

Cross-Fertilisation Between Human-Computer Interaction and Artificial Intelligence



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Abstract Human-Computer Interaction (HCI) and Artificial Intelligence (AI) are two disciplines that followed parallel trajectories for about four decades. They also both complement each other and overlap in various problem-rich domains. This chapter is far from being exhaustive, but provides a representative story of how HCI and AI cross-fertilise each other since their inception. It reviews the following domains: intelligent user interfaces and more specifically conversational animated affective agents; capitalisation, formulation and use of ergonomic knowledge for the design and evaluation of interactive systems; synergy between visualisation and data mining.

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1 Introduction

Goals of this chapter are to study the various interfaces between Human-Computer Interaction¹ (HCI) and Artificial Intelligence (AI), and to advocate their necessary association. AI purpose is to create and develop intelligent systems (i.e., systems that are capable to perceive, reason, act and learn by themselves). This fundamental objective led to the development of methods, techniques and tools that enabled systems to effectively perceive, reason, act and learn, within limited narrow environments. Even if first results were limited, AI ambition and framework clearly lead to a long-term endeavour. For example, robotics made impressive progress. Most recent example is “Curiosity”, the NASA robot that is currently exploring planet Mars. HCI is more focused on usability of new technology, promoting creativity and innovation. HCI always had shorter-term goals. We should note that remote Curiosity operations from the Earth cannot be performed without user interfaces based on solid HCI concepts and principles, more specifically regarding planning of its activities. In other words, NASA ground operators must have the best situation awareness of how Curiosity’s instruments can be used and what are resources required for the various scheduled activities.²

It is useful to realise that both AI and HCI have to take into account people who will be involved in the use of technology being developed. On one side, AI attempts to mimic human beings and rationalise their behaviours to build various types of intelligent systems, including robots. On the other side, HCI attempts to understand the human being to better adapt machines that improve safety, efficiency and comfort experience. AI focuses on internal mechanisms of a rational intelligence. Instead, HCI focuses on fundamental phenomena of interaction among people and tools, which they created and use.

It is now obvious that HCI specialists use more AI techniques to improve interaction. They use machine learning to contextualise Web search for example. AI specialists need user interfaces appropriate to the use of intelligent systems. Human-robot interaction is an excellent example of HCI-AI fusion. The writer, Isaac Asimov, provided his famous Three Laws of Robotics in 1941: “(Law 1) a robot may not injure a human being or, through inaction, allow a human being to come to harm; (Law 2) a robot must obey the orders given to it by human beings, except where such orders would conflict with the First Law; and (Law 3) a robot must protect its own existence as long as such protection does not conflict with the First or Second Law.” (Asimov 2008). Here we find again the concepts of safety, efficiency and comfort fit for human-computer interaction (Boy 2013).

This combination of HCI and AI is gradually emerging from increasing needs of meaning, knowledge, skills, experience... and finally common sense. The success of a new technology is often the product of an intelligent and meaningful integration of

¹The term “Human-Computer Interaction”, still very much used, is shifting toward “Human-Systems Interaction” since we are developing “systems” that include both computing and physical things.

²<http://hci.arc.nasa.gov/mslice.html>.

various methods, techniques and systems. AI provides tools for externally automating human behaviour, as well as creating new cognitive prostheses (Ford et al. 1997). HCI provides tools for safer, more efficient and more comfortable human interaction with resulting technology. It is certainly more interesting to head toward a more comprehensive approach to systems design which incorporates both intelligence and interaction, taking into account the use of computer science and social sciences in concert to go to human-centred design (Boy 2013).

The second part of the chapter presents a design history and genesis of interfaces between HCI and AI.³ Intelligent user interfaces are presented in the third part. Among recent advances in the field, emotional embodied conversational agents will be presented in Part Four. Part Five is devoted to capitalisation, formalisation and use of ergonomic principles for the design and evaluation of interactive systems. Part Six is devoted to visualisation and data mining. The last part of the chapter concludes on cross-fertilisation between HCI and AI.

2 History of Interfaces Between HCI and AI: A Genesis

AI and HCI are two branches of computer science. They are complementary disciplines that have different objectives and natures. AI is studying intelligent agents (i.e., any entity capable of perceiving, inferring and acting on its environment using its own knowledge). In 1955, John McCarthy named and defined AI as a scientific and technical discipline that supports the making of intelligent machines. HCI studies devices to be used for the control of and communication with a machine, or with other people through a machine. ACM SIGCHI provides the following definition⁴: “Human-computer interaction is a discipline concerned with the design, evaluation and implementation of interactive computing systems for human use and with the study of major phenomena surrounding them.” (Hewett et al. 1992).

It is certainly interesting to start talking about automatic control before talking about artificial intelligence. Although these two disciplines do not belong to the same scientific fields, they are continuous in the field of automation, this is to say in the industry. We automated transport aircraft since the nineteen-thirties. This type of automation enabled the implementation of analogue and then digital techniques to develop and use symbolic techniques and tools. Automation increasingly became a software engineering issue. For example, we observed the evolution of aircraft cockpits electronic equipment to computing equipment. In the nineteen-eighties, the Flight Management System (FMS) was introduced as an onboard database management system for commercial aircraft. It enabled freeing the aircrew from flight planning and navigation tasks. FMS includes necessary flight management intelligence that was previously the only ownership of pilots. Underlying methods were

³See also Grudin (2009).

⁴ACM (Association for Computing Machinery)-SIGCHI (Special Interest Group on Computer-Human Interaction).

based on rule-based systems and trajectory optimisation. In the beginning, the FMS, as a computing system, was often more difficult to handle and manage than paper maps and documents. Intelligence was transferred to the machine with very little care about human-computer interaction, generating new types of human errors. The interface was complicated due to technology limitations (it would not be done the same today). Its use was difficult to learn and remember. In short, if automation was good, pilot-FMS interaction required a lot more work. We had to wait for more mature technology to get the type of user interface that we know today in the cockpit of the A380, for example. It is interesting to notice that this type of cockpit is now called “interactive cockpit” not because of the interaction with systems’ mechanical parts of the aircraft but with the onboard user interface that involves a pointing device and screens.

The term HCI includes the term “human”. The human entity is difficult to identify, define and model. For a long time, the Human Factors and Ergonomics (HF&E) community has addressed this issue (Woodson and Conover 1964). The human being can be characterised by various properties. Firstly, the human has a physical and physiological body (e.g., an issue that HF&E experts have questioned since the end of World War II with the development of digital manikins). The biomechanical aspects, fatigue, age and other human factors have been and are still widely and deeply considered. Physical ergonomics was that we experienced in the early nineteen-eighties when we had to certify transport aircraft cockpits designed for two crewmen cockpits. We very quickly realised that physical and physiological ergonomics was not enough and was very limited with respect to the evaluation of new aircraft systems. We had to go to cognitive ergonomics in order to properly support analysis of information processing (Norman 1986). In addition, conventional automation techniques were not sufficient. HCI techniques addressing highly automated systems became the central focus of problems to be solved. HCI was entering the cockpit, as it made its entrance in areas of critical systems in the years that followed. At the time, we focused on information processing and that is why cognitive science has taken a considerable extent in the engineering community. Cognitive ergonomics and cognitive engineering have become key disciplines for the analysis, understanding, design and evaluation of modern human(s)-machine(s) systems. Cognition has become a central must (Card et al. 1983; Hutchins 1995; Boy 1998).

The cognitive approach then gave birth to an organisational point of view with the introduction of groupware and collaborative work (CSCW: Computer-Supported Cooperative Work) (Grudin 1994). For these HCI specialists, the human became a worker in an organisation. Computer science suddenly became a strong support to management and business. In the background, Internet was becoming more persistent, since Douglas Engelbart’s work in the sixties until the advent of the World Wide Web in 1992 by Tim Burners Lee and his team at CERN in Geneva. The Web has really established a drastic practice change in modern societies. The human has gradually become “informavore” (term introduced by George Miller in 1983). Information sciences took this new object and topic. The main issue then became information management using the Web. HCI cooperated with AI to optimize and adapt information search to users (Bellot 2011; Boy 1991a). The Web has become the

Semantic Web (Berners-Lee et al. 2001; Shadbolt et al. 2006), adding the intelligence of an universal librarian.

HCI evolution led us then to a new stage, that of social networks. The human becomes a social being for IT professionals in the field. The introduction of systems such as Google, Facebook, LinkedIn and Twitter led to the emergence of new practices. No need for structure, knowledge could be completely distributed, we could find it anywhere anytime. Research scientists and practitioners in sociology and anthropology came on stage to study this new type of environments. Interactions among people and systems are now inherently social but also emotional; human emotions can be both positive and negative facing an interactive system. Artificial intelligence of a system then also lies in its ability to manage the emotional aspects of interaction through interfaces capable of adapting to the social context and user's emotions. This research problem has created an IT research trend lying on the border between HCI and AI: affective computing (Picard 1997).

Where are we today? Information technology development brought us a lot of techniques and tools. Certainly too many for us to be able to reasonably integrate them easily, with respect to our problems to solve. It is time to ask the question of meaning. What is making sense? We are going from the problem of knowing to the problem of being. That is why design (in the sense of integrated design and aesthetics) is increasingly becoming a necessity in engineering sciences, and computing in particular. The design approach to problem solving uses creativity rather than already-made, blocking and ultimately sterile procedures. What characterises our 21st century society is certainly complexity. On this point, AI and HCI must get together to solve problems whose complexity is at the centre. We must all converge towards an ontological approach of problem stating and problem solving. Indeed, before solving a problem, it must be stated well! This is the art of abduction (i.e., knowing how to imagine assumptions and goals, look for opportunities and ultimately seek meaning) (Boy 2013).

3 Intelligent User Interfaces

Intelligent User Interface (UI) design and evaluation is a vast and rich research and development area, which is at the intersection of human-system interaction and artificial intelligence, but also of cognitive sciences. Research on such user interfaces appeared in the early 80s (see for instance Edmonds 1981); in fact the first concepts date from late 70s in terms of so-called adaptive approaches. Many definitions have been proposed in the literature. So (Hancock and Chignell 1989) defined them as interfaces which provide tools to help minimise the cognitive distance between the mental model which the user has of the task, and the way in which the task is presented to the user by the computer when the task is performed. It even seems possible to go beyond this definition because, starting from the model of the theory of action of Norman (1986), while lying in an adaptive approach (many others were studied in

literature, see below), it is possible to locate different cognitive stages, against which one or more adaptations are especially important, Fig. 1.

Among the many other definitions include that of Maybury (1999): “*Intelligent User Interfaces (IUI) are human-machine interfaces that aim to improve the efficiency, effectiveness, and naturalness of human-computer interaction by representing, reasoning, and acting on models of the user, domain, task, discourse, and media (e.g., graphics, natural language, gesture). IUI are multifaceted, in purpose and nature, and include capabilities for multimedia input analysis, multimedia presentation generation, model-based interfaces, agent-based interfaces, and the use of user, discourse and task models to personalize and enhance interaction. [. .]*”.

Consequently, the field of intelligent interfaces covers a disciplinary field representing the intersection of human-system interaction, software ergonomics, cognitive science and artificial intelligence, including their respective sub-disciplines such as computer vision, automatic language processing, knowledge representation and reasoning, machine learning, knowledge discovery, planning, modeling of software and human agents, modeling of speech. It is also commonly accepted that the field of intelligent interfaces represents the intersection of human-system interaction and artificial intelligence, as well as Engineering of Interactive Computing Systems (EICS) represents the intersection of the human-system interaction and software engineering.

The definition of Maybury is interesting because it highlights that such user interfaces are designed to provide solutions in relation to different underlying criteria for human-system interaction, and they need to take into account explicitly several models to cover a set of steps in relation to Perception, Cognition and Action (if one refers to the PCA model well known in Artificial Intelligence). Included are problems and recurring locks associated with the recognition of user (or user group) intention, modeling knowledge and preferences, communication with the user, and

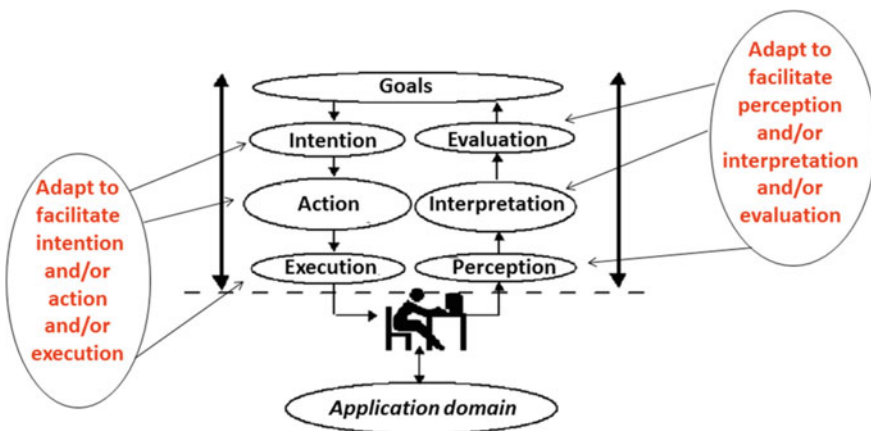


Fig. 1 Adaptation(s) in the light of the Norman’s Theory of Action (adapted from Norman 1986)

also the reasoning and the decision making (what, when, where, to whom, how, why to present the information).

Intelligent user interfaces are now a field in its own right. It is important to emphasise that famous conference of the Association of Computing Machinery (ACM) is dedicated to them. This is called ACM IUI (Intelligent User Interfaces). From a historical perspective (see also <http://www.iuiconf.org/IUI/History>), the idea started with a workshop in March 1988 entitled “Architectures for Intelligent Interfaces”, resulting in 1991 in the book “Intelligent User Interfaces” published by J.W. Sullivan and S.W. Tyler, workshop organisers). After a first workshop sponsored by the ACM in 1993, IUI has become an annual conference in 1997. In the call of the 2018 edition, note that the topics highlighted were the following: “Health and intelligent health technologies, Information retrieval and search, Intelligent assistants for complex tasks, Intelligent wearable and mobile interfaces, Intelligent ubiquitous user interfaces, Intelligent visualization tools, Interactive machine learning, Knowledge-based approaches to user interface design and generation, Modeling and prediction of user behavior, Multi-modal interfaces (speech, gestures, eye gaze, face, physiological information etc.), Natural language and speech processing, Persuasive and assistive technologies in IUI, Planning and plan recognition for IUI, Proactive and agent-based user interaction, Recommender systems, Smart environments and tangible computing, Social media analysis, User Modelling for Intelligent Interfaces, User-Adaptive interaction and personalization”.

In addition to the regular publication of many books and articles on intelligent user interfaces in various journals and conferences, both in human-system interaction and in Artificial Intelligence, we can point out that both journals are dedicated to them: *User Modeling and User-Adapted Interaction* (Springer); *ACM Transactions on Interactive Intelligent Systems*.

Many approaches contributing to intelligent user interfaces can be found in the literature. It is not possible to mention them all here; the interested reader can find in various books or review papers further details on this topic (Chignell and Hancock 1988; Kolski and Le Strugeon 1998; Hook 2000; Jameson 2007; Akiki et al. 2014):

- The so-called adaptive approaches are those that led to most proposals (cf. Kolski et al. 1992; Schneider-Hufschmidt et al. 1993; Jameson and Gajos 2012), the adaptation being usually relatively different user and/or task characteristics or task.
- In continuation of work on adaptation, there are approaches on the current trend of providing more personalised services to users of information systems at large. It is in this case to adapt to the goals (needs or reasons that led the user to query the system), habits/preferences (all the criteria that distinguish a solution of another for the same query), the user capabilities (including both hardware and software capabilities available to the user, as its own physical or cognitive abilities, possibly related to disabilities). It is important that the system learns during the interaction with the user, as well as with users with close profile, to further customise, exploiting for example collaborative filtering algorithms (Su and Khoshgoftaar 2009). The works are numerous in this area (Abed et al. 2011; Brusilovsky et al.

2007; Peintner et al. 2008; Findlater and Gajos 2009; de Oliveira et al. 2013; Germanakos and Belk 2016).

- Certain intelligent user interfaces are called tolerant to human error (Rouse and Morris 1987; Beka Be Nguema et al. 2000). In this case the adaptation operates a classification of possible human errors and their consequences. Their goal of such IUI is to correct human error or alert the user in case of potential problems.
- Another category includes assistants, in the broadest sense of the term. They are at the service of the users, listening to them, to assist them in case of problems (Lieberman 1995) (see also Shneiderman and Maes 1997). A typical example is the assistant, called Clippy, integrated in several previous versions of the Microsoft Office environment. This assistant was made available to the user and advising (requested or not) on appropriate procedures (like how repaginate a document). Such approach was originally proposed in the aviation field, under the name of intelligent assistant systems, acting as co-pilot in a cockpit and reasoning in parallel to the user considered as the final decision maker (Boy 1991a). To improve human-system interaction, to make it more natural, design choices may include a human physiognomy of the assistant, see about the “Affective Embodied Conversational Agents” section of this chapter.
- Many researches focus on context in general and how to take it into account in UI design. The definitions of Abowd et al. (1999), Dey (2001) on this subject are the most cited. Different types of context-aware systems are also studied. It is in fact possible to find in the literature the following qualifiers: Context-aware and Context-sensitive, which denote the fact of using the context or the one to adapt to it. The works are numerous in this area (Boy 1991b, 1992; Winograd 2001; Coutaz and Rey 2002; Limbourg et al. 2004; van den Bergh 2006; Brossard et al. 2011; Moussa et al. 2015; Bauer et al. 2014; Bauer and Dey 2016).
- The objective of the so-called plastic user interfaces is to adapt to their context of use in respect of their usability (Thevenin and Coutaz 1999). The context of use must consider the characteristics of the user, platform of interaction, and environment (Calvary et al. 2004; Sottet et al. 2009; Coutaz and Calvary 2012).
- A more prospective approach considers the intelligent user interface and its socio-technical environment as a multi-agent system. It corresponds to a distributed approach to human-system interaction. It is important to note that, more generally, distributed user interfaces are subject of much research currently (Gallud et al. 2011; Lozano et al. 2013; Gallud et al. 2014). Such an interface, suggested by Mandiau et al. (1991); Kolski and Le Strugeon (1998), is composed of cognitive and reactive agents, working in parallel and/or cooperating in order to solve different problems relating to the tasks. The result of their treatment is provided to users through acts of communication, but we can imagine a variety of other actions directly on the system, for example. This principle was implemented as part of a road traffic simulation on interactive tabletop with RFID technology, virtual agents representing vehicles responding to the activation of tangible objects manipulated by users (Kubicki et al. 2013; Lebrun et al. 2015).

Areas of application of intelligent user interfaces are multiple, since they can be a contribution when a semi-automatic or automatic aid should be implemented by the interactive system, while taking into account different criteria or user preferences. Research and development focused as well on tasks considered as relatively simple (office, information retrieval, e-commerce, etc.) than on complex tasks, even critical (transport, supervision, health).

4 Affective Embodied Conversational Agents

Computers are increasingly used in roles that are typically fulfilled by humans, such as virtual tutors in a learning class or virtual assistants for task realisation. When computers are used in these roles they are often embodied by animated cartoon or human like virtual characters, called *Embodied Conversational Agents* (ECA) (Cassell 2000). An example of an ECA is illustrated Fig. 2. This enables a more natural style of communication for the human and allows the computer to avail of both verbal and non-verbal behaviour channels of communication. Several studies have demonstrated the acceptance and the efficiency of such agents (Hoffmann et al. 2009); indeed, the *persona effect* reveals that the presence of an ECA improves the subjective experience of an interaction for the user. Moreover, when people interact with such virtual agents, they tend to react naturally and socially as they would do with another person (Hoffmann et al. 2009).

The ECAs are not only simple humanoid graphical representations but embody (1) cognitive agents able to reason on complex internal semantic representation, (2) interactive agents able to interact in a multimodal way with a user, and (3) expressive agents able to show, through their verbal and non-verbal behavior, a particular cognitive and affective mental state. These three dimensions—cognitive, interactive and expressive—are essential to design an ECA to improve the interaction both regarding satisfaction of the user and user's performance in task execution. For instance, several research efforts have shown that agents expressing emotions improve interaction (Beale and Creed 2009). However, the expressive capacity of the agent is not sufficient: an emotion expressed in an inappropriate situation during an interaction may have a negative impact on the user's perception (Ochs et al. 2012b). That is the three dimensions—*cognitive*, *interactive* and *expressive*—that enable the agent to adopt an affective behavior relevant and efficient during the interaction with the user.

The cognitive dimension of an ECA implies knowledge representation and its reasoning capacity.⁵ Knowledge refers to information related to both application domain and task: but corresponds also to the knowledge related to the social and emotional dimension of the interaction. Indeed, an ECA has to be able to represent and reason on its own emotions and those of its interlocutor given the social context. The

⁵The reader can refer to several papers in Volume 1 for an overview of the methods in Artificial Intelligence for the representation of knowledge and the reasoning.



Fig. 2 Example of an embodied conversational agent: the ECA Greta (Pelachaud 2009). Expressions of joy, sadness, and anger (from left to right)

cognitive representation of emotions has to include a representation of the conditions of emotions elicitation, i.e. when an individual may feel which emotion(s) given a situation. This information may be used by the ECA to identify when the ECA itself may express which emotion(s) but also which emotion(s) the user may potentially feel during the interaction. The elicitation of emotion being tightly related to the achievement or failure of a goal (Scherer 2000), the BDI representation (Belief, Desire and Intention) of emotions—through syntactic abbreviations of combinations of mental attitudes—is particularly adapted to this problematic.⁶ Such a formalization has for instance been used to develop an ECA that is capable to express empathy

⁶An example of a BDI formalisation of emotions is proposed in chapter “Formalization of Cognitive-Agent Systems, Trust and Emotions” of Volume 1.

toward the user during a dialogue (Ochs et al. 2012b) or a virtual tutor that adapts its pedagogical strategy to the inferred emotions of the user (Jaques and Vicari 2004). Other methods have been proposed to represent emotions. For instance, to illustrate the dynamical aspect and the non-determinism of emotions, a representation based on Bayesian network (de Melo et al. 2012) and Dynamic Belief Network (deRosier et al. 2003) has been developed.

Moreover, the emotions of an agent may be used to determine the appropriate behavior of the agent in a virtual environment. The emotions are then integrated in the decision making process for the actions selection (Canamero 2003). Inspired by the coping theory claiming that people used specific cognitive strategy to cope with their emotions (Lazarus 1991), the impact of emotions on an ECA's behavior may be modeled by a modification of its mental state, i.e. a modification of its beliefs, desires and intentions (Gratch and Marsella 2004). For instance, if the ECA has a negative emotion, it can adopt an acceptance strategy implying the fact that the agent gives up the intention that has elicited the negative emotion by its failure. By consequence, the negative emotion of the agent will disappear.

During the interaction with the user, the emotional knowledge of the agent should be enriched given the progress of the interaction. Indeed, even if a formalisation of emotions may enable the agent to infer the user's emotions, a system to recognise in real-time the emotions expressed by the user may validate, refute or refine the agent's emotional knowledge, in particular concerning the effects of agent's actions on user's emotions. During the interaction, the user expresses her/his emotions through her/his non-verbal behavior (e.g. facial expressions and voice), her/his verbal behavior (e.g. emotional words) and through physiological signals (e.g. skin conductance). The system to automatically recognised emotions are generally constructed on an offline learning of the non-verbal, verbal or physiological characteristics of emotions based on real or acted corpus of data of individual feeling or expressing emotions. For instance, audio-visual corpora are collected to analyse the facial, gestural and acoustic characteristics of emotions expressed by individuals. The corpora of emotion expressions are generally manually annotated with different types of emotion and sometimes with associated intensity values. A method to extract emotional knowledge from these corpora consists in exploiting machine learning methods,⁷ and more precisely supervised algorithms to correlate expressive characteristics (such as muscles activation of the face or acoustic parameters of the voice) to emotion types and intensity (Caplier 2011; Clavel and Richard 2011).

Machine learning methods are also used for the generation of expressive behaviors of ECAs (head movements, gaze direction, posture, etc.). The analysis of interpersonal interactions in corpora can be exploited to identify how an affective or cognitive state is expressed through facial expressions gestures or postures; but also how individuals coordinate their non-verbal behavior (e.g. mimicry). In this learning perspective of ECA's non-verbal behavior, two approaches may be distinguished. Al-

⁷Machine learning methods are presented in details in chapter "Designing Algorithms for Machine Learning and Data Mining" of Volume 2.

gorithms said “black box”⁸ can be used to model ECA’s non-verbal behavior that is reflex or slightly correlated to another modality. For instance, a learnt Hidden Markov Model is used to predict the head movements of an ECA during an interaction with a user or for its lips synchronisation with its speech (Hofer and Richmond 2010). Conversely, algorithms said “white box” are used to extract knowledge that then are explicitly represented in the ECA. For instance, a classification method based on decision tree is used to identify the morphological and dynamic characteristics of different types of smile for ECA (amused, polite and embarrassed smiles) (Ochs et al. 2012a); and sequence mining algorithms are exploited to extract knowledge on the multimodal signals that the ECA may use to convey social attitudes (Chollet et al. 2017; Porhet et al. 2017). Models have been proposed to convey emotion expression variability, which integrate uncertainty of activation of human face muscles and some gestures based on fuzzy logic rules (as for instance in Niewiadomski and Pelachaud 2007).

Finally, ECA design implies various kinds of AI problems: knowledge representation, decision making, planning and learning. These problems, applied to model this complex phenomena of emotions, aim at integrating emotional intelligence into interactive systems (Salovey et al. 2000), need to be solved for optimizing human-machine interaction.

5 Consolidating, Formalizing and Exploiting Usability Knowledge for Designing and Evaluating Interactive Systems

Designing and evaluating interactive systems have been very active research domains since more than three decades primarily to formalise usability knowledge that could be useful in a computational framework. The framework should support high level abstraction, access, testing and fixing potential usability problems. The goal is to be released from the empirical assessment traditionally induced by various approaches using this usability knowledge. For instance, Ivory and Hearst (2001) observed that different software for evaluating accessibility guidelines on the same web site may produce inconsistent results. Several reasons explain this: accessibility guidelines are not formalised, if they are, the formalisation is varying depending on the interpretation used by different methods. Jambon et al. (2001) listed and classified several dozens of methods and techniques for specifying an interactive system that largely vary depending on their perspective: psycho-ergonomic, Engineering of Interactive Computing Systems (EICS), software engineering. Vanderdonckt and Coyette (2007), as well as Beaudouin-Lafon and Mackay (2003) also reported on several techniques and software for prototyping user interfaces in order to assess them as early as possible. Since the eighties, research and development mainly fo-

⁸The results of such algorithms are difficult to explain and to interpret, for instance System Vector Machine (SVM) or Neural Networks.

cused on model-based methods for designing user interfaces: the designer creates one or many models (e.g., a domain model, a task model, a user model, etc.) which are subsequently used for semi-automatic generation of user interface code and/or evaluating it. If this generation is not made possible, at least a structured development life cycle is induced by the models. Literature is significant in this area: (Szekely 1996; Vanderdonckt and Puerta 1999; Paterno 1999; Kolski and Vanderdonckt 2002), . . . Later on, research and development progressively shifted its focus of attention to structured methods based on Model-Driven Engineering (MDE) in line with the initiative launched by the *Object Management Group* (www.omg.org). Most approaches adopt a top-down life cycle in which models are progressively transformed until the code of a final user interface is obtained. The Cameleon Reference Framework (CRF) (Calvary et al. 2003) now reached a consensus in the community that four levels of abstraction could structure this development life cycle: task and domain, abstract user interface, concrete user interface, and final user interface. This framework is now recommended by the W3C Group on Model-Based User Interface (MBUI) (Gonzalez Calleros et al. 2010), <https://www.w3.org/TR/mbui-intro/>. Several works are compliant with this W3C recommendation, such as, but not limited to: (Jacob et al. 2004; Calvary et al. 2008; Seffah et al. 2009; Hussmann et al. 2011), etc. Regarding evaluation of interactive systems, especially with respect to usability and accessibility (Nielsen 1993; Bastien and Scapin 2001), but also with respect to acceptability (Stephanidis 2009), many methods, techniques, and software also exist that offer ample possibilities depending on the availability of the user interface (vs a prototype of it) and real users (vs a representation of these users). For instance, when real users are not available, a model of these users is used instead. Further reading can be found in Nielsen (1993), Baccino (2005), Huart et al. (2008), Ezzedine et al. (2012), Jacko (2012). A problem subsumed by designing and evaluating interactive systems consists in how to create and manipulate the knowledge bases containing the usability knowledge required for the knowledge-based approaches for design and evaluation. Vanderdonckt (1999) discusses five major milestones required to create a usability knowledge-based software: guidelines collecting, guidelines organisation, guidelines incorporation into approach, guidelines operationalisation, and guidelines usage. Probably the most critical step is the operationalisation since a guidelines as initially stated in a source could be significantly reduced or constrained when incorporated in a knowledge-based approach.

Any guideline could be related to important ergonomic criteria (Bastien and Scapin 1993) for guidance, dialogue control, error management, consistency, workload, adaptability, compatibility, and code significance.

Usability and accessibility guidelines are considered to be a valuable source for supporting the (semi-)automated detection of potential usability/accessibility problems for designing as well as for evaluating (Grammenos et al. 2000; Tran et al. 2013). A usability guideline (Vanderdonckt 1994) is hereby referred to as any design and/or evaluation principle that could be used to produce and/or guarantee the usability quality of a final user interface. Five categories of usability guidelines could be distinguished: design standards, usability principles, usability guides, style guides, and algorithms for knowledge-based generation of user interfaces. For instance, a

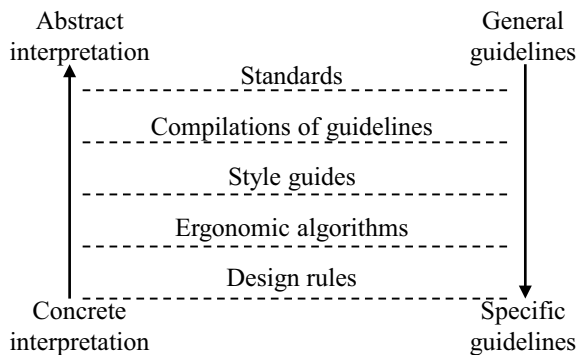
guideline could be expressed depending on a particular domain of application (Scapin 1986; Smith and Mosier 1986) or independently, as in standards. A guideline could be specifically made applicable for a style guide that is related to an operating system. Many standards contains a significant section of guidelines (Stewart and Travis 2002), such as international norms (e.g., ISO 9241, ISO/IEC 9126), national ones (e.g., HFES, AFNOR, BSI . . .). Figure 3 sorts these five types of guidelines according to their level of applicability: standards are considered as the most general sources of usability knowledge, therefore widely applicable in principle, but also requiring some interpretation to be correctly applied depending on the context of use and all its dimensions (user, platform, and environment). On the other side of this continuum, design rules only require a minimal interpretation before applying them since their applicability is specific. The more general a guideline is, the more interpretation it may require in order to properly apply it.

Figure 4 locates guidelines depending on two axes: the need for interpretation and the level of precision required to implement them in a software. Algorithms are straightforward to be applied since they require almost no interpretation, but are totally driven by their specifications, which make them notably hard to modify. On the other side, principles require a high level of interpretation, thus making them cautious to apply. A particular condition imposed by a context of use may validate or invalidate the application of such principles.

Several research and development problems related to intelligent user interfaces, which is often considered as the overlapping of human-computer interaction and artificial intelligence, are still open, such as:

- Consolidation of knowledge-based approaches for user interface design and evaluation: there is a lack of systematic method, a lack of consensus in which approach could be considered valuable, and a lack of properly integrating techniques from knowledge engineering (see chapter “Knowledge Engineering” of Volume 1).
- Uncertainty of usability knowledge: many guidelines used in knowledge-based approaches are intrinsically uncertain: they are fuzzy, incomplete, redundant, hard to access and to modify by a non-expert person, and their notable independence

Fig. 3 Five types of guidelines sorted by level of applicability



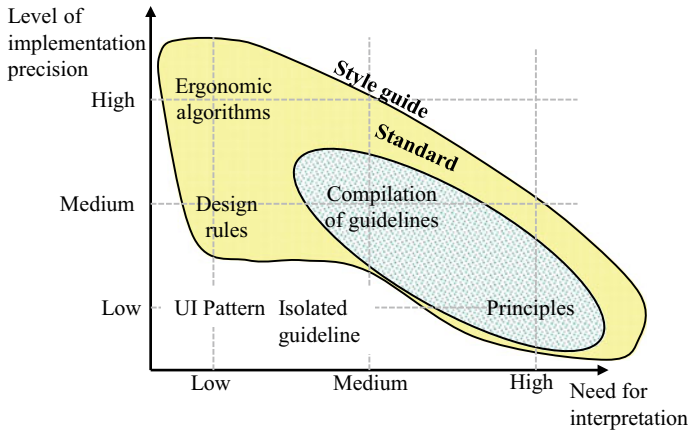


Fig. 4 Guidelines sorted by their level of interpretation and their implementation precision

with respect to the context of use unless such a context model is used (Vanderdonckt 1999).

- Lack of knowledge evolution: knowledge contained in knowledge bases used for user interface design, generation, evaluation is often constant and hard to modify, which may not satisfy the need for making it evolving depending the context of use, but also depending on the dynamic evolution of users. Machine learning techniques are particularly welcome for this purpose, which explain why knowledge could be improved by actual data of its usage.

6 Visualisation and Data Mining

Data processing and mining are nowadays a priority both in research and industry, small or large. Organisations now produce loads of data on their internal processes as well as on their client activities. Technological or strategic watch requires to collect and forage all available data in order to gain a competitive edge over competing organisations, or to better position themselves in the socio-economical context (Provost and Fawcett 2013).

Data can be massive—as in “big”. Data is also complex, just as the phenomenon they emerge from, but also because it often is non-structured. Seeking for the information encapsulated within the data is difficult, discovering new insights from data is challenging (Zhang et al. 2012).

Data mining develops algorithms capable of identifying structural patterns, expressed as association rules for instance. A classical example is that of a supermarket seeking a better understanding of consumers’ habits, typically through the use of fidelity cards or mobile application account, in order to refine its marketing strategy. A

telecom company will foresee the possibility to better understand how the teenager market differs from adult consumers. Data mining results can be complex just as the data that needs to be processed; they often need to be sorted, organised or classified before decision can be made.

Data mining is all about discovering structural patterns. Information visualisation relies on a crucial observation, that around 40% of our cortex activity is devoted to processing visual signals (Ware 2000). The challenge is thus to propose users with a graphical representation from which patterns in data now turned into visual patterns can be inferred. Being able to interactively manipulate and query the map additionally allows users to gain insight on the visual display of information. The literature gathers tons of approaches to graphically display data on the screen, often targeting specific types of data: temporal data (Silva and Catarci 2000; Daassi et al. 2006), geospatial data (Andrienko and Andrienko 2006), networks (Herman et al. 2000; von Landesberger et al. 2011) or multi-dimensional data (Hoffman and Grinstein 2002).

Visualisation aims at solving a problem which, although it can easily be formulated, can turn out to be quite complex. Computing cartesian coordinates of data points is but the first step. Visualisation also requires to use relevant visual variables (color, shapes, saliences, etc.) to highlight attribute properties (statistical distribution, correlation, proximity distortion, etc.). Computing screen positions most of the times is a combinatorial optimisation problem while visual encodings involve graphics semiotics (Bertin 1998; Ware 2000) and escape purely computational approaches.

Visualisation is part of data and information processing. This process traditionally is represented as a pipeline chaining data processing steps, starting from data curation and organisation, statistical/combinatorial analysis up to computing a representation in (usually 2D) Euclidean space and its rendering on a screen (Card et al. 1999; Chi 2000; dos Santos and Brodlie 2004). This process, although depicted as a pipeline, does not necessarily deploy itself in sequence, but rather as iterations allowing structure to emerge and hypothesis to be formed: early iterations help focus on relevant subsets of data that need further investigation, leading to hypothesis that can be tested; visualisation will additionally be useful to disseminate results and support decision making. This process echoes Shneiderman's mantra ("Overview first, zoom and filter, then details on demand"; (see Shneiderman 1996)) and has been termed the "Sense-making loop" (cf. Fig. 5) by the Visual Analytics founders Thomas and Cook (Thomas and Cook 2006).

Because the data is complex, uncertain and changing, human intelligence resides at the heart of the foraging process. Echoing Shneiderman's mantra, Visual Analytics promoted by Thomas and Cook has established as a research area since a few decades. More than data analysis or pattern recognition, Visual Analytics aims at knowledge discovery.

The visualisation pipeline and the Sense-Making loop places users at the centre of the knowledge discovery process (van Wijk 2005). While the pipeline maps to a high level data processing architecture, it is human-computer interaction that enables users to drive data foraging. As a consequence, identifying why and how a given visualisation technique is more "efficient" in supporting human driven knowledge discovery is crucial. Controlled user experiments, often exercised in the area of

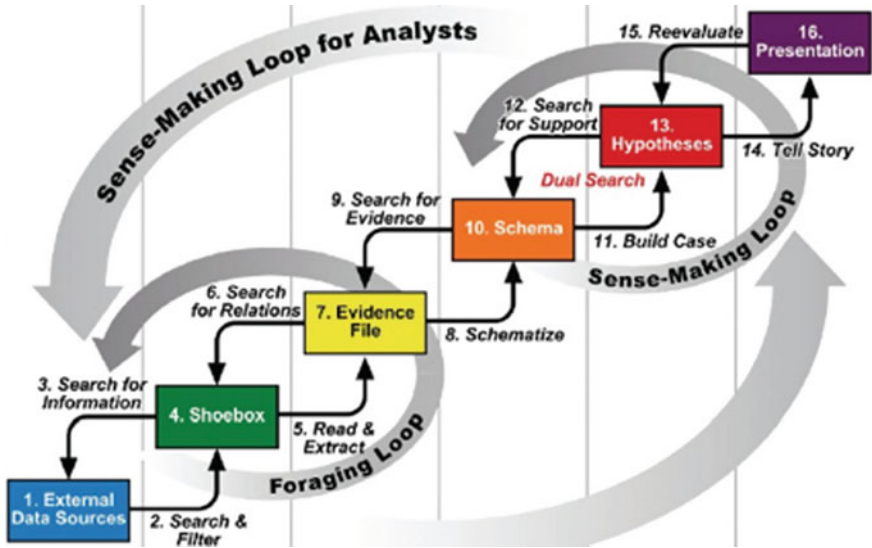


Fig. 5 The “Sense-Making Loop” illustrates the iterative process relying on visualisation as a main driver of the analytical process (Thomas and Cook 2006)

human-computer interaction studies, has now become common practice to validate visualization techniques (Purchase 2012; Sedlmair et al. 2012; Isenberg et al. 2013).

These controlled experiments indeed can help compare techniques supporting low-level, fine grained tasks (Amar et al. 2005; Lee et al. 2006). Knowledge discovery however is a high-level cognitive process. Controlled experiments can hardly validate that a technique (or more often a combination of techniques) favors knowledge discovery. Evaluation high-level cognitive processes does not boil down to error rates and time to task completion. They are more conveniently described in terms of design principles and best practices. Munzner (2009) (see also Meyer et al. 2012, Brehmer and Munzner 2013) proposes a nested model for the design of visualisation systems where data abstractions and user interactions are derived from domain questions. User tasks derived from these questions then specify requirements on visual encodings, including interaction, relevant visual representations and visual variables. Validating of a visualisation then unfolds in the opposite direction: algorithms must run under proper time complexity to insure fluidity of user action and are measured either theoretically or tested against benchmark datasets. Controlled experiments may be used to assess the efficiency of combined visual encodings and interaction techniques. User interviews can assess usability of the overall system (as an aid to decision making, for instance). User adoption of the system is the ultimate demonstration of the value of a visualisation technique (van Wijk 2005).

Visualisation can thus reveal structures hidden in data that is uncovered by analysis and mining approaches. It becomes a natural companion to artificial intelligence precisely because it engages human cognitive capabilities and intelligence. And be-

cause it addresses complex phenomenon emerging from real world situations, often explored and examined in an uncertain and changing environment.

7 Conclusion

The main goal of this chapter was to provide an overview of cross-fertilisation between HCI and AI focused on several key representative research areas without exhaustivity constraints. Significant work at the intersection of these two fields started forty years ago in the aeronautical field, closely combining intelligence and interactivity. This work is now continuing in different areas (simulation, semantic web, e-commerce, social networks, complex dynamic systems, ambient intelligence, and so on). Smart user interfaces quickly took advantage of the complementarity of HCI and AI to become a multifaceted domain. Approaches to user interfaces and affective embodied conversational agents, put forward in this chapter, have particularly promising prospects. Capitalization, formalization and operation of ergonomic knowledge for the design and evaluation of interactive systems have been the subject of many studies since the early 1980s. This work will be expanded, since the potential of HCI and AI cross-fertilization will continue to be a huge endeavor.

Finally, visualization and data mining, which have close ties, have been reviewed in the last section of this chapter, are also particularly representative of areas where HCI and AI naturally merge.

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