceptance of the "life-like" character "Merlin".[1] According to Prendinger and Ishizuka (cf. [Prendinger et al. 04]), such avatars can reduce stress during interaction with the user. Hence, the agent "Merlin" was implemented in the IIA tool to offer his help every 30 seconds. On the one hand, according to cultural dimensions, which describe the behaviour of human beings of different cultures, like high uncertainty avoidance or high task orientedness, it was expected that German users switch off the avatar very soon (compared to Chinese users), because they do fear uncertain situations (cf. [Hofstede et al. 05]). Furthermore, they do not like to be distracted from achieving the current task (cf. [Halpin

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1 The virtual assistant „Merlin" is part of the interactive help system of Microsoft Office™.

et al. 57]). On the other hand, if applying the cultural dimension of face saving, it should be the other way around. If Chinese users make use of help very often, they would loose their face (cf. [Victor 97]). The test with the IIA tool was designed to help to reveal the empirical truth to such questions amongst other things (cf. [Heimgärtner 05]).

2.2 Finding Use Cases and Test Tasks

The most interesting use cases possess a high degree of interactionality. In order to limit the scope of research, representative and demonstrative use cases have been restricted for cross-cultural human machine interaction (HMI) in automotive navigation systems (cf. [Heimgärtner 05]). One such significant use case is e. g. map display. What map direction is best according to the user's cognitive style? How many points of interest (POI) should be presented to the user? A hypothesis like "there is a high correlation of high information density to relationship-oriented cultures such as China" should be confirmable by adjusting more POI by Chinese users compared to German users. So, the use case "map display" was simulated by the *map display test task* to measure the number of pieces of information on the map display regarding information density (e. g. restaurants, streets, POI, etc.) (Figure 1).

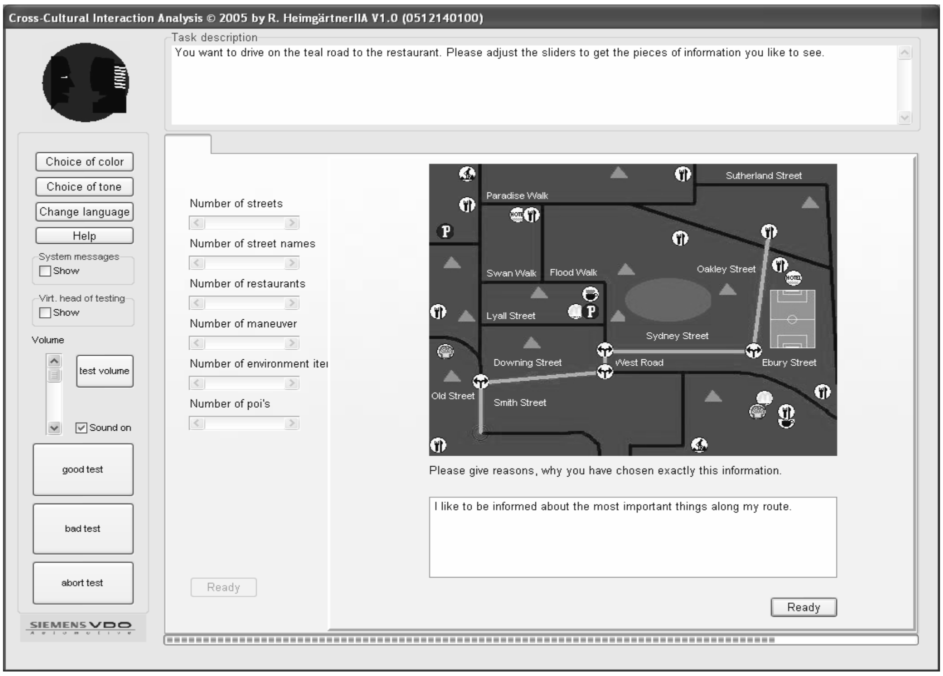

Figure 1: *Screenshot of the "map display test task" during the test session with the IIA data collection module. The user can define the amount of information in the map display by adjusting the scroll bars.*

Based on this principle, this test tool can also be used to investigate the values of other cultural variables like widget positions, menu structure, layout structure, interaction speed, speed of information input, dialog structure, etc. Every one of the test tasks serves to investigate other cultural aspects of HCI. E. g., the special use case "manoeuvre guidance" has been implemented into the *manoeuvre guidance test task*, where the test user has to adjust the number and the time distance of the manoeuvre advice messages on the screen concerning frequency and speed of information. The test tasks (use cases) are localized but designed semantically identical for all users: participants of many different cultures can do the test. The collected data is partly quantitative (related to all test persons, e. g. like the mean of a Likert scale) and partly qualitative (related to one single test person, e. g. answering open questions) (cf. [De la Cruz et al. 05]). Moreover, the collected data sets have standard format so that anyone can perform own statistical analyses. This also means that the results of this study are verifiable because they can be reproduced using the IIA tool.

2.3 Test Setting with the IIA Tool

A user test session with the IIA tool comprises five parts: collection of demographic data, test tasks, VSM94 questionnaire, evaluation of results by the user, and debriefing questionnaire. The demographic questionnaire delivers knowledge about the cultural background of the user (like mother tongue, languages, nationality, and residence in foreign countries). The developed and implemented test tasks in the IIA tool serve to motivate the user to interact with the computer and to test hypotheses. To analyze the cultural attitudes of the users, the value survey module (VSM94) has to be filled in by the user (cf. [Hofstede 94]). The VSM94 contains 26 questions to determine the values of the cultural dimensions using the indices from Hofstede that characterize the cultural behaviour of the user (cf. [Hofstede 91]). The results of the VSM94 and of the test tasks are presented to the user who then has to estimate whether or not the cultural and informational values found correlate or match to him. The debriefing part reveals the purpose of the test to the user in detail and collects data regarding the usability of the test system, the perceived difficulty of the test in general as well as if the user has recognized the implemented hypotheses in the test tasks. During the whole test session, the IIA tool records the interaction between user and system, e. g. mouse moves, clicks, interaction breaks, and the values and the changing of slide bars set up by the users in order to analyze the interactional patterns of users of different cultures. All levels of the (physical, lexical, syntactic, semantic, pragmatic, and intentional) interaction model necessary for dialog design can be analyzed (cf. [Herczeg 94]).[2]

[2] For more details about the IIA tool and the test setting, please refer to [Heimgärtner 05] and to [Heimgärtner 06].

2.4 Description of the Studies

First efforts to get cultural differences in HCI scanning interaction behaviour for cultural adaptability happened in April 2005 by doing a very small local offline heuristic pre-study in Huizhou (China) and in Regensburg (Germany) with seven Chinese and eleven German students and employees of SiemensVDO. The purpose of this study was to check the usability of the IIA tool for Chinese and German users.[3] The two extended online studies served additionally to verify the functionality and reliability of the IIA tool and to get the preferences of users according to their cultural background. Randomly selected employees from SiemensVDO all over the world were invited per email to do the test session using the IIA data collection module by downloading it from the corporate intranet. Table 1 characterizes the two online studies regarding sample size, tests downloaded, tests aborted, valid test data sets, and return rate.

Study	*Sample size*	*Survey period*	*Number of downloaded tests*	*Tests Aborted [%]*	*Number of valid test data sets*	*Return Rate [%]*
1	600	12/14/05 – 01/14/06	166	41,5	102	16,6
2	14500	11/14/06 – 01/19/07	2803	66,8	916	6,3

Table 1: Characterization of the two online studies conducted with the IIA tool

The tests have been aborted due to the following reasons: download time too long[4], no time to do the test now, test is not interesting or appealing. This type of qualitative data can help to optimize the testing equipment or to steer the direction of data analysis by asking the user for the reasons of his behaviour during the test. Only complete and valid data sets have been analyzed using the IIA data analysis module and the statistic program SPSS. The discrimination rate of classifying the users to their selected test language by the variables concerning the cultural background of the users (mother tongue, nationality, country of birth and primary residence) is 83.3% for the first and 81.9% for the second study.[5] Therefore, the differences in

[3] The IIA tool consists of three elements: a data collection module, a data analysis module and a data evaluation module. The data evaluation module serves to cross-validate the results from data analysis.

[4] Notably in China because of slow network connections.

[5] The discrimination rate has been calculated using discriminance analysis (cross validated and grouped, Wilk's Lamda in study 1: λ_{1-2}=.072**, λ_2=.568**, Wilk's Lamda in study 2: λ_{1-2}=.192**, λ_2=.513**). The level of significance is referenced with asterisks in this paper (* p<.05, ** p<.01).

HCI in these studies have been analyzed in relation to three groups of test persons according to the selected test languages (Chinese (C), German (G), and English (E)) in order to reduce data analyzing costs.

3 Study Results

The qualitative offline pre-study, done by participative observation during and interviews after the test sessions, showed first interesting results regarding cultural dependent differences in using the IIA tool running on computer systems. There are differences between (C) and (G) concerning the order of pictures (more ordered by (G) than by (C)), test duration (longer for (C)), error clicks ((C) more than (G)) and telling the truth regarding computer experience ((C) understated their experience pretty much). In the following two online studies, some values of the implemented variables in the IIA tool show significant differences, which represent differences in user interaction according to the different cultural background of the users. Therefore, these variables can be called *cultural interaction indicators* (Table 2).[6]

Cultural interaction indicator	*First study*	*Second study*
Speed (MG)	$F(2,102)=8{,}857^{**}$	$\chi^2(2,916)=29{,}090^{**}$
MessageDistance (MG)	$F(2,102)=7{,}645^{**}$	$F(2,916)=16{,}241^{**}$
POI (MD)	$F(2,102)=3{,}143^{*}$	$\chi^2(2,916)=32{,}170^{**}$
MaximalOpenTasks	$\chi^2(2,102)=12{,}543^{**}$	$F(2,916)=15{,}140^{**}$
MaximalOpenTasks ratio (C,G,E)	2.5 : 1.4 : 1	1.7 : 1.03 : 1
Information speed value	$\chi^2(2,102)=17{,}354^{**}$	$\chi^2(2,916)=82{,}944^{**}$
Number of chars	$\chi^2(2,102)=16{,}452^{**}$	$\chi^2(2,916)=67{,}637^{**}$

Table 2: Cultural Interaction Indicators found in both studies

[6] One-way ANOVA as statistical method for comparing the means of more than two independent samples, was used to get significant cultural differences in variables, which are distributed normally. The results of the test of homogeneity of variances indicate whether ($p>.05$) or not ($p\leq.05$) the variables are distributed normally. A third of the potential variables was distributed normally, and hence analyzed by ANOVA. The interactional differences between the user groups separated by the test languages have been identified using the Tukey-HSD-Post-Hoc-Test after one-way ANOVA. For the remaining variables, which are not distributed normally, Kruskal-Wallis-test has been applied. The variables in the valid test data sets are not distributed comparably in the first and the second online study. Therefore, partly the same variables have been analyzed either by ANOVA or by Kruskal-Wallis-test (indicated with F or χ^2 in Table 2).

Speed (MG) means the driving speed of the simulated car in the manoeuvre guidance test task ((C) less than (G) and (E)). *MessageDistance (MG)* denotes the temporal distance of showing the manoeuvre advice messages in the manoeuvre guidance test task. (C) desired about 30% more pre-advices ("in x m turn right") than (G) or (E) before turning right. This can be an indication for higher information speed and higher information density in China compared to Germany, for example. *POI (MD)* counts the number of points of interest set by the user in the map display test task. Information density increases with the number of POI and is two times higher for (C) than for (G) or (E). *MaxOpenTasks* represents the maximum number of open tasks in the working environment (i.e. running applications and icons in the Windows ™ task bar) during the test session. (C) tend to work on more tasks simultaneously than (G) or (E) which can be possibly explained by the way of work planning (polychrome vs. monochrome timing, (cf. [Hall 76])) or the kind of thinking (mono-causal (sequential) vs. multi-causal (parallel) logic, (cf. [Röse et al. 01])). *Information speed value* represents the time the manoeuvre advice message is visible on the screen. (C) and (G) wanted the messages to be visible about 40% longer than (E) do. *Number of Chars* contains the number of characters entered by the user during the manoeuvre guidance and map display test tasks in answering open questions. This is explained by the fact that the Chinese language needs considerably less characters to represent words than the English or the German language.

There have also been implemented assumed cultural interaction indicators that are statistically not discriminative. In the first study, e. g. *ScrollBarChanges_norm* ($F(2, 102) = 0.954$, $p=.389$) shows that the number of the scrolling events triggered when moving a scroll bar slider by the user is not significantly different between the groups (C), (E) and (G).[7] In the second study, e. g. *TotalDialogTime* ($F(2, 916) = 1.370$, $p=.255$) indicates that the time needed by the users to pass the dialogs of the test tasks is not significantly different between the groups.

4 Discussion of the Results

In this section, the disturbing variables, the classification power of the cultural interaction indicators and the reliability of the IIA tool will be discussed to argue for and to underline the plausibility of the results.

[7] The suffix "_norm" means the value of ScrollBarChanges (= total number of scroll bar changes during the whole test session) divided by the duration of the whole test session.

4.1 Disturbing Variables

If disturbing variables are known, they can be controlled in data analysis. E. g. age, gender and computer experience are variables, which can influence the results negatively. The controlled disturbing variable *Age* should not correlate with the selected test language by the user – even if it correlates only slightly. The Pearson correlation coefficients in Table 3 show that age is linearly related to test language in contrast to gender and computer experience.

Pearson correlation matrix	*First study*	*Second study*
Controlled disturbing variable	Test language	Test language
Test language	1,000**	1,000**
Age	0,370**	0,161**
Gender	-0,038	-0,017
Computer experience	0,174	-0,048

Table 3: Relationship between test language and controlled disturbing variables

This possible bad influence of the disturbing variable *Age* on the validity and the values of the cultural interaction indicators can be weakened by the fact that the age of the test persons of the different countries was not distributed equally in the samples. There were no Chinese test persons above the age of 40 in the first study (n=102). The effect was lower using only test persons whose age is distributed equally in the user groups (separated by the test language) or by calculating partial correlations. This conclusion has been confirmed by the collected data of the second study: Pearson correlation and Kruskal-Wallis-test showed a lower correlation coefficient for the variable *Age* than in the first study because of n=916.

Even if computer experience is intuitively the most significant variable directly connected to interaction behaviour (e. g. interaction speed and frequency), it did not interfere significantly with the measuring process of the interaction behaviour of the users. This can be explained by the fact that computer experience was almost equally distributed in the test users at the worldwide locations of SiemensVDO because the link to the IIA tool has been sent per e-mail only to users who have Internet access and hence, who have some basic interacting experience with computers. In addition, gender does not have significant influence on the test language. Hence, in both studies, the statistical methods justified the results of the studies as correct and representative for employees of SiemensVDO: none of the controlled disturbing variables influenced the cultural interaction indicators in a way that they cannot be called *cultural interaction indicators*.

4.2 Classification Power of the Cultural Interaction Indicators

The cultural interaction indicators can be used to recognize the cultural interaction behaviour of the user and to relate these cultural interaction patterns to the characteristics of the user's culture. The discriminatory power of these cultural interaction indicators has been calculated using discriminance analysis. Several combinations of cultural interaction indicators contribute positively to a high discrimination rate in assigning users to their test language without knowing their nationality: only the interaction patterns within use cases or applications are known. Step-by-step discrimination analysis ("Jackknife-Method") offers iterative analysis of the best discriminating cultural interaction indicators automatically out of a given set of potential ones. The following cultural interaction indicators have been identified for the data sets of both studies exhibiting the highest classification power: interaction speed, information speed value, interaction exactness value, number of manoeuvres, ~maximal open tasks, ~POI, ~restaurants, ~streets and ~chars as well as uncertainty avoidance value. The resulting discrimination rate for classifying all test users simultaneously and correctly to their selected test languages (i.e. to the groups (C), (E) and (G)) is 60.8% for the first and 59.9% for the second study. This points to a strong similarity of the collected data as well as to the correctness of the methodology and the results of the studies (Table 4).

			Predicted group membership [%]		
Study	*Classification rate [%]*	*Test language*	*Chinese*	*German*	*English*
1	Cross validated total: 60,80	Chinese	58,82	29,41	11,76
	Wilk's $\lambda_{1\text{-}2}$=.574**, λ_2=.855**	German	9,09	70,45	20,45
	$p_{inclusion}$=.05, $p_{exclusion}$=.1	English	29,17	25,00	45,83
2	Cross validated total: 59,90	Chinese	35,58	23,08	41,35
	Wilk's $\lambda_{1\text{-}2}$=.649**, λ_2=.850**	German	4,55	61,76	33,69
	$p_{inclusion}$=.05, $p_{exclusion}$=.1	English	6,45	29,49	64,06

Table 4: Classification Power of the Cultural Interaction Indicators

However, the Chinese interaction behaviour is not classified very clearly in the second study (35.58%, cf. Table 4), which indicates that *in this case* the controlled disturbing variables could influence the classification power of the cultural interaction indicators. One possible explanation for this are differences in the sample sizes (n_C=1500, n_E=4500, n_G=8500). Probably there are too few Chinese data sets for reasonably conducting discriminance analysis for classification to all three groups simultaneously. This fact required deeper analysis. Hence, applying the method of discriminance analysis classifying the cases into two groups (instead of three groups at the same time), the discrimination rate increases tremendously: it goes up to 70.4% for (G) and (E) and is even 85.4% for (C) and (G). This outcome in conjunction with the weak influence of disturbing variables supports the high reliability and criteria validity of the statistical results received in the two online studies as well as the functional correctness and appropriateness of the IIA tool. Additionally, to verify the discriminating rate by a more practical method, a back propagation network has been implemented into the IIA data evaluation module. All values of the potential cultural interaction indicators of all data sets have been z-transformed and normalized to the range of [0;1] to be able to feed the input neurons with comparable data. Three output neurons indicated the test languages Chinese, German, and English. According to the network topology and learning rate, the discrimination rate climbed up to 80% for correctly classifying the users to the used test language, which also supports the correctness of the study results.

4.3 Optimizing the Test Design by Intercultural Usability Engineering

The variation of the classification power of the cultural interaction indicators (cf. Table 4) can probably also be explained by different test conditions or test tasks whose design still has to be optimized applying the intercultural usability engineering process and methods even more profoundly (cf. [Honold 00]). E. g., in both studies, *NumberOfHelp* counts the number of initiations of online help by the test persons. Usually this variable was zero, which shows that help was not needed. This fact can be exploited, e. g. to indicate that the test tasks were self-explaining and comprehensible for the users. Nevertheless there are differences between the groups ((C), (G) and (E)) in using the help function (χ^2 (2, 916) = 1.619, p=.445, ratio (C:G:E) = 5.6:1:1.4). This can possibly explained by the fact that a German designer developed the IIA test (I). Hence, the German imprinted design as well as the explanation of the test tasks shall be optimized for Chinese users in future tests.

4.4 General Cultural Interaction Indicators

The results of the two online studies show that *HCI between the Chinese, German, and English-speaking participants differs significantly.* A possible explanation of this fact is probably grounded in subconscious cultural differences imprinted by primary culture and learning the mother tongue, which leads to different HCI of the users independently of their conscious cultural propositional attitudes. However, this hypothesis has to be verified in future studies. Nevertheless, *some cultural interaction indicators are expected to be valid for HCI design in general* because there are culturally sensitive variables that can be used to measure cultural differences in HCI only by counting certain interaction events without the necessity of knowing the semantic relations to the application. Such indicators are e. g. number of mouse moves, number of breaks in the mouse movements, speed of mouse movements, number of mouse clicks, number of interaction breaks, and possibly the number of acknowledging or refusing system messages. Surely, all those indicators can also be connected semantically to the use cases or applications. However, the values of the cultural interaction indicators change in a similar way even if different use cases and test tasks are applied. Hence, simply counting such events related to the session duration from users of one culture and comparing them to users of another culture is obviously sufficient to indicate differences in the interaction behaviour of culturally different users with the system. Further research should bring forward more details.

5 Conclusion

The intercultural interaction analysis tool serves to record the user's interaction with the computer to be able to identify cultural variables like color, positioning, information density, interaction speed, interaction patterns, and their values, which enable the deduction of design rules for cross-cultural HCI design. The analysis of the collected data in two online studies with Chinese, German and English speaking employees of SiemensVDO all over the world using this tool showed that there are correlations between the interaction behaviour of the users with the system and their cultural background. The following reciprocal confirming aspects of the two studies quantitatively and qualitatively attest the good reliability and criteria validity of the statistical results received in these two studies:

- High discrimination rate by the cultural interaction indicators of over 80%,
- High accordance of the cultural interaction indicators found by applying different statistical methods,
- High correlated quantitative comparable results of two separated studies.

Moreover, several results presented in this paper are in accordance with other studies, which support their mutual correctness of methodology and outcome (e. g. [Vöhringer-Kuhnt 06], [Kralisch 06], [Kamentz 07]). There are different interaction patterns according to the cultural background of the users ((C) vs. (G) or (E)) regarding e. g. design (complex vs. simple), information density (high vs. low), menu structure (high breadth vs. high depth), personalization (high vs. low), language (symbols vs. characters) and interaction devices (no help vs. help). Furthermore, the results imply that the recognition and classification of cultural interaction patterns in HCI can also be done quantitatively. This is a precondition for adaptability in the sense of the automatic adaptation of the system to the user by the system itself (through monitoring and evaluating the user interactions to be able to implicate the right adaptation) (cf. [Heimgärtner 05] and [Heimgärtner 06]). Hence, this work contributes a good part to establish cultural adaptability in user interfaces by determining cultural differences in HCI concerning interaction patterns. More detailed studies must show whether changing the metrics of potential indicators (or using them in other situations, use cases or circumstances) will improve their discriminating effect and yield appropriate values accordingly to show the *general validity* (i.e. the independency from applications or use cases) of some cultural interaction indicators. Moreover, future studies have to be done to yield relevant cultural variables according to other user groups (e. g. elderly vs. younger people, experienced vs. beginners, female vs. male, drivers of different vehicles etc.).

6 Outlook

The validity of the methods implemented in the IIA tool proved by the results of the two online surveys justifies and encourages optimizing and using this tool for more detailed studies in future to refine and explore new cultural interaction indicators. The near-term objective is to develop enhanced techniques for the IIA data analysis module using statistical methods (factors analysis, structure equation models, cluster analysis etc.), data mining, and semantic processing to extract the cultural variables and its values as well as the guidelines for cross-cultural HMI design in a more automatic way. Moreover, the method to implement new use cases easily into the IIA data collection module will be extended (e. g. by employing authoring tools or HMI description languages). Furthermore, applying questionnaires in conjunction with recording biofeedback signals (heart rate and skin response) will give better-controlled insights into the user preferences. The best discriminating algorithms for cultural adaptability found, using the methods mentioned above, can be implemented in, and tested with the IIA data evaluation module to prove their applicability. Qualitative evaluation studies using intercultural usability tests with users of the respective countries also under mental stress e. g. in realistic driving situations (using the IIA tool in combination with a driving simulator) or in real driving situations (in field studies) must verify the usability of cultural adaptability.

7 References

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