Challenges in Developing User-Adaptive Intelligent User Interfaces

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Abstract

As user interfaces become more and more complex and feature laden, usability tends to decrease. One possibility to counter this effect are intelligent user interfaces (IUIs) that support the user's interactions. In this paper, we give an overview of design challenges identified in literature that have to be faced when developing user-adaptive IUIs and possible solutions. Thereby, we place special emphasis on design principles for successful adaptivity.

1 Introduction

The increasing complexity in today's applications, e.g. the number of available options, often leads to a decreased usability of the user interface. This effect can be countered with intelligent user interfaces (IUIs) that support the user in performing her tasks by facilitating the interaction as much as possible. IUIs facilitate information retrieval by suggesting relevant information or they support the system use, e.g. by providing explanations, performing tasks for the user, or adapting the interface. In this paper, we focus on user-adaptive IUIs which are able to adapt their behavior to individual users. In our opinion this is a key feature for IUIs as the support that should be provided by an IUI heavily depends on the needs and preferences of each user.

We present here the results of a literature survey of the main design challenges that have to be faced when designing a user-adaptive IUI and list existing approaches how to cope with these challenges. We thereby focus on issues relevant for human computer interaction and not on the underlying algorithms.

The remainder of this paper is structured as follows. In Section 2, we provide a definition of user-adaptive IUIs. In Section 3, we then describe the challenges which have to be faced in developing IUIs. As adaptivity plays a crucial role for user-adaptive IUIs, we place special emphasis on the adaptivity of IUIs, and review the main results gathered from user studies that were performed for evaluating which factors influence the value of an adaptation for a user (Section 4).

2 User-Adaptive Intelligent User Interfaces

The area of IUIs is one of the most heterogeneous research subjects, covering all kinds of different disciplines, which makes it difficult to give a common definition. IUIs try to solve the standard user interface question how the interaction between user and computer can be facilitated by means of artificial intelligence. In contrast to traditional human computer interaction (HCI), IUIs do not only focus on enabling the user to perform intelligent actions but on ways to incorporate knowledge to be able to assist the user in performing actions. In contrast to traditional research in artificial intelligence (AI), IUIs do not focus on making the computer smart by itself but to make the interaction between computer and human smarter.

The goal of IUIs is to make the interaction itself as well as the presentation of information more effective and efficient to better support the user's current needs. The way to achieve this ranges from supporting a more natural interaction, e.g. by allowing multimodal or natural language input, to intelligent tutoring systems and recommender systems. Based on the definition by Maybury and Wahlster [1998], we define IUIs as follows:

> ***Intelligent User Interfaces*** *are human-machine interfaces that aim to improve the efficiency, effectiveness and naturalness of human machine interaction by representing, reasoning and acting on models of the user, domain, task, discourse, context, and device.*

In this paper, we focus on user-adaptive IUIs which are a subset of IUIs. User-adaptive IUIs hold a model for each individual user to be able to adapt its behavior accordingly, which is not necessarily the case for all IUIs as often a generic user model suffices.

3 Challenges in Developing IUIs

The main goal in developing IUIs is that they should be usable, useful and trustable [Myers, 2007]. This aligns with the main challenges identified by Maes [1994]: *Presentation*, *Competence* and *Trust*. **Presentation** is concerned with the human computer interaction part of IUIs, whereas **Competence** focuses on the artificial intelligence techniques that can be applied. The development of IUIs has to take special care of **Trust**, as the user is not willing to delegate tasks to an IUI she does not trust, thus rendering the IUI useless. However, for IUIs it is much more challenging to induce user's trust in the system than for traditional user interfaces, because IUIs apply artificial intelligence techniques whose results can often not be directly foreseen by the user and thus reduce the user's feeling of being in control of the system. In the following, we point out for each of these issues which challenges have to be faced when developing user-adaptive IUIs and describe possible ways to cope with them. An overview of the identified challenges is given in Table 1. The challenges are not disjunctive and heavily interrelated, they should just give some of the focus points for developing user-adaptive IUIs. Further, this list is not meant to be complete and not all challenges have to be faced in each IUI, e.g. collaborative filtering systems usually do not have to cope with the problem of few usage data.

Presentation	Interaction design
	Unobtrusiveness
	Adaptivity
Competence	Few usage data
	Changing user behavior
	Accuracy
Trust	Controllable behavior
	Intelligibility
	Privacy

Table 1: Challenges in developing user-adaptive IUIs

Presentation

For the presentation of IUIs, we at first need to consider how to **design the interaction** between the user and the IUI. Many IUIs are also augmentations of existing user interfaces, thus they have to be integrated into the existing layout offering the user a way to communicate with the IUI itself. Thereby, the IUI should not hamper the normal usage of the application. The interaction should also support some kind of forgiveness that is allowing the user to easily correct previously performed actions using an undo capability [Apple, 2008]. Further, the design of the interaction tackles whether and how the user can instruct the IUI [Norman, 1994] or whether an anthropomorphic agent is used for allowing the user to communicate with the IUI [Wexelblat and Maes, 1997]. These issues are closely related to trust issues that will be discussed later, i.e. how the user can control the system and which expectations are raised by the IUI.

Another important factor regarding the presentation is **unobtrusiveness** [Jameson, 2007; Langley and Fehling, 1996]. The intelligent support should not distract the user from normal usage of the application. A counterexample for this factor is Microsoft's Office Assistant that is constantly moving and thus drawing the user's attention to it without providing any relevant help for the user's current task. Wexelblatt and Maes [1997] propose to reduce the distraction of the user by minimizing the amount of interruptions and deferring interruptions until they are less disruptive. Another way to cope with this issue is to support different levels of obtrusiveness (or proactivity) depending on the information importance or the certainty in the action (e.g. applied by [Maes, 1994; Horvitz, 1999; Hartmann *et al.*, 2009]).

Furthermore, the user-adaptive IUI should be able to **adapt** its presentation to different users, devices and situations. For example, a novice user needs more explanations than an expert user and voice output is perhaps suitable for mobile usage, but not if she is sitting in a library. Further, as the interaction costs for interacting with applications via a mobile phone are much higher than in a traditional desktop setting, more support may be desirable in these settings. However, adaptivity does not only influence the presentation of an IUI, but also how much the user trusts the system or which demands it puts on the underlying algorithms (i.e. affecting the competence of the IUI). We review the main findings from studies regarding which factors influence the value of an adaptation in Section 4.

Competence

The competence of an IUI is determined by the underlying algorithms. However, as we focus in this paper on human computer interaction issues, we only provide here a short overview of the main challenges that have to be faced for the competence of a system.

At first, many user-adaptive IUIs cannot rely on a huge amount of training data at the beginning, especially if they need training data for each individual user. Thus, the algorithms used for user-adaptive IUIs mostly have to be able to deal with **few usage data**. For that reason, systems that just learn from observation are usually not of great aid at the beginning ("slow-start problem"). This problem can be faced e.g. by relying on predefined models or by using a default model that is inferred from the models of other users. However, the former requires great modeling effort by a developer and the latter can cause privacy problems (as discussed below).

A second problem that arises is that the **user's behavior changes** over time [Höök, 2000]. Especially when she starts interacting with an application as novice, her usage patterns as expert will later dramatically differ from the initial patterns. For that purpose, ageing can be used that weighs older interactions as less important than more recent interactions.

Finally, in order to be beneficial for the user, the artificial intelligence of course needs to produce correct results with a high **accuracy**. This is especially important as erroneous support can easily lead to losing the user's trust [Leetiernan *et al.*, 2001].

Trust

The trust the user puts in an IUI is influenced by many factors especially by presentation issues as discussed before. In the following, we state the main challenges identified in literature that have to be considered when building trustable IUIs. At first, it is essential that the user feels in **control** of the system. The user should be able to correct and adjust the IUI's actions and to control its autonomy [Höök, 2000; Bellotti and Edwards, 2001; Glass *et al.*, 2008; Dey and Newberger, 2009]. One possibility to control the system's actions is to require the user to approve or disapprove the system's actions [Cypher, 1991] or by letting the user specify confidence thresholds for actions [Maes, 1994]. However, giving the user the maximal control at all times is usually not desirable as the users differ in their desire for control [Jameson and Schwarzkopf, 2002] and too much control may lead to distraction and time-wasting [Kay, 2001]. The amount of control should also depend on the criticalness of the task, e.g. for non-critical tasks, like prefilling data in input fields, a lower level of control is needed than for automatically buying goods. Another factor that influences how much control the user wants to exert is her trust in the system that (hopefully) evolves over time. For all those reasons, an IUI should support variable levels of control that can also be adjusted by the user.

Another important issue for establishing the user's trust in the system is **intelligibility**, i.e. to enable the user to understand the system's actions [Bellotti and Edwards, 2001; Dey and Newberger, 2009]. As stated by Maes [1994] a user more likely trusts an IUI if she sees in advance what the agent would do. One way to achieve intelligibility is *transparency*, i.e. that the IUI helps the user understand its actions. Transparency can be realized by an IUI for example by giving feedback of its actions [Maes, 1994], by being able to justify its actions, or by making the user aware of automatic adaptations [Hartmann *et al.*, 2009]. Another way of increasing the system's intelligibility is to give the user *access to the knowledge source* that was used for providing support [Glass *et al.*, 2008]. For example, Cook and Kay [1994] argue that the system should let the user inspect and modify the system's user models. The intelligibility of the system's actions should thus support the user to develop an appropriate model of the IUI's behavior. Thereby, it is not necessary to mediate a complete model of the IUI, as "understanding comes from a careful blend of hiding and revealing [system] state and functioning" [Wexelblat and Maes, 1997]. They argue that for example for driving a car, it is also not necessary to have a complete model of how the engine or the breaks work. This blend can be achieved by applying a black box in a glass box system [Höök *et al.*, 1996], i.e. complex inferences are hidden from view in a black box system, whereas a simpler model is conveyed to the user, e.g. cartoons illustrating the system's state as used by [Kozierok and Maes, 1993]. Another factor influencing the intelligibility of the system is how *predictable* the system's actions are perceived by the user and finally which *expectations* she poses in the system [Glass *et al.*, 2008]. Erroneous higher expectations can easily lead to disappointing the user and thus stopping the user from using the system. This is also one of the main reasons why many researchers argue against using anthropomorphic agents for communicating with IUIs (e.g. [Shneiderman, 1997]), as they are perceived by the user to be similar to a human being and that they thus could also take responsibility for their actions.

Finally, for IUIs that share information between users, **privacy** has to be regarded. Thereby the requirements that are posed on privacy differ between applications. For example, the users of FireFly[1], an application for sharing preferences for music or movies, did not perceive this sharing as critical, whereas users of the Doppelgänger system [Orwant, 1994] that provides personalized news which also considered the news that a colleague is usually reading, had strong privacy concerns against the system. This might be the case as the data differed in their level of importance to the user and as the data was not anonymized in the Doppelgänger system in contrast to the Firefly system. Besides anonymizing the data, another solution proposed for this problem is to split the user model in a private and a public part [Cook and Kay, 1994].

4 Adaptivity Challenges

There has been a debate for years whether automatic adaptation optimizes the user interface or disorients the user [Greenberg and Witten, 1985; Mitchell and Shneiderman, 1989; Shneiderman and Maes, 1997]. The IUI community often favors automatic adaptivity, whereas the HCI community tends towards adaptable approaches that allow the user to customize her interface herself without any automatism. However, many studies have shown that users often fail to use the offered adaptation mechanisms [Oppermann and Simm, 1994], and when they do, they often do not re-customize it if their working habits change [McGrenere *et al.*, 2002].

The value of an adaptation for a user is usually measured as the user interface's usability, i.e. the user's efficiency, effectiveness and her satisfaction. Findlater and McGrenere [2008a] propose to take another factor into account when evaluating adaptive user interfaces: the user's awareness of advanced features. They noted that increased efficiency can lead to a decreased awareness of advanced features, probably because the adaptivity allows them to focus more on the task itself and not on the available menu elements [Findlater and McGrenere, 2008b]. Thus it can hamper the learning of novel user interfaces. However, for seldom used applications or applications in which the user is already an expert, no awareness of advanced features is needed.

In this section, we focus on the usability aspect and summarize the main results from user studies reported in literature. They investigate when an adaptation is useful and how adaptation has to be designed to improve the usability and to avoid confusion. The identified factors thereby comprise presentation as well as competence issues and also influence the trust in the system. An overview of these factors can be found in Table 2.

Presentation	Spatial Stability
	Locality
Competence	Accuracy
	Predictability
Further factors	Interaction frequency
	Task Complexity
	Average interaction costs

Table 2: Factors influencing the value of an adaptation for a user

Regarding the presentation of the adaptation, Gajos *et al.* [2006] found that **spatial stability** increases the user satisfaction and that **high locality** improves discoverability of the adaptation, i.e. that the promoted user interface element appears close to its original position. The spatial stability is required to enable the user to maintain a mental model of the application. An example for spatial in/stability are the Smart Menus used in Microsoft Office, in former versions they hid infrequently used items from view, which caused many negative reactions among users due to their spatial instability, whereas in Office 2007 the menus contain predefined adaptive parts (e.g. displaying the most recently used items) which seems to have much more supporters.

Another important factor is the behavior of the algorithm that adapts the UI, i.e. its **accuracy** and its **predictability** (which is of course closely related to the accuracy issue discussed before). Gajos *et al.* [2008] found that an increase in each of the factors leads to a strongly improved user satisfaction. An increased accuracy moreover leads to improved user performance and more frequent use of the adaptive part. The increase in accuracy thereby had stronger effects on user performance, on how often they utilized it, and on some satisfaction ratings. Another study by Tsandilas and Schraefel [2005] also showed that participants performed faster and utilized the adaptive parts more often at higher accuracy levels. Further, they noted that users tend to underestimate the accuracy of algorithms when the algorithm has a low accuracy (in the study many users estimated a 60% accuracy with an accuracy of under 50%). Findlater and McGrenere [2008b] also showed that the accuracy influences the user's perception of the algorithm's predictability. Higher accuracy user interfaces were perceived as more predictable and consistent.

Gajos *et al.* [2006] state that the **interaction frequency**

[1] A company founded by a group of engineers from MIT media lab including Pattie Maes and sold to Microsoft in April 1998.

and the **task complexity** also play a role in the perceived value of the adaptation. If the task is rather simple and largely mechanical interactions need to be performed, the locality of the adaptation plays a more important role than for more complex tasks. Further, users are more likely able to build mental models for applications which are of low complexity or with which they frequently interact. These mental models can reduce the positive effect of adaptive parts if the interaction costs for using the unadapted version and the adapted version do not differ much, e.g. the amount of required clicks is about the same.

Another factor that is noted by Gajos *et al.* [2006] is the frequency of the adaptation. However, there was no study that directly compared the influence of adaptation frequencies; this was just concluded from two studies about split menus[2] by Sears and Shneiderman [1994] and Findlater and McGrenere [2004] that differed in the adaptation frequency and also in the received results. They both compare non-adaptive menus to an adaptive split menu, whereby Sears and Shneiderman adapt the elements that are displayed only once per user and session, whereas the interface by Findlater and McGrenere can adapt up to once per interaction. Sears and Shneiderman found that the users were faster and more satisfied with the adaptive version, in contrast to the findings by Findlater and McGrenere. However, the static version that was used by Findlater and McGrenere is also a split menu containing the most relevant commands in the usually adaptive part. Thus, it is similar to the adaptive menu used by Sears and Shneiderman and is already the best possible single menu for the experimental task. Thus, the adaptive menu in the experiment by Findlater and McGrenere did not have much of a chance (see also [Jameson, 2007]). For that reason, we state that the adaptation frequency just influences the spatial stability and the predictability of an algorithm, but is no factor on its own.

A final factor that was not considered by Gajos *et al.* [2006] are the average **interaction costs**. This factor is especially important in the area of ubiquitous computing where the interaction costs can heavily vary as not only standard desktop computers with large screen, mouse and keyboard are used, but also small screen devices like mobile phones and various input devices like a Wii. Findlater and McGrenere [2008b] recently showed in a user study that interaction on small screen devices benefits more from adaptive menus than interaction on large screens. They showed that the user's performance and the utilization of the adaptive parts increased more for small than for large screen devices compared to their static counterparts.

5 Summary

In this paper, we gave an overview of the major design challenges that have to be faced when developing user-adaptive IUIs. In summary, the following challenges were identified: Regarding the presentation of intelligent support mechanisms, special attention has to be paid to the design of the interaction, that it does not disrupt the user's normal workflow and that it is adapted to the specific user needs and the given situation. The algorithms for computing the support have to be able to cope with few usage data and changing user behavior. They should be able to provide accurate support whenever possible as erroneous support has a strong adverse effect on the user's trust in the system. Other factors that influence the user's trust are whether the user feels in control of the system, whether she can understand the system's behavior and whether the user's privacy is sufficiently protected.

As adaptivity plays an important role in user-adaptive IUIs, we also reviewed the major factors that influence the benefit of a user interface adaptation. At first, the adaptivity should be realized in predefined areas, so that the greater part of the user interface remains stable. If the adaptation relocates user interface elements, this should be realized close to their original position to facilitate the discoverability. Further, the algorithm used for the adaptation should provide highly accurate results and the results should be predictable for the user. If the user knows how to interact with an application (i.e. interaction frequency and the task complexity), this can lower the additional benefit which can be yield from an adaptation. Finally, the interaction costs influence the benefit of an adaptation: the higher the interaction costs, the more does an adaptation pay off.

[2] A split menu is a menu that contains an adaptive part that is clearly separated from the rest of the menu (e.g. used for selecting the font in Microsoft Office 2007)

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