J. Pokojski et al. (Eds.)

doi:10.3233/ATDE200076

Transdisciplinary Assessment Matrix to Design Human-Machine Interaction

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Abstract. Successful interaction with complex systems is based on the system ability to satisfy the user needs during interaction tasks, mainly related to performances, physical comfort, usability, accessibility, visibility, and mental workload. However, the "real" user experience (UX) is hidden and usually difficult to detect. The paper proposes a Transdisciplinary Assessment Matrix (TAS) based on collection of physiological, postural and visibility data during interaction analysis, and calculation of a consolidated User eXperience Index (UXI). Physiological data are based on heart rate parameters and eye pupil dilation parameters; postural data consists of analysis of main anthropometrical parameters; and interaction data from the system CAN-bus. Such a method can be adopted to assess interaction on field, during real task execution, or within simulated environments. It has been applied to a simulated case study focusing on agricultural machinery control systems, involving users with a different level of expertise. Results showed that TAS is able to validly objectify UX and can be used for industrial cases.

Keywords. Human-centered design, User eXperience (UX), Ergonomics, Human Factors, Workload

Introduction

Design of complex systems has to take into account numerous requirements, merging both technical and social aspects, according to a typically transdisciplinary approach [1]: from engineering issue like functionality and performance, to user requirements, business aspects, until government regulations. Indeed, systems has to work properly, but also satisfy the users' needs during their use. The introduction of ergonomics or human factors (HF) in engineering purposely aims at considering both technical and social issues in the development of complex systems, including the human perspective into engineering design [2]. Indeed, HF is a multidisciplinary science that involves different disciplines (e.g., psychology, anthropometry, biomechanics, anatomy, physiology, psychophysics) all related to the study of the interaction between humans and the surrounding environment. HF suggests to start from the study of the characteristics, capabilities and limits of the user, and applies it to the design of a system

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as well as to the evaluation of the human-machine interaction. This approach is fundamental to guarantee the best possible interaction with the user.

This research focuses on the design of tractor cabins. The cabin, indeed, represents the main workspace but also the central interface between the user and the machine, where the interaction happens. In particular, modern machines have rapidly evolved in the last ten years, in terms of technologies on board, and nowadays traditional means (e.g., leverages, buttons) coexist with novel technologies (e.g., touch screens, multi-functional armrests) [3]. New technologies have been frequently added to traditional tools with the aim to improve user comfort and task efficiency, and reducing the physical workload. However, only in few cases there was a clear planning about how the new interaction is taking place, and how is the generated user experience (UX). In fact, working with these new types of machinery involves a bigger mental workload, requiring an extensive expertise and greatly modifying the final UX with respect to older systems. As a result, in some cases new devices included on-board are not used properly in practice by users, or even risk to complicate the human-machine interaction.

The paper presents a transdisciplinary method based on collection of physiological, postural and interaction data for the analysis of the human-machine interaction. Such a method has been defined transdisciplinary as it includes both technical and social aspects and certainly involves people from practice. Technical science concerns with the design of machines, interfaces and information system. Social science assists in identifying the needs of users in order design usable and useful interfaces and interaction systems [4]. About the societal impact, the presented methodology could enhance the quality of products, helping engineers and designers in detecting possible issues in advance and including human factors along the design process.

1. Research Background

Ergonomics and HF aim at assuring the human comfort and safety, and consequently improving the work performance. Indeed, there are many factors both physical and cognitive, that affect the users' performance and the quality of human-machine interaction: from physical workload, due to uncomfortable postures, to task complexity, overload of information, or time pressure [5]. Moreover, the response to same stimuli is not equal among different users, since every user will reply according to his/her own capabilities. UX is based on the personal perceptions and responses that result from the use or anticipated use of a product, system or service", including users' emotions, beliefs, preferences, perceptions, physical and psychological responses, behaviours and accomplishments that occur before, during and after use [6]. It can be stated that UX during human-machine interaction can be analysed by a set of objective parameters, referring to the three above-mentioned aspects. For instance, measuring the user's physiological response allows creating knowledge about how he/she is interacting with an industrial machine / system thanks to objective data. Such knowledge can be used to design human-centred, ergonomic, and more usable systems. Moreover, the analysis of the postures assumed during the interaction can express the level of physical comfort. Finally, interaction data are crucial for the UX analysis during interaction with control and management systems, like dashboards, cockpits or joysticks.

According to the scientific literature review, the most reliable set of physiological parameters to be used to measure the UX are: heart rate (HR) defined as the number of heart beats per minute, heart rate variability (HRV) defined as the temporal variation between sequences of consecutive heart beats), pupil dilatation (PD) and eye blinks. Heart monitoring is one of the most common methods used especially in medical and fitness contexts. Nowadays, HR and HRV measuring is quite simple and cheap thanks to low cost wearable sensors. Previous researches showed the correlation between HR and HRV with the physical and mental workload [8]. In addition, pupillometry and electrooculography are nowadays widely diffused, due to the increased performance of eye-trackers, the improved ergonomics of devices (e.g., glasses) and the gradual cost reduction. The most frequently parameter used is the PD, which provide information on the individual's attention source and stress [9] [10]. It has been found that PD changes under stress situations and can be measured by the dilation mean value. Also, the increase of the eye blink frequency and latency, that can be deduced together with PD analysis using an eye-tracker, can highlight an increase in the human workload [11]. Eye-tracker analysis allows also to investigate visibility: eye movements data can be also used to map the visual interaction into two main modalities: gaze fixation data are then analysed to visualize the so-called gaze plot, and a heat maps to show the most visualized areas. Gaze plot indicates the attention span of each visualization and a corresponding time series, whereas heat map shows the frequency of each gaze.

As far as the postural comfort is concerned, there are several well-known methods. They are mainly based on user observation and analysis of anthropometrical data and joint angles. For instance, the National Institute of Occupational Safety and Health (NIOSH) allows measuring the user parameters relating to the level of musculoskeletal comfort considering also the intensity, frequency, and duration of the particular task [12]. There are also specific methods, to be used according to the specific context of use and type of tasks: Ovako Working posture Analysis System (OWAS) [13], Rapid Upper Limb Assessment (RULA) [14], Rapid Entire Body Assessment (REBA) [15], or the most recent Workplace Ergonomic Risk Assessment (WERA) [16]. More generally, single joint angles of the diverse body parts can be analysed and compared with a set of pre-defined comfort angles, according to the Dreyfuss 3D study [17]. Such comfort values have been defined from a variety of sources, from academic and NASA studies, to evaluate the range of comfortable bending of every joint for a user driving a machine in a determined position.

Finally, interaction with controls is objectify by the system Controller Area Network (CAN-bus). This is the vehicle bus standard designed to allow microcontrollers and devices to communicate with each other's' applications without a host computer. For each device, the data in a frame is transmitted sequentially but in such a way that if more than one device transmits at the same time the highest priority device is able to continue while the others back off. Frames are received by all devices, including by the transmitting device. CAN data has been recently used for UX testing [18].

In addition, the user comfort can also be assessed considering the subjective impression. Subjected judgement is an important aspect in UX, due to the individual nature of the outcome to be analysed. For these purposes, self-reported questionnaires are frequently used before and after task execution with two different purposes. Pre-questionnaires aim at providing an ex-ante evaluation of the users' habits and interaction style, in order to create a baseline to properly interpret the analysis of data collected during task execution. Post-questionnaires aim at self-reporting the level of comfort and stress in order to rate the perceived workload in order to properly assess the given performance.

For this study, focusing on tractor cabin design where one of the main activities is driving, two types of pre-assessment questionnaires have been selected from literature:

DSQ (Driving Style Questionnaire) and LCB (Locus of Control of Behavior scale). DSQ is a psychological questionnaire for the evaluation of the users' driving style [19]. It deals with a self-assessment 15-item questionnaire that uses a six-value scale for the identification of the user's driving profile. LCB has been defined as the degree to which an individual can perceive a causal relationship between his own behaviour or actions and ultimate consequences or reward [20]. LCB questionnaire is a 17-item Likert-type scale to measure the extent to which a person perceives events as a consequence of his own behavior and believes that they are potentially under personal control (internal locus of control), or instead that events are determined by fate or outside forces that are beyond his own personal (external locus of control). In this study, LCB allows having information on the degree of participation of the user in his vehicle and task execution, in order to better interpret their feedback, actions and reactions. About post-questionnaire, NASA-TLX (Task Load Index) is widely used to provide a subjective, multidimensional assessment of the perceived workload [21]. NASA-TXL is applied to a variety of domains, including aviation, healthcare and other complex socio-technical domains.
Nowadays human monitoring is a relevant topic, due to the increasing attention to new technologies for preventing accidents and providing assistance during the driving task (e.g. Advanced Driver Assistance Systems, ADAS). Vehicles are getting ready with biometric low-cost tools, today commonly used in fitness, in order to carry out real check-ups of the driver then the passengers, reporting in real time health problems or inhibiting driving hazards. These systems focused on responding effectively to actions taken by the driver to control the vehicle optimally and safely, but don't concern with the psychological state of the driver [22]. Despite this, many studies demonstrated the correlation between psychological features and physiological characteristics of the driver, so the same tools used in driver health monitoring (e.g., EEG, ECG, GSR, facial recognition) can be used to recognize emotions as demonstrated in several studies [23, 24, 25] and, more broadly, UX. Different protocols for driver emotions assessment have been recently developed to comprehend how they can affect drivers performance [26] but they aren't able to give a feedback for the enhancement of the vehicle. On this topic, a technological set-up has been studied and tested in order to monitor driver's workload in real time, with the final aim to configure and adapt the car interfaces and according to the specific driver's needs [27]. The research novelty is the application of human monitoring tools for human-centered design, testing in an early phase the system ability to quench the user needs. Moreover, this approach could be applied not only for commercial vehicle but for a wide range of vehicles (e.g. buses, tractors).

2. Research Approach

The research approach integrates the analysis of both physical, physiological and interaction parameters in order to objectify the users' experience and the perceived workload. In particular, a general framework for the analysis of the human-machine interaction has been defined, as presented in Fig. 1. The research approach is based on the combination of:

- Physiological data (HR/HVR analysis and PD analysis);
- Postural data (postural analysis by Dreyfuss 3D);
- Interaction data (CAN-bus data analysis about command activation on the machine interface);

- Subjective data about:
  - users' personal data (anamnestic data questionnaire)
  - users' driving style and locus of control (DSQ and LCB pre-questionnaires),
  - perceived workload (NASA-TXL post- questionnaire).

For each task, data are collected before, during and after task execution with the involvement of users, and properly synchronised and correlated in order to have valuable results. Synchronisation of data collected during task execution is basically a time synchronization. Data correlation is firstly based on the Pearson's correlation *r* to quantify the reliability of the data collected, expressing the relationship between two variables. Indeed, the Pearson's correlation does not include cause-effect relations, but only mere relationship between variables, thus allowing to affirm the systematic relationships between two variables, but not to determine reciprocal cause and effect. Such correlation also considers the subjective post-assessments results, on the basis of the baseline created for each user thanks to the pre-questionnaires data.

Finally, the collected data are properly "summed up" considering a weighted factor (0, 3, 9) according to the satisfaction of the pre-defined UX target values, to fill the so-called TAS (Transdisciplinary Assessment Matrix). UX target values are reference targets to judge if the measured parameters can guarantee a positive UX, according to the following scale:

- Green mark = the UX target is guaranteed, good design!
- Yellow mark = the UX target is close; design could be improved to achieve the comfort level until the green mark;
- Red mark = the comfort is compromised, with risk of excessive physical and cognitive workload. Design could be urgently improved.

At the end, the UXI (UX Index) is calculated as the sum of all weighted values collected, in a discrete way, for all the time step. In order to have a continuous time trend of the UXI function, a linear interpolation between the detected points is expected. The result is then compared with the perceived comfort from NASA-TXL.

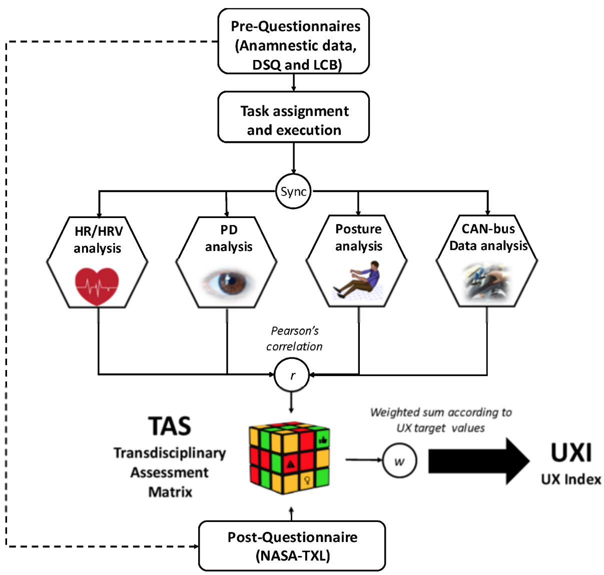

Figure 1. TAS (Transdisciplinary Assessment Matrix) framework for Human-Machine Interaction analysis.

The research approach can be practically adopted by a set of metrics, able to measure the users' conditions and interaction, and tools able to collect the necessary metrics. Table 1 shows the selected metrics and tools used to collect the different type of data, as described in the research framework. In particular, the tools adapted are as follows:

- Physiological data (i.e., HR/HVR analysis and PD analysis) are monitored during tests with users by wearable technologies, respectively Zephyr BioSensor BH3 and Tobii eye-tracking Glass 2;
- Postural data are retrieved by the user's motion capture by a GoPro Hero+ camera, which data are integrated with a human simulation system (Siemens Jack, OPT package) to carry out Dreyfuss 3D postural analysis. A professional motion capture system cannot be used due to difficulties to collect on-field data;
- Interaction data are collected by the machine CAN-bus, which records the specific command activation on the machine interface, and post-processed by CANAnalyzer software toolkit);
- Subjective data about pre-assessment (i.e., users' personal data, driving style and locus of control) and post-assessment (i.e., perceived workload) are carried out by fill in paper-based questionnaires.

Table 1. Metrics and tools for data collection according to the TAS framework

Data	Metrics	Tools
Subjective data	Pre-Questionnaires: - **DSQ** (Driving Style Questionnaire) - **LCB** (Locus of Control of Behavior scale) Post-Questionnaire: - **NASA-TLX**	Paper-based
Physiological data	**HR** (Heart Rate) and **HRV** (Heart Rate Variability): - RR deviation in frequency domain - RR mean value in frequency domain **PD** (Pupil Diameter): - PD mean value in time domain	Biosensor: Zephyr BH3 + OmniSense Eye Tracker: Tobii Glasses 2 + Tobii Pro
Postural data	Angles of comfort: - **Dreyfuss 3D** angles analysis in time domain	Motion capture: GoPro camera + Siemens Jack
Interaction data	**CAN-bus** user input: - no. of clicks / actions - time to find a command	CAN-bus data: Telemaco + CANalyzer

3. Experimental study

The experimental study was developed in the University Lab with the scope to validate the proposed TAS framework for the design of human-machine interaction, to be subsequently applied on tractor's cabins in collaboration with CNH Industrial. The final aim is to define a set of design guidelines to improve the UX of the operators, using their products (tractors). As the study was developed in Lab, a simulated driving activity was asked to users using a mock-up replicating the tractor seats and the main control board. Fig.2 shows the simulation environment in Lab. Fig. 3 shows the experimental set-up adopted for tests with users. Each testing session was structured as follows:

- Pre-questionnaires (5 mins);
- Monitoring tools wearing and tools set-up (3 mins);
- Tools calibration (1 mins);

- Baseline on the mock-up: seating relaxed (2 mins);
- Task execution (5-10 mins);
- Relaxing (1 mins);
- Post-questionnaires (3 mins).

20 users with different level of expertise were involved in the experimental tests. For each user, UX target values were defined during the baseline analysis and checked during the final relating phase. Data collected from all users were analysed and synchronized. Matlab was used for data post-processing and correlation. In particular, the beat-to-beat interval sequence (RRcurve), pupil diameter measures (PD) and Dreyfuss 3D angles data are post-processed. All these parameters have therefore been considered as input of the TAS, that filtered the input signals, associates with each signal certain values based on pre-set thresholds, and produced a continuous comfort function. In order to support TAS, classic assessment tools such as Heat Maps and Gaze Plots of fixations and assessment questionnaires have been added. Moreover, the use of pre- and post-questionnaires were found remarkably useful, as they provide support to correct data interpretation. Indeed, the subjective impressions represented the main criterion to judge the UX target value taken during the baseline.

Figure 2. Simulation environment in Lab: mock-up used during user testing (left) and virtualization (right).

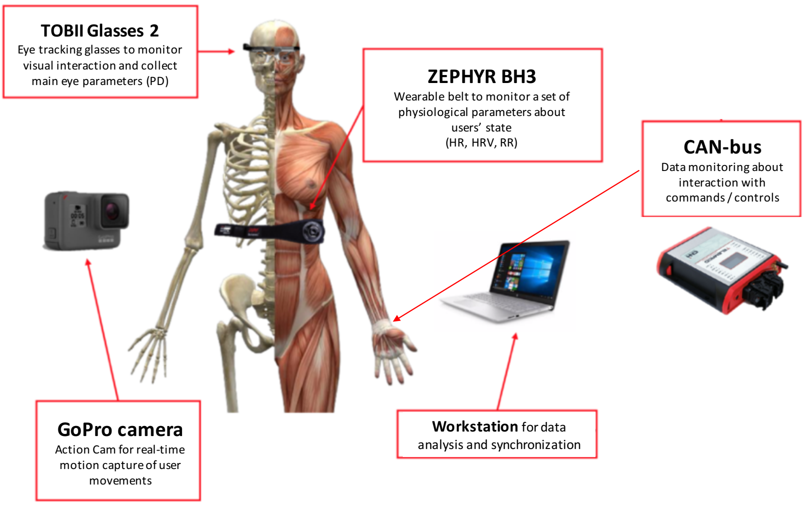

Figure 3. Experimental set-up.

4. Results

Experimental results showed a good correlation between the comfort index obtained by the new approach and the subjective questionnaires. In particular, UXI values on 17 out of 20 users are in line with the evaluation of the perceived comfort in NASA-TLX. The mental workload seems to be higher during specific phases (e.g., during manoeuvres like direction reversal), when users had to interact with various commands. It emerges from the analysis of the beat-to-beat interval sequence (RR curve), turned out to be a fairly reliable metric to assess the mental load (i.e., low values correspond to poor ability to cope with situations stressful). Similarly, pupil diameter (PD) data are used to confirm this state. This feature make understand how commands are used in different situations, from higher psychophysical commitment phases from less critical ones. Contrarily, during the driving phase, the mental effort is lower but users are more stressed from the physical point of view. Indeed, the use of some commands, especially the gear lever forces the drivers in a stressful position, highlighted by the UXI and confirmed by Dreyfuss 3D data (compared to the condition of optimal comfort). Moreover, the use of the CAN-bus helps to recognize commands, levers and buttons that are poorly positioned and that are advisable to move in another location. A further assessment with Heat Maps and Gaze Plot, could aid in detecting commands that are not sufficiently visible. As expected, people with a poor experience in tractor driving showed up a lower mean value of UXI than the more experienced ones, demonstrating a different level of effort in accomplishing the tasks.

5. Conclusions

This paper presented a transdisciplinary methodology to support the design of systems based on a multi-dimensional analysis of different parameters. It allows to have a holistic assessment of the interaction quality and to find out specific correlations between the assessment metrics, such as Heart Rate (HR), Heart Rate Variability (HRV) and pupil diameter (PD), with the use of commands as registered by the system CAN-bus. This approach fuses different branch of knowledge in order to assess the UX, according to a transdisciplinary approach. The combination of human monitoring and ergonomics methods allowed the evaluation of the users' physical comfort and mental effort. Results showed that TAS is able to validly objectify UX and quickly identify system design optimization in terms of interface layout and workstation features. The combined evaluation of mental and physical workload could enhance the quality of product, revealing possible issues. Therefore, TAS could be an interesting tool that provides feedback during the design stage. TAS is ready to be applied to industrial cases.

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