User Behavior Patterns: Gathering, Analysis, Simulation and Prediction

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Abstract. This paper presents methods and tools for gathering, analyzing and predicting behavior patterns. Considered both for a single user and for groups of users, behavior patterns may impact at a local and/or global level. The first part explains how to gather behaviors in various situations and how to drill from overt behaviors into deeper cognitive processes. The rationale of cognitive modeling and guidelines to perform it are provided. The second part deals with analysis methods that enable to detect behavior patterns. Bottom-up analysis based on existing data is augmented with top-down analysis based on conceptual design choices and hypotheses. The last part emphasizes the needs of data storage and data sharing in the organization. Beyond data storage and sharing, it presents the benefits of using Adaptive Business Intelligence in order to simulate and predict possible situations as well as the appropriated behavior patterns that enable to adapt.

Keywords: Behavior patterns, modeling, Ontology systems, Multi-Agent Systems, Agent Oriented Programming, Adaptive Business Intelligence.

1 Introduction

In Human-Machine Interaction (*HMI*), the concept of *interface patterns* was massively implemented and popularized by end-user consumer devices such as Apple iPhone™ and by gaming consoles such as Sony Play Station EyeToy™ or Nintendo Wii™. The transition from classic control devices equipped with buttons, knobs and joysticks to natural-interaction based essentially on gestures is revolutionary. The evolution of technology from touch-screens to various sensor equipped interfaces make possible for the user body to become an interaction mean [30].

This induces changes in the Human Factors (*HF*) field, because new user needs have to be taken into account. The main part to consider in HF is not necessarily the novelty, but the way of dealing with criteria and functionalities as well as with contexts of use that were specific in the past. For example, not so long ago, sets of criteria and functionalities were clearly defined for mobile phones. A mobile phone was intended to communicate. Thus the screen size and the phone functionalities were homogeneous. But the introduction of new functionalities such as Internet, games and music, and also Global Positioning Systems (*GPS*) on mobile phones made mandatory to consider

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different criteria and functionalities and to combine them in new ways in order to provide the best design for new devices.

Beyond the infatuation for gesture recognition, one has to consider all the HMI interaction modalities and how to get the best benefits from studying and using them. Humans are endowed with complementary senses. In their natural environment, they have not lived based mainly on one of them. So, from a HMI perspective, taking into account these different modalities makes possible to link overt observable user behaviors to user high-level processes (what the user thinks and feels) that are covert. The complexity of users' processes depends on the complexity of the task. In the mobile phone example, the tasks that are performed may seem quite simple, even for last generation sophisticated devices, compared to the tasks users have to perform in safety critical domains. Thus, even if the HF methods and tools attempt to be generic, their use and importance differ from one domain to another. The HF and HMI challenge is to continuously adapt the methods and tools in various domains to the technological infrastructure that is transversal to these domains.

Another mandatory aspect that has to be considered is the last decades' acceleration of product life cycle. The design, implementation and commercialization of products in local and global markets are getting shorter and shorter. This means that to succeed in new products, the whole process of product development as well as the whole Information Technology (*IT*) system have to be improved. In the actual global Knowledge Economy (*KE*), cross-domain and cross-country information flows are one of the key factors that contributes to growth and development and offers a solution for the *Creative Destruction* that was studied more than half of a century ago [33]. In order to ensure these information flows, it is not sufficient anymore to integrate data coming from various sources, but to perform data unification.

Business Intelligence (*BI*) may have lots of definitions. As it is considered in this paper, it is related to Knowledge Management (*KM*) and to HF. It provides a clear approach through industry proven solutions in order to perform unification of data coming from various cross-organizational data sources on one hand and on the other hand it enables to transform data in valuable cross-domain information, by providing analysis and decision making support. BI is a combination of methods and technology that provides key information to support decisions and actions in order to improve an agency's mission [3]. From a Human Factors intrinsic commitment augmented with a Human Factors vision of economics, the agency mission should focus individuals' (i.e. final users, operational people, customers) maximized utility and well-being [2], [18] rather than only on agency's maximized profits. Non-financial performance measures based on organizational strategy [17] are supported by the proven importance of innovations in the Knowledge Economy [29] as well as by the value of the Human Capital [21] that both contribute to endogenous and sustainable growth. Emerging as theory, these concepts were implemented as methods (i.e. the Baldrige National Quality Program [1], the European Foundation for Quality Management (EFQM) [13], the Knowledge Assessment Methodology [8]) that are used by worldwide organizations. Thus, the main role of BI as considered here is to improve Research and Development (*R&D*) local and global units [28] and the innovation processes that are essential in the organizational governance.

Simply stated, the link between user behavior patterns, BI and simulation is to create data unification, to obtain and store human behavior patterns, and finally to inject them in a Human Behavior Simulator (*HBS*). The particularity of the HBS is that it is mainly based on real patterns. The next step is to couple the HBS with technical simulators (*TS*). Technical simulators range from simulators that offer complete HMI (i.e. flight and drive simulators) to calculation simulators, based on formulae employed in mathematical and statistical models, that offer only calculation results (i.e. specific consumer behavior according to a specific economics model). The use of such HBS in research studies is wide and encompasses both studies involving few users (i.e. HF studies in aircraft cockpits with two pilots) and studies involving large samples of users (i.e. behavioral economics studies with hundreds of users, Customer Relationship Management, etc.). The final interest of using HBS based on real patterns is to participate in assessing and validating models and thus to enable predictions, optimization and co-adaptability of socio-technical systems. Prediction, optimization and adaptability are the key components of Adaptive Business Intelligence [23].

2 User Behavior Patterns

2.1 Cognitive, Emotional

The main part of the studies carried out in Human Centered Design (*HCD*) focus the cognitive aspects of users. The legitimacy of taking into account the cognitive side of users was reinforced since HF penetrated industry. In the industrial context where HF specialists had to work together with engineers, the rational aspects of users had to be dealt with in the first place. However, the cognitive side does not cover entirely humans, neither in description nor in understanding. In order to complete the missing parts of the puzzle, the emotional aspects of users started to be re- investigated, especially since neurobiology demonstrated the emotion circuits in the human brain [5], [11]. On the other hand, the market moved massively to end-user consumer products designed for entertainment. So the transition from industrial products to entertainment products was beneficial to stimulate research that focuses user emotions. Originating in Japan, Kansei Engineering is also supported in northern European countries [34].

So user behavior patterns are considered both on their cognitive (rational) as well as on their emotional sides. A simple rational behavior pattern could be: the phone rings, the user grasps the phone, presses the green button and says ‘hello’. A simple emotional pattern could be: the phone rings, the user enjoys the phone design and tone (and wants to buy the same if s/he does not own it). In the first case the HMI may be addressed from a usability perspective; in the second case it may be addressed from a marketing one. It is obvious that depending on the domain, the importance of emotions and the rationale of considering them in studies may be very different (i.e. pilot fear and panic in the cockpit due to engine failure and consumer feelings related to entertainment). But in all cases, HF are involved.

2.2 Setting Up Surveys and Experiments

2.2.1 Who Are the Users?

Depending on the goals of the design-evaluation process, HF have to set-up appropriated surveys and experiments. One of the determinant factors in the study is ‘who are the users?' The answer to this question might be quite complicated for the same culture, and it gets even more complicated when users come from different cultures, as it happens currently nowadays. There are cross-cultural dissimilarities in behavior such as language, decision making styles and conflict management styles. Decision making is a transparent process, but its form is grounded in a culture's value, standards of behavior, and patterns of thinking [16], [20], [25]. So lots of intra and cross-cultural differences should be considered, especially in the actual globalization.

2.2.2 Modalities Taxonomy (Fractioned vs. Continuous)

The first category of user behaviors consists of directly observable user actions (i.e. the user presses a button) and user communications (i.e. with other users or with the machine via speech recognition). A subtler category consists of user behaviors that are not directly observable, such as eye-movements and physiologic reactivity. These last behaviors have to be measured by appropriated devices.

A main point to be emphasized is the difference between modalities (gestures, speech, eye-movements and physiologic events) in terms of distinction between fragmented and continuous series of events.

Gestures and speech are fragmented, i.e. they happen for determined periods in time, they stop and then they restart. Behavior fragmentation impacts directly the observation methods and the analysis process. Behavior events that are relevant to HMI or to interaction in general are clearly defined and separated, as well as their relevance in the context of the task to be performed or in the context of the given usability scenario.

For behaviors such as eye-movements and physiologic reactivity, behavior events occur continuously, and in parallel with other user actions. The visual modality may be considered as the supervisor of other modalities in the highly visual environments to which users are exposed. In general all the eye-movements recorded during an experiment are not directly relevant. Compared to the fragmented modalities, further work has to be accomplished in order to identify the relevant ones.

It is valuable to consider not only an observation by modality (i.e. recording the user gestures alone) but to combine the observation of several modalities in order to understand the information flows and the action flows. For example, the user gathers information from the environment. What will s/he do next? If actions are possible, then they should be observed. An event occurs, the user presses a button and then looks at the changes on the display: information gathering is a trigger for action, and the actions performed become triggers for information gathering.

The combination of several observation methods enables to determine cycles of information gathering and actions, as triggers for each other.

2.2.3 Objective and Subjective Assessment Methods

Objective Assessment methods employ various types of devices. The intrusiveness of the equipment that is used, as well as the impact it might have on users have to be considered when designing experiments. Furthermore, there are experiments that do not allow at all specific types of equipment.

A gesture means basically to move a part of the body. Observation tools such as cameras are sufficient to assess gestures. The same equipment and some more specific light conditions are necessary for the recording of facial expressions. Facial expressions could be considered as a particular category of gestures. Facial Action Coding System (*FACS*) [9] provides a complete reference to observe and encode facial expressions. Automated encoding software is also in progress [10]. Eye trackers enable to gather the gaze position on the visual scene. Eye-trackers devices are proposed in two configurations: head-mounted or remote. In order to improve the gaze accuracy, they can be completed with Magnetic Head Trackers [12].

Physiologic reactivity employs various devices of measurement such as skin-conductance patches, ECG, EEG, breath frequency, etc.. However, because of their intrusiveness, such devices are hardly usable in common experiments.

Subjective Assessment Methods employ self reporting, questionnaires and rating scales that are designed for specific fields of investigation, such as performance, workload, situation awareness, user satisfaction, human error, team assessment. Some of the methods are usable as such, other methods require a specific implementation (i.e. question design, schedule for making the questions, etc.) depending on the evaluation goals.

In order to assess user behaviors in terms of cognition and emotion, objective and subjective methods should be integrated. Cognitive and emotion assessment methods are fully described in Human Factors Methods [36] and Handbook of Emotion Elicitation and Assessment [7].

3 Quantitative Analysis, Modeling and Qualitative Interpretation

In general, data collected during experiments or surveys is analyzed using quantitative statistical methods. The results obtained are presented as histograms or graphs. The quantitative analysis focus isolated entities in terms of frequency of occurrence or in terms of variation.

A further stage that aims to extract knowledge from data and to discover relationships between entities (hidden patterns) is data mining [3], [23], [32]. Linking entities is performed via various statistic analysis and algorithms, but the linking is mainly expressed in terms of influence of an entity on another. The data mining process starts with the data sampling stage, followed by the data exploration that eventually enables to find and refine models. Such models are composed by several modules or nodes ranging from statistics to complex algorithms (i.e. decision trees, regression, neural networks) [32]. Even though it reflects a conceptual process, the model emerges bottom-up and is highly dependent on the data sample selected initially [3]. The models are statistical and algorithmic and aim to solution specific problems.

The opposite way is to build systematically a conceptual model top-down, based both on knowledge extracted from domain experts and users and on scientific information. Techniques such as knowledge elicitation are very useful when building top-down models [4], [14]. Having a conceptual model enables to reinforce the structuring in data exploration and analysis according to the entities that constitute the model. They provide also the rationale for selecting the appropriated data collection methods. In general, models employed in Human Factors are built top-down and use various conceptual inputs [15], [38]. The conceptual models aim to be generic.

Furthermore, conceptual relationships between entities that are already systematically specified in the conceptual model induce a qualitative shift in data exploration because they guide the investigations beyond isolated entities, aiming to find complex relationships at the results (instance) level. For example, an experiment that used a cognitive model guided the employment of the most appropriated analysis method [22] and enabled to find user visual patterns that link various visual items and user behaviors in complex structures. Moving form quantitative results related to isolated entities to patterns that combine several entities is valuable because the patterns obtained in this way express higher level complex cognitive processes [37]. The top-down model influences the shift from quantitative aspects to qualitative interpretation of the results.

Both bottom-up and top-down modeling have their own benefits, and both aim to understanding and prediction. Mixing both approaches improves the overall reliability of models. However, conceptual models enable to capitalize knowledge in a structured manner. Thus they should be considered and used as a top container that can hold data-driven models.

4 Storage

4.1 Bottom-Up and Top-Down Storage

Bottom-up storage is the common way of storing data. Bottom-up storage is data-centric. Results obtained via analysis of data may be stored also, but generally only the calculation functions, requests and procedures that enable to obtain results rather than the results themselves are stored. In most cases, results expressed at a self-explanatory level, such as graphs, curves, etc., are included in reports, but not stored in the data base systems. Storing only row data means that data are loosely coupled from a study to another. Data comparisons may be performed, but the understanding of differences or similarities between the data sets is limited (i.e. when comparing the levels of Situation Awareness of pilots between several experiments, the stored data show the variations but do not show directly neither why nor how such variations occurred). Moreover, collected data do not confer stability because they depend on each acquisition situation. Large variations may be observed between studies and the understanding becomes even more complicated without referring to the corresponding reports and reading lots of pages. An improvement is to store also the context (i.e. the conditions and circumstances under which data were obtained) of each study, but this is not enough.

The optimum in the storing process is to store what is generic and stable and that enables to provide a reference for understanding, traceability and reuse. Such top-down storage implies to store the model, cognitive or organizational. Top-down storage is model-driven. Such type of model-driven storage is new and rare in the software market; however an integrated implementation is proposed by Kalido. The model is expressed as meta-data and uses semantic associative relationships. One of the main advantages of this solution is that the conceptual definitions layer is separated from the physical implementations [27], [31]. But the most common means in which models are stored are ontology systems. Relational Data Base Systems (*RDBMS*) do not allow storing such models directly, but ontology systems may be plugged with RDBMS. Furthermore, there is a growing interest to store Multi-Agent

Systems using ontology systems [39]. Thus, in such an IT architecture, the top layer (ontology) contains the model and the lower layer (RDBMS) contains the contextual instances. For example, components of the cognitive model such as the visual agents and resources may be stored in the ontology system, and instances such as the time to detect visual items in a particular visual scene, the moment of occurrence of visual alerts, the scan-paths and visual patterns may be stored in the RDBMS. Using top-down storage enables to structure data in respect with the model and thus encourages not only to store the results but also to link them with the model.

4.2 Unified Storage

An important issue that is faced in organizations is that data is stored then provided by various data sources. In HF, such sources may be technical simulators and human collection methods, both subjective (i.e. forms, rating scales, surveys) and objective (i.e. physiologic devices, various analysis software). The reliable solution to this issue is the Data Warehousing (*DW*) process that uses an Extract-Transform-Load (*ETL*) stage, that enables to feed the DW with unified data, and a data preparation stage of data as Data Marts that are domain specific and user-centered (i.e. Marketing Data Marts, Financial Data Marts, etc.). DW answers cross-organizational issues by providing a single version of the 'truth' or a common reference for the whole organization [3], [24], [35].

4.3 Human Behavior Simulation

4.3.1 Rationale and Benefits

Most of the existing simulators are technical systems or artifact simulators (i.e. flight simulators, drive simulators, calculation simulators). Artificial Intelligence enables at some extent to simulate human behavior, but is mainly based on algorithms, expert systems, heuristics, fuzzy logic, neural networks, etc. that implement rationality.

Taking into account that it is possible to obtain and store real behavior patterns, it would be useful to use these patterns in a dynamic manner. This means to create a hybrid Human Behavior Simulator (*HBS*) based on one hand on the real patterns and on the other hand on Artificial Intelligence (*AI*) features.

The interest in this approach is the hybrid nature of such a HBS, because real human behaviors are combined with IA features that enable to act or play these behavior patterns dynamically. Gestural patterns were already injected into technical products (i.e. EyeToy™, Wii™ and iPhone™). From a wider research perspective that includes surveys, observations, experiments, data analysis and interpretation it would be useful to reuse static data (i.e. observed behaviors recorded on video tapes, proprietary analysis software patterns expressed as diagrams or trees, etc.) in a dynamic way. A first benefit would be to inject new patterns into new products, or to make a better use of the obtained patterns. But a step beyond would be an important contribution to prediction. Let's imagine that in the current configuration (the given technical system, the given task and procedure) specific behavior patterns were obtained. Now, in case of changes of the current configuration (that is possible to simulate via the technical simulators) what would be the behavior patterns? Without a HBS, lots of experiments or new sets of observations or surveys would be necessary. With a HBS, the possible user behavior patterns could be predicted via simulation. An HBS would improve and speed-up the HCD iterations. Furthermore, in terms of possible configurations, simulation on both technical and human sides would lead not only to prediction, but also to optimization and socio-technical co-adaptability.

4.3.2 Translating the Behavior Patterns into Agent Oriented Programming Language

The Belief Desire Intention (*BDI*) model of Multi Agent Systems (*MAS*) is inspired by a model of human behavior [6], [19]. Beyond the overall descriptive formalism itself, BDI proposes AgentSpeak(L) [26] that is a pure Agent Oriented Programming (*AOP*) language, in contrast with other efforts that implement AOP principles using Object Oriented Programming (*OOP*) languages.

Taking into account the origins of BDI, it seems natural to translate human behavior patterns into BDI AOP. AOP confers the advantage to use an understandable way to deal with large and complex systems and implement parallel processes, being suitable for process modeling. Furthermore, BDI AOP enables to preserve the links between behavior patterns and essential entities of their context of occurrence, such as active goals, triggering events, procedures and scenarios, organizational relationships. BDI AOP provides also a programming structure in terms of perception, situation assessment, belief selection, communication. The reasoning cycles that are the core interpreter of BDI AOP provide a powerful support for Decision Making modeling and implementation.

From a conceptual IT architecture perspective, it is important to emphasize that AOP enables to ensure a continuity between the model and its' implementation.

Translating behavior patterns into AOP would improve data usability and would change data nature by replacing 'static' data (diagrams, graphs) with dynamic results expressed as chunks of executable code. This would not only enrich the sources of information (i.e. interoperable format of results [3]) but would improve the final reporting by providing animated views of information instead of static bar-charts, graphs, cubes, etc.

5 Discussion

The Human Centered Design approach became central in other domains than Human Factors (*HF*) where it mainly originated and was developed. Behavioral economics, behavioral finance and more widely economics started to use human-centric methods. Beyond methods, HF may bring to these domains their expertise in socio-technical systems. In return, HF should take a better advantage of organizational means, from project sponsoring to a better integration of HF in organizations in general and in the organizational IT systems in particular. HF may create their own dedicated module in industry solutions as such modules were created for other organizational departments considered as important (i.e. Accountancy, Human Resources Management, Production, Maintenance, Marketing & Sales, etc.).

The techniques and methods described in this paper aim to an improved formalism, storage, assessment, understanding, prediction and co-adaptation of socio-technical systems, the central concept being behavior patterns. They may also contribute to improve existing solutions for the whole organization in general, or specify and implement an integrated HF technical and functional module in particular.

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