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# Adaptation des interfaces utilisateurs aux émotions

Julian Galindo Losada

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## THÈSE

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Présentée par

**Julián Galindo**

Thèse dirigée par **Sophie DUPUY-CHESSA** et  
co-encadrée par **Eric CERET**

Préparée au sein du **Laboratoire d'Informatique de Grenoble** du  
**Centre de Recherche Inria Grenoble-Rhône-Alpes**, dans l'École  
**Doctorale Mathématiques, Sciences et Technologies de  
l'information, Informatique**

## **UI adaptation by using user emotions**

**Application to GUI personalization by facial  
expression depending on age and gender**

Thèse soutenue publiquement le 14 Juin 2019, devant le jury  
composé de :

**Mme. Sylvie PESTY**

Professeure à l'Université Grenoble Alpes, Président

**M. Jean VANDERDONCKT**

Professeur à l'Université catholique de Louvain (LRIM), Rapporteur

**M. Nicolas SABOURET**

Professeur à l'Université Paris Saclay (LIMSI), Rapporteur

**Mme. Elise LAVOUE**

Professeure associée à l'Université Jean Moulin Lyon 3,  
Examinatrice

**Mme. Nadine MANDRAN**

Ingénieure pour la recherche à l'Université Grenoble Alpes, Invitée

**Mme Sophie DUPUY-CHESSA**

Professeure à l'Université Grenoble Alpes, Directrice de thèse

**M. Eric CERET**

Maître de conférence à l'Université Grenoble Alpes, Co-encadrant  
de thèse





# Abstract

**Keywords:** *User experience, user interface adaptation, face emotion recognition*

User experience (UX) is nowadays recognized as an important quality factor to make systems or software successful in terms of user take-up and frequency of usage. UX depends on dimensions like *emotion*, aesthetics or visual appearance, identification, stimulation, meaning/value or even fun, enjoyment, pleasure, or flow. Among these dimensions, the importance of usability and aesthetics is recognized. So, both of them need to be considered while designing user interfaces (UI).

It raises the question how designers can check UX at runtime and improve it if necessary. To achieve a good UI quality in any context of use (i.e. user, platform and environment), plasticity proposes to adapt UI to the context while preserving user-centered properties. In a similar way, our goal is to preserve or improve UX at runtime, by proposing UI adaptations. Adaptations can concern aesthetics or usability. They can be triggered by the detection of specific emotion, that can express a problem with the UI. Thus the research question addressed in this PhD is how to drive UI adaptation with a model of the user based on emotions and user characteristics (age & gender) to check or improve UX if necessary.

Our approach aims to personalize user interfaces with user emotions at run-time. An architecture, *Perso2U*, “*Personalize to You*”, has been designed to adapt the UI according to emotions and user characteristics (age and gender). *Perso2U* includes three main components: (1) Inferring Engine, (2) Adaptation Engine and (3) Interactive System. First, the inferring engine recognizes the user’s situation and in particular him/her emotions (happiness, anger, disgust, sadness, surprise, fear, contempt) plus neutral which are into Ekman emotion model. Second, after emotion recognition, the best suitable UI structure is chosen and the set of UI parameters (audio, Font-size, Widgets, UI layout, etc.) is computed based on such detected emotions. Third, this computation of a suitable UI structure and parameters allows the UI to execute run-time changes aiming to provide a better UI. Since the emotion recognition is performed cyclically then it allows UI adaptation at run-time.

To go further into the inferring engine examination, we run two experiments about the (1) genericity of the inferring engine and (2) UI influence on detected emotions regarding age and gender. Since this approach relies on emotion recognition tools, we run an experiment to study the similarity of detecting emotions from faces to understand whether this detection is independent from the emotion recognition tool or not. The results confirmed that the emotions detected by the tools provide similar emotion values with a high emotion detection similarity.

As UX depends on user interaction quality factors like aesthetics and usability, and on individual characteristics such as age and gender, we run a second experimental analysis. It tends to show that: (1) UI quality factors (aesthetics and/or usability) influences user emotions differently based on age and gender, (2) the level (high and/or low) of UI quality factors seem to impact emotions differently based on age and gender. From these results, we define thresholds based on age and gender that allow the inferring engine to detect usability and/or aesthetics problems.

# Résumé

*Mots-clés : expérience utilisateur, adaptations des interfaces, reconnaissance des émotions du visage*

L'expérience utilisateur (UX) est aujourd'hui acceptée comme un facteur de qualité important pour le succès des systèmes informatiques ou des logiciels. Elle dépend de dimensions comme l'émotion, l'esthétique, le plaisir ou la confiance. Parmi ces dimensions, l'importance de la facilité d'utilisation et de l'esthétique est reconnue. Ces deux aspects doivent donc être considérés lors de la conception d'interfaces utilisateur. Cela soulève la question de comment les concepteurs peuvent vérifier UX à l'exécution et l'améliorer si nécessaire. Pour obtenir une bonne qualité d'interface utilisateur en tout contexte d'usage (c.-à-d. utilisateur, plate-forme et environnement), la plasticité propose d'adapter l'interface utilisateur au contexte tout en préservant l'utilisabilité. De manière similaire, notre objectif est de préserver ou d'améliorer UX à l'exécution, en proposant des adaptations des interfaces utilisateur aux émotions des utilisateurs. Les adaptations peuvent concerner l'esthétique ou l'utilisabilité. Ainsi la question de recherche abordée dans ce doctorat est comment conduire l'adaptation des interfaces utilisateur avec un modèle de l'utilisateur basé sur les émotions et les caractéristiques de l'utilisateur (âge et sexe).

Notre approche vise à personnaliser les interfaces utilisateurs avec les émotions de l'utilisateur au moment de l'exécution. Une architecture, *Perso2U*, "*Personalize to You*", a été conçue pour adapter les interfaces en fonction de leurs émotions et de leurs âge et sexe. Le Perso2U comprend trois composantes principales : (1) un moteur d'inférence, (2) un moteur d'adaptation et (3) le système interactif. Premièrement, le moteur d'inférence reconnaît la situation de l'utilisateur et en particulier ses émotions (joie, colère, dégoût, tristesse, surprise, peur, mépris) qui sont dans le modèle d'émotion Ekman plus l'émotion neutre. Deuxièmement, après l'inférence sur les émotions, la structure d'interface la mieux adaptée est sélectionnée et l'ensemble des paramètres de l'interface utilisateur (audio, taille de la police, Widgets, disposition de l'interface utilisateur, etc.) est calculé en fonction de ces émotions détectées. Troisièmement, ce calcul d'une structure d'interface utilisateur et de paramètres appropriés permet à l'interface utilisateur d'exécuter des changements à l'exécution visant à fournir une meilleure interface utilisateur. Puisque la reconnaissance des émotions est exécutée cycliquement, alors il est possible d'adapter les interfaces utilisateur à l'exécution.

Puisque cette approche repose sur des outils de reconnaissance des émotions, nous avons mené une expérience pour étudier la similitude de la détection des émotions des visages à partir d'outils existants afin de comprendre si cette détection est indépendante de l'outil de reconnaissance des émotions ou non. Les résultats ont confirmé que les émotions détectées par les outils fournissent des valeurs émotionnelles similaires. Comme l'UX dépend de facteurs de qualité de l'interaction utilisateur comme l'esthétique et la facilité d'utilisation, et de caractéristiques individuelles telles que l'âge et le sexe, nous avons effectué une deuxième analyse expérimentale. Elle tend à montrer que : (1) les facteurs de qualité de l'interface utilisateur (esthétique et/ou utilisabilité) influencent les émotions de l'utilisateur en fonction de l'âge et du sexe, (2) le niveau (élevé et/ou faible) des facteurs de qualité de l'interface utilisateur semblent avoir une incidence différente sur les émotions selon l'âge et le sexe. À partir de ces résultats, nous définissons des seuils en

fonction de l'âge et du sexe qui permettent au moteur d'inférence de détecter les problèmes d'utilisabilité et/ou d'esthétique.

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*“It is not enough that we build products that function, that are understandable and usable, we also need to build products that bring joy and excitement, pleasure and fun, and, yes, beauty to people’s lives.” – Don Norman (Norman, 2004a)*

**1.1 User Experience**

User Experience (UX) stands for the “person's perceptions and responses resulting from the use and/or anticipated use of a product, system or service” (DIS, 2009). It is nowadays recognized as an important quality factor to make systems or software successful in terms of user take-up and frequency of usage (Winckler, Bach, & Bernhaupt, 2013). According to (Bernhaupt, 2010), UX depends on dimensions like *emotion*, aesthetics or visual appearance, identification, stimulation, meaning/value or even fun, enjoyment, pleasure, or flow. Among these dimensions, the importance of usability and aesthetics is recognized (De Angeli, Sutcliffe, & Hartmann, 2006; Tractinsky, Katz, & Ikar, 2000; Tuch, Roth, Hornbæk, Opwis, & Bargas-Avila, 2012). For instance, the aesthetical quality of elements such as shape, text and color has been shown to influence user’s attitudes and determines the success and credibility of an interface (De Angeli et al., 2006; Robins & Holmes, 2008). Interestingly, the User Interface aesthetics is a sub part of usability as stated by the software product quality (ISO, 2011). Similarly, a low degree of usability can cause a negative UX by producing discouragement, dissatisfaction and distrust when using a UI (Flavián, Guinaliú, & Gurrea, 2006). So, both of them need to be considered while designing user interfaces (UI) (Galitz, 2007; Stone, Jarrett, Woodroffe, & Minocha, 2005).

Aesthetics involves the philosophical study of two elements: beauty and taste (merriam-webster, 2006). The term comes from the Greek word “aisthetikos,” which stands for “of sense perception,” and is related to the study of sensory values. Particularly, they include the study of subjective and sensori-emotional values seen as judgments of sentimental taste (Anteneh & Wubshete, 2014). In a design perspective, the visual attractiveness of a product is a matter of aesthetics (Van der Heijden, 2003). Studies have proven that creating good aesthetics in a product leads to better usability and user experience (Tractinsky, 1997) (Chawda, Craft, Cairns, Heesch, & Rüger, 2005). Regarding user experience and interaction design, aesthetics plays an important role as it impacts the UX of a product in different manners (interaction-design, 2015a). First, as humans are influenced by beautiful things then it creates an attractiveness bias. In fact, users make a quick decision on whether or not to continue with the interaction of a website where the first impression is crucial: “You have 50 milliseconds to make a good first impression” (Lindgaard, Fernandes, Dudek, & Brown, 2006). The majority of that impression depends on the

aesthetic appeal of the design. Second, users are more tolerant of usability issues when a good aesthetics is present (Moran, 2017). As argued by (Norman, 2004b), visually appealing websites are assessed as more usable than they really are, since their attractiveness causes pleasant emotions to users.

Furthermore, aesthetics impacts UX. In fact, UX is impacted by “**brand image, presentation, functionality, system performance, interactive behavior and assistive capabilities of the interactive system, the user's internal and physical state resulting from prior experiences, attitudes, skills and personality, and the context of use.**”(DIS, 2009, n. 2) .For instance, (Djamasbi, Siegel, & Tullis, 2010) studied the level of likeness in fifty designs of informative websites by using electronic surveys and eye-tracking. Users watched each individual web page for 10 seconds. Figure 1-1 shows the most liked web designs including their heat map. This visual appeal rating from ninety-eight participants reveals user preferences in aesthetic elements such as main large image and images of celebrities with attractive colors as shown in the third preferred web page (top-right).



A second recognized dimension of User Experience is usability. It denotes to “the ease of access and/or use of a product or website.” (interaction-design, 2015b). According to the official ISO 9241-11 definition, usability stands for “the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use.” (iso, 2018). Normally, usability is measured by designers throughout the development process, it starts from web designs (mockups and prototypes) to the last deliverable. It is assessed in this manner because usability plays an important role to define which design characteristics must be preserved or removed (interaction-design, 2015b).

Furthermore, usability impacts UX regarding perceptual and *emotional* aspects: “Usability, when interpreted from the perspective of the users' personal goals, can include the kind of perceptual and *emotional* aspects typically associated with user experience.” (DIS, 2009, n. 3). From this, several studies have been conducted. For instance, the usability impact regarding user’s trust has

been examined by numerous authors (Benbasat & Wang, 2005; Cheung & Lee, 2006; Flavián et al., 2006; Komiak & Benbasat, 2004; Koufaris & Hampton-Sosa, 2004; Rattanawicha & Esichaikul, 2005). Moreover, website satisfaction as a consequence of web design efficiency can be seen as the overall pleasure in user experience (Fogg, Soohoo, Danielsen, Marable, & Stanford, 2002; Lindgaard & Dudek, 2003; Palmer, 2002).

We can remark that our previous discussions related to UX, aesthetics and usability, include a mention to emotions. UX is closely related to the study of *emotional* responses to Human Computer Interaction (HCI) (Hassenzahl, Diefenbach, & Göritz, 2010; Hassenzahl & Tractinsky, 2006a; Law, Roto, Hassenzahl, Vermeeren, & Kort, 2009; Wright & McCarthy, 2004). In fact, UX includes person responses as “users' *emotions*, beliefs, preferences, perceptions, physical and psychological responses, behaviors and accomplishments that occur before, during and after use” (DIS, 2009, n. 1). For instance, the measure of overall enjoyable user experience has been shown in Games interfaces (Lowry, Gaskin, Twyman, Hammer, & Roberts, 2013). In this case, user experience is measured with many user responses: joy levels, perceived ease of use and usefulness, control, curiosity, intention and immersion.

Moreover, User Experience relies on subjective factors that impact the user's perception of UI quality and depend on user's individual characteristics such as age and gender. In (Cyr & Bonanni, 2005), the level of appreciation of a website has been found as a factor of the user's gender. Age also causes different preferences in website design (Bakaev, Lee, & Cheng, 2007) (Djamasbi et al., 2010). Thus, UX depends on gender and age distinctions among users.

## 1.2 Challenges and research question

Beyond design, it would be interesting to maintain UX at runtime. To achieve a good UI quality in any context of use (i.e. user, platform and environment), plasticity (Gaelle Calvary et al., 2002) proposes to adapt UI to the context while preserving usability. In a similar way, our goal is to preserve or improve UX at runtime (why do we need adaptation?, (Knutov, De Bra, & Pechenizkiy, 2009)), by proposing UI adaptations. Adaptations can concern aesthetics or usability. They can be triggered by the detection of negative emotions, as these emotions can express a problem with the UI. But to categorize emotions as negative, we need to understand what variables impact UX.

So a first challenge is related to understanding UX (Forlizzi & Battarbee, 2004). The large number of UX factors and users' characteristics provides the first difficulty. Thus, as the literature recognizes each of them, we think that the influence of aesthetics and usability needs to be explored depending on the two fundamental distinctions between users, i.e. age and gender. First, we consider aesthetics and usability as UI quality factors for some reasons:

- they can influence UX together (Tuch et al., 2012) or individually (aesthetics (Djamasbi et al., 2010), usability (Flavián et al., 2006)),
- they need to be considered while designing user interfaces (Galitz, 2007; Stone et al., 2005),
- they can be considered in interactive system adaptation (Hudlicka & Mcneese, 2002), (Märtin, Herdin, & Engel, 2017), and

- it is feasible to study the impact of aesthetics and usability in relation to emotions (Lavie & Tractinsky, 2004) (Porat & Tractinsky, 2012).

Second, we are interested in gender and age as user characteristics because: they can influence user experience in terms of web site design (Cyr & Bonanni, 2005) (Bakaev et al., 2007), they can be used to model the user (Heckmann, Schwartz, Brandherm, Schmitz, & von Wilamowitz-Moellendorff, 2005) as key element of the context of use (Gaëlle Calvary et al., 2003), and they can be studied in relation to emotions age (Djamasbi et al., 2010) and gender (Moss, Gunn, & Heller, 2006).

Another difficulty is related to the ability to collect and interpret users' feedbacks. User perception can be collected thanks to explicit (e.g. surveys) and implicit methods (e.g. brain activity sensors) (Mezhoudi, 2013). While explicit approaches may be found intrusive (Middleton, De Roure, & Shadbolt, 2001), tedious (Eyharabide & Amandi, 2012) and inaccurate (Joachims, Granka, Pan, Hembrooke, & Gay, 2017); users' emotions (declared or detected) might be considered for determining the user perception of a system, which in turns represents user's experience (Steunebrink & others, 2010, p. 8).

Interestingly, some authors state that the emotions felt by the user during interaction (Reeves & Nass, 1996) should be taken into account by systems (Carberry & Rosis, 2008) and more specifically by user interfaces (UI) (Nasoz, 2004a). Indeed, emotions are the user's response to aspects of objects, consequences of events and actions of agents (Steunebrink, 2010). Different user emotions were measured with respect to design factors: shapes, textures and color (Kim, Lee, & Choi, 2003), visual features of web pages (Lindgaard et al., 2006) and aesthetics aspects (Michailidou, Harper, & Bechhofer, 2008). Emotions thus have the potential to highlight user experience but their understanding is challenging. Humans seem to be inconsistent in their rational and emotional thinking evidenced by frequent cognitive dissonance (*Cognitive dissonance*, 1999) and misleading emotions (Goldie, 2000). Complexity is then related to the categorization of emotions as negative to be able to trigger UI adaptation. It is even more difficult while considering categorization at runtime.

In terms of UI adaptation, using emotions to trigger UI adaptation is a complex task because an effective adaptation needs mainly three features: (1) emotion recognition (Carberry & Rosis, 2008), (2) adaptation to these emotions and (3) UI actions (Nasoz, 2004a) to deal with dynamic changes in user's emotions. Existing approaches consider a variety of users' elements, such as preferences (Gajos & Weld, 2004), intentions (Horvitz, Breese, Heckerman, Hovel, & Rommelse, 1998), interactions (Hartmann, Schreiber, & Mühlhäuser, 2009)(Krzywicki, Wobcke, & Wong, 2010), interests (Orwant, 1991), physical states (Nack et al., 2007), controlled profiles (Thomas & Krogsaeter, 1993) and clusters (Krulwich, 1997); however, except from (Märting et al., 2017), they do not drive widely UI adaptation by emotions as the main source of modeling and adaptation to the user (Peissner, Häbe, Janssen, & Sellner, 2012).

Overall, these challenges motivate us to go beyond in the understanding of UI adaptation considering user characteristics to check or improve UX if necessary.

The research question addressed in this PhD is:

*“How to drive UI adaptation with a model of the user based on emotions and user characteristics (age & gender) to check or improve UX if necessary?”.*

### 1.3 Approach

To answer this question, we propose an architecture, *Perso2U*, for adapting the UI regarding with emotions and user characteristics (age and gender).

Our goal is to preserve or improve UX at runtime (why do we need adaptation?, (Knutov et al., 2009)), by proposing UI adaptations thanks to emotions. Adaptations can concern aesthetics or usability. They can be triggered by the detection of specific inferred emotion, that can express a problem with the UI. Thus, our work focus on adaptivity in which “a system adapts automatically to its users according to changing conditions” (Oppermann, 2005). In this context, the system aims to adapt the GUI (Graphical User Interface) automatically to its users (emotions, age and gender) according to changing conditions of the context of use (user, platform and environment).

To go further, one central component in this architecture is the inferring engine which is in charge of interpreting emotions to trigger UI adaptation when required. Hence, we explored deeply the inferring engine examination. We run one experiment with three analyses: (1) the genericity of the inferring engine from facial emotion detection tools and (2) the UI quality influence on detected emotions regarding age and gender, and (3) how to use such emotions to trigger UI adaptation.

Overall, our contributions harmonize a (1) literature review about interactive system adaptation based on emotions and UX (Aesthetics/Usability, age and gender), (2) the design of an architecture for UI adaptation with an inferring engine for interpreting emotions (Galindo, Céret, & Dupuy-Chessa, 2017a) (Galindo, Dupuy-Chessa, & Céret, 2017b), (3) the study of the UI influence depending on user characteristics (age and gender) and UI quality factors (aesthetics/usability) (Galindo, Mandran, Dupuy-Chessa, & Céret, 2019), and (4) the exploration of how to use such influence to trigger UI adaptation (Galindo, Dupuy-Chessa, Céret, & Mandran, 2018).

### 1.4 Outline of the thesis

This thesis includes seven chapters underlined below.

- **Chapter 2** presents the theoretical background of our work. It provides the key definitions to understand User Experience through emotions. It introduces the background knowledge related to emotions followed by how emotions can be detected automatically by emotion recognition tools.
- **Chapter 3** describes a list of approaches to study UI adaptation and User experience regarding emotions. It is divided in two main axes: (1) UI adaptation approaches, in which the papers related to the use of emotion recognition to drive the adaptation are analyzed and (2) approaches studying UX and each one of its facets (aesthetics/usability,

age/gender). This related work is analyzed with respect to a set of criteria, and the limitations and needs for a new approach are underlined.

- **Chapter 4** introduces our global approach to personalize UIs relying on emotions. With this goal, our designed architecture, *Perso2U*, is shown along with its three components: Inferring Engine, Adaptation Engine and Interactive System. Moreover, the experiment protocol used for all analyses is shown. With this, the first analysis is run to explore the genericity of the inferring engine at detecting emotions. The results confirmed that the emotions detected by the tools provide similar emotion values with a high similarity.
- **Chapter 5** details our second analysis to explore whether the UI influences on detected emotions depending on age and gender and aesthetics or usability aspects. The results tend to show that: (1) UI quality factors (aesthetics and/or usability) influences user emotions differently regarding age and gender, (2) the level (high and/or low) of UI quality factors seem to impact emotions differently based on age and gender.
- **Chapter 6** takes advantage of the previous findings to explore how to preserve or improve UX at runtime, by triggering UI adaptations thanks to emotions. It shows our last analysis to define emotion thresholds based on age and gender that allow the inferring engine to detect usability and/or aesthetics problems. Moreover, it details the implementation and tests of the thresholds and inferring rules into *Perso2U*.
- **Chapter 7** highlights the contributions of the thesis, gives concluding remarks and proposes possible directions for future work.

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This chapter provides an overview of the most important concepts to understand User Experience through emotions. First, it introduces the background knowledge related to emotions. Secondly, it presents how emotions can be automatically detected.

**2.1 What are emotions**

**2.1.1 Affect, Emotions, and Moods**

*Affect*

The definition of **Emotions** is a constant challenge in many disciplines (Scherer, 2005) because various aspects of this concept. Some efforts have been done to have a common agreement in what emotions are by starting with the definition of a core concept, **affect**. It is a generic concept which involves a broad range of feelings that people experience (Hume, 2012, p. 260). Feelings are “mental experiences of body states. They signify physiological need (for example, hunger), tissue injury (for example, pain), optimal function (for example, well-being), threats to the organism (for example, fear or anger) or specific social interactions (for example, compassion, gratitude or love)” (A. Damasio & Carvalho, 2013). This people experience called affect can be in the form of **emotions** or **moods**. Thus, **affect** serves as an umbrella concept that includes both emotions and moods (George, 1996, p. 145).

## *Emotions*

**Emotion** are feelings expressed with intensity which are directed at someone or something (Frijda, 1993, pp. 381–403). They are perceived as “**reactions** to situational events in an individual’s environment that are appraised to be relevant to his/her needs, goals, or concerns” (Zhang, 2013, p. 11). Once activated, emotions generate feelings as brain interpretations of emotions. Then, emotions generate motivational states with action tendencies which arouse the body with energy-mobilizing responses. It means that “emotions are closely and intimately related to action by way of their nature as motivational states” (Frijda, 2004). Finally, the body is prepared for “adapting to whatever situation one faces, and express the quality and intensity of emotionality outwardly and socially to others” (Zhang, 2013, p. 251).

Moreover, since these **reactions** (emotions) are appraised for each individual, they are related to needs, goals and concerns which also depend on user’s individual characteristics (e.g. gender and age) (Gove, 1985; Sanz de Acedo Lizárraga, Sanz de Acedo Baquedano, & Cardelle-Elawar, 2007; Strough, Berg, & Sansone, 1996). Thus, people evaluate emotions in relation to their own situation and intrinsic characteristics.

## *Moods*

**Moods** are feelings which tend to be less intense than emotions with often a lack of contextual stimulus or incentive (Weiss & Cropanzano, 1996, pp. 17–19). Moods are nonintentional as “they are not directed at any object in particular” (Brave & Nass, 2002, p. 56) while emotions are intentional (Frijda, 1994). Hence, this nonintentional experience is more global, general and unclear than the one of emotions. For instance, a person may be sad about something, happy with someone and surprised about some event, all these representing an emotional experience; while generally depressed without a specific link with something which characterizes his/her mood (Brave & Nass, 2002, p. 55,56).

Another key difference between **emotions** and **moods** is related to their application (general/specific) and duration. Emotions are more specific and numerous in nature than moods (Hume, 2012). For instance, nine users emotions can be detected (pleasant, terrible, delighted, frustrated, contented, unhappy, gratified, sad, joyful) while they are interacting with a hotel website (Coursaris, Swierenga, & Pierce, 2010); against more general dimensions in moods such as the positive and negative mood measured by asking users how they feel before assessing users response to an interface (Brave & Nass, 2002, p. 56). In terms of duration, emotions are more short-lived than moods with a time duration of seconds or minutes against hours, days or weeks (Steunebrink, 2010, p. 6).

Although **affect**, **emotions** and **moods** are three terms mostly used interchangeably (Ekkekakis, 2013), it is important in HCI to state clear distinctions among them (Brave & Nass, 2002), particularly to understand that **emotions** are individual responses caused by an specific event, more clear and specific and with a brief duration than moods.

## 2.1.2 Philosophical and Cognitive view

**Emotions** are the essence of what makes us human characterized as *the passions of the soul* (Descartes, 1953). According to Descartes, **emotions** happens in both (1) one's soul and (2) one's body. First, he claimed that *soul* explains people thinking aspect. From this perspective, emotions arise from the cognitive of people regarding the outside world (Steunebrink, 2010, p. 2). For instance, when musicians interact with instruments (e.g. piano, violin and drums) in Music therapy, this causes whether a sense of happiness or relax, improving mood, and reducing anxiety to listeners (International Chiropractic Pediatric Association, 2005). Here, it is not also our thinking which is influenced but also the body may interact by clapping hands while listening to the music.

Emotions impact one's body (e.g. tears of joy) (Steunebrink, 2010, p. 2). *Passion* emphasizes something suffered by a person, the perceptions, sensations or commotions of the soul (Descartes, 1953). For instance, the emotional and body responses of individuals were measured while listening music (pop and rock). It includes the measure of tempo, mode and percussiveness (van der Zwaag, Westerink, & van den Broek, 2011). Therefore, in this perspective of *soul* (one's thinking aspect) and *passion* (one's sufferings), Steunebrink argues that the expression "*the passions of the soul*" clarifies that **emotions** are the things suffered by our **thinking** aspect which are mirrored in our body.

Since people **thinking** is involved, emotions can be seen as a logical structure. The cognitive structure of emotions provides a model to classify 22 types of emotions also known as OCC (Ortony, Clore & Collins) (Ortony, 1990). Mainly, this model considers that human estimate situations within three types of perceptions: 1) as responses to **events**, 2) actions of **agents** or 3) aspect of **objects**. These types of human perceptions are evaluated against goals, standards and attitudes. To clarify this vision, the following paragraphs introduce events, agents and objects with examples in each case.

First, if a user focusses mainly on a consequence of an **event** in the user interface, he can evaluate this consequence as desirable or undesirable with respect to his own goals. To illustrate this case, users who interacts with five different web-poll designs (Cyr, Head, & Ivanov, 2009) had more positive impressions with attractive websites at filling polls that release additional and attractive flash animations in the rating scales when users click on them.

Second, in the case of a user focusing on the action of an **agent** (third party like another person or even an avatar), he can appraise an action as praiseworthy or blameworthy in relation to his own standards (Steunebrink, 2010, p. 19). Let's consider the case of a user interacting with an online shopping assistant (Benbasat & Wang, 2005). If the virtual assistant is perceived by the user as similar in behaviors and personality to him, then it is more positively evaluated by him.

Third, users evaluate a situation based on the aspect of **objects** which can lead to appealingness or unappealingness (Steunebrink, 2010, p. 20). For instance, there was a different impact of the use of human and no-human images in ecommerce websites across different cultures (Cyr, Head, Larios, & Pan, 2009). Particularly, Germans and Canadians perceived a website with no-human

images as functional; whereas Japanese participants had a total negative reaction estimating the website as unfriendly and not affective.

Overall, beyond a philosophical emotions view, the cognitive structure of emotions also known as OCC model provides a logical structure of emotions by defining three types of perceptions of situations: consequences of **events**, actions of **agents** (third party) and aspect of **objects**. Since perceptions are seen as “awareness of the elements of environment through **physical** sensation” (merriam-webster, 2006), we will study deeply the biological side of emotions.

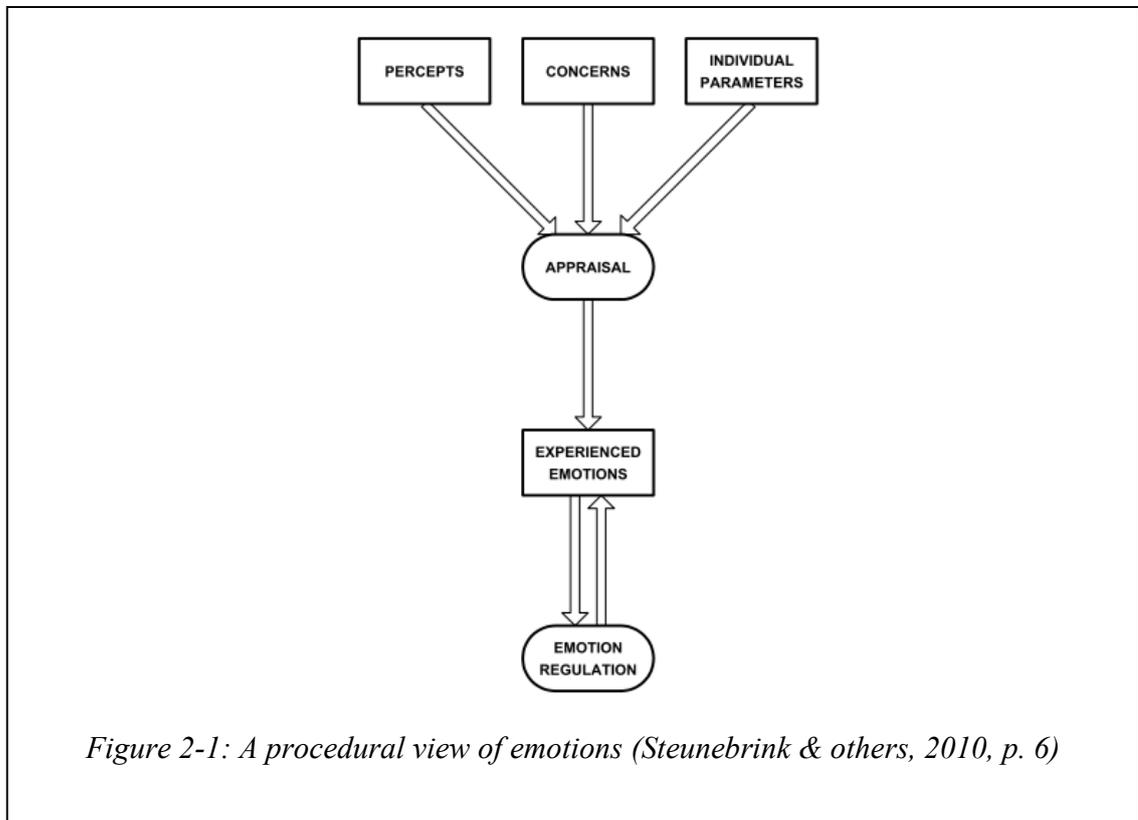
### 2.1.3 Aspects of emotions

There are some other fundamental aspects of emotions that can help us to understand how emotions work such as their biology, sources and representation. We start with the biology aspect.

#### *Biology of emotions*

Another point of view about emotion is given by **biology** and **reactions** to emotional stimuli. Stimuli is conceived as “something that rouses or incites to activity” (merriam-webster, 2006). **Biology** studies where emotions are created from events, actions or objects by understanding how emotion processes are and how the brain works as a vital part of cognition (Hook, 2012). Mainly, these two elements can be explained by the procedural view of emotions (Steunebrink & others, 2010, p. 6) and the neurological structure of emotions (Brave & Nass, 2002, p. 54).

First, a more closely view of how emotion works into the brain can be explored by the procedural view of emotions (Steunebrink & others, 2010, p. 6). It explains the cognitive aspects of emotions which distinguishes three phases: **appraisal**, **experienced emotion** and **emotion regulation** ( Figure 2-1).



First, any perceived situation is *appraised* by individuals according to what they think is important or relevant to their *percepts*, *concerns* and *parameters*. A *percept* signifies anything observed in the environment (event, action or object). *Concerns* involves any representation of personal values such as goals, interests, standards, norms, ideals, or attitudes. *Parameters* stand for “individual response propensities” or the emotional character of a person. They explain that “different individuals with similar concerns in similar situations can still have different emotional reactions” (Steunebrink & others, 2010, p. 7). This appraisal is seen as emotions or reactions to situational events in an individual’s environment relevant to his/her needs, goals, or concerns (Ortony, 1990). For instance, Juliet, who likes receiving presents, receives a necklace from Cristofer (Steunebrink & others, 2010, p. 6). Then, Juliet judges receiving it as desirable and Cristofer action as praiseworthy. As a consequence, the appraisal or evaluation of these actions and its outcome causes gratitude towards Cristofer to be triggered for Juliet. We can remark that there may exist different types of emotions triggered simultaneously by the same situation, which can be seen as conflicting. To illustrate, Juliet may be disappointed at the same time as it was not the design that she prefers.

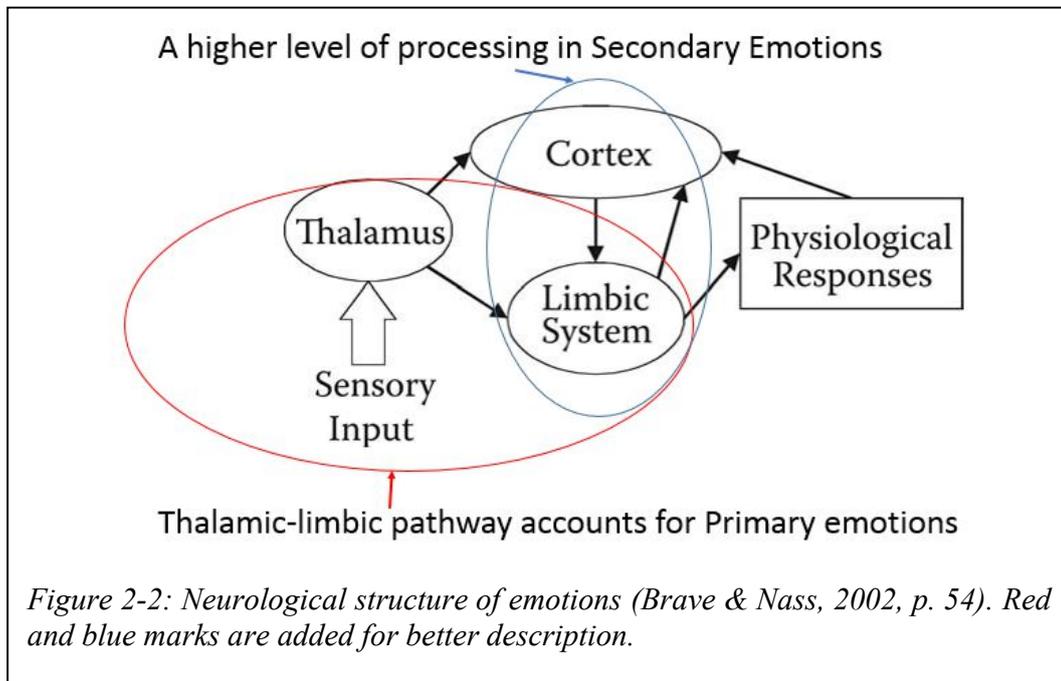
Second, triggered or evoked emotions can be caused by the appraisal of a particular situation (appraisal phase). Once these emotions are activated and strong enough, they create a conscious awareness of emotional feelings which leads to the *experience of emotion*. For instance, Juliet’s gratitude towards Cristofer will have a certain intensity and will probably drop over a certain

amount of time. All this may be influenced by the degree of desirability of getting a necklace and by the previous attitude of Juliet towards Cristofer.

Third, the experienced or evoked emotions need to be *regulated*. To illustrate, Juliet may shape or adapt her behavior in the sense that positive emotions are triggered as often as possible and negative emotions are avoided or covered by positive ones. Consequently, she can use an emotional strategy to be nice to Christopher so that he will give more presents, or in contrast avoiding him to be never again confronted with a bad taste of jewelry. Such behavior is expressed in different body answers such as facial expressions (Pantic & Rothkrantz, 2000), voice tones (Stevens, Charman, & Blair, 2001) or eye movements (Mathews, Fox, Yiend, & Calder, 2003). In fact, (A. R. Damasio, 1994) (Oatley, Keltner, & Jenkins, 2006) argued that the main purpose of emotion is to serve as an exploratory mechanism for selecting behaviors at facing situations. This is a mental phenomenon linked to the context of individuals interacting in an environment (A. R. Damasio, 1994, p. 18).

Thus, the emotion process shows that when people interact in a particular environment they react to situational events expressing emotions. Once these emotions are activated (triggered), it generates emotional responses (such as expressions of happiness, sadness or anger) in an emotion experience process. Then, these emotions arouse the body with energy-mobilizing responses to prepare an individual to adapt to whatever situation evoking different levels of emotions. Emotions which can be regulated to shape behaviors.

In complement with the procedural view of emotions, we can consider their neurological structure by studying how emotions are processed by the brain (Brave & Nass, 2002, p. 54). Figure 2-2 illustrates that this structure harmonizes three main regions of the brain: the *thalamus*, the *limbic system* and the *cortex*. The *thalamus* receives all sensory input from the external environment working as basic signal processor. Then information is sent simultaneously to the *cortex*, for higher-level processing and the *limbic system* (LeDoux, 1995) called also as the set of emotion, which evaluates the need or goal relevance of each of its inputs in a cyclical manner. If this relevance is retrieved, then appropriate signals are sent by the limbic system to both the body and the cortex. The former coordinates the physiological response while the latter impacts attention and other cognitive processes.



Moreover, two types of emotions are underlined in this structure: primary and secondary emotions (Brave & Nass, 2002, p. 55). On the other hand, the direct thalamic-limbic pathway explains the more primitive emotions, such as startle-based fear, and innate aversions and attractions (A. R. Damasio, 1994). In a HCI context, the potential activation of such emotions are performed by on-screen objects and events (Reeves & Nass, 1996). For instance, objects that appear unexpectedly (e.g. pop-up windows or sudden animations) and sharp noises that may trigger startle-based fear (Brave & Nass, 2002, p. 55). On the other hand, secondary emotions require more cognitive processing such as frustration, pride and satisfaction. They result from the limbic system activation being processed in the cortex. Finally, an emotion can result from a combination of both mechanisms: the thalamic-limbic and the cortical-limbic mechanisms. Let's consider that an event causes a fear reaction in first place but then a more extensive rational evaluation can lead to the recognition of a harmless event (i.e. when people realize that the screen flash of their computer suddenly appears blank where it is just the screen saver initiation (Brave & Nass, 2002, p. 55)).

### *Sources of emotions*

There are different **reactions** to emotional stimuli depending on personality, day time, age and gender which can affect emotions (Hume, 2012). We start exploring personality.

## *Personality*

Some emotions and moods experienced are based on *personality* differences (Weiss & Cropanzano, 1996). For instance, some people are often calmer or more relaxed no matter the situation while others feel anger and guilt more readily than others do; in other words, people can develop frequent tendencies to experience certain moods and emotions (Hume, 2012, p. 266).

Furthermore, people that show these tendencies (calm vs. anger) evidence individual differences in the strength with which they experience their emotions (Larsen & Diener, 1987). In fact, while most people may feel a little sad at watching one movie or be mildly pleased at another, someone would cry at a sad movie and laugh a lot at a comedy (Hume, 2012, p. 266). These individuals are described as people being emotional or intense. Hence, emotions differ in their intensity depending on people characteristics and also differ in the level of predisposition to experience emotions intensely.

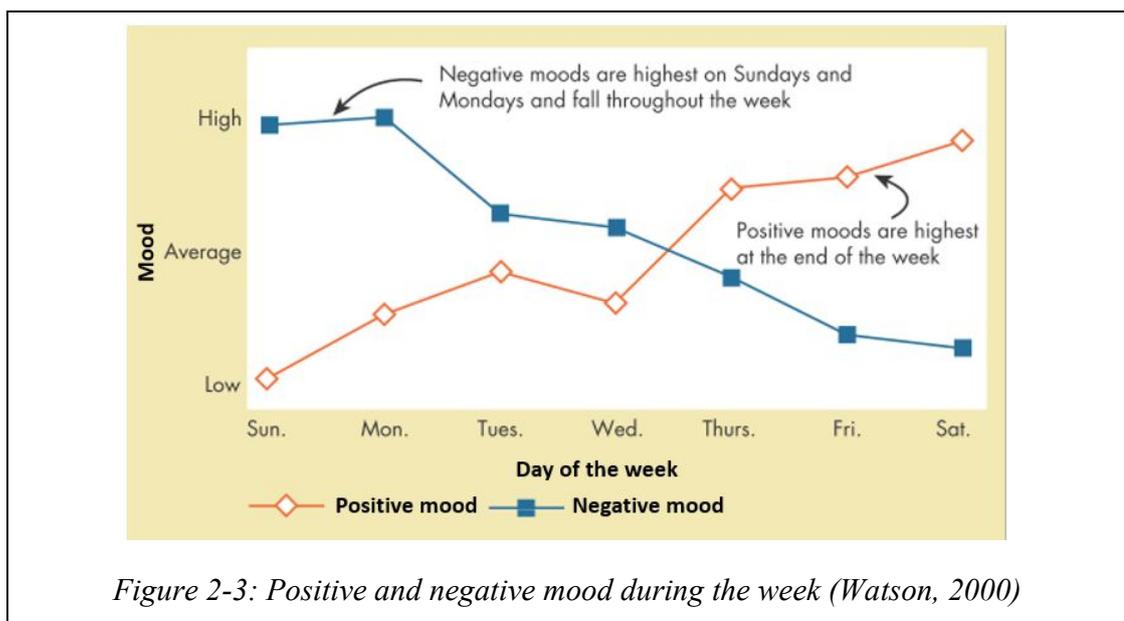


Figure 2-3: Positive and negative mood during the week (Watson, 2000)

## *Timeline*

Another key component to clarify these different reactions is *timeline*. We explore this in moods and then emotions as moods can be seen as repetitive emotional experiences (Brave & Nass, 2002, p. 60). Moods often change based on the *day* of the week and time of the day (Watson, 2000). In fact, people tend to show a highest negative and lowest positive mood early in the week (Figure 2-3). In contrast to a highest positive and lowest negative mood late in the week. As illustrated in Figure 2-3, the positive mood represents a continuous growth with a peak evidenced

at the end of the week (Friday and Saturday). Logically, a complete opposite behavior or tendency is exposed by the negative mood with bigger values reached at the beginning (Sunday and Monday) and lower ones at the end of the week.

In addition, positive and negative moods are related to *time* of the day. As argued by (Hume, 2012), people often follow the same pattern: lower spirits early in the morning but higher ones at night. Thus, during the course of the day, our affect tends to improve and gradually decline in the evening. This pattern is exhibited by Figure 2-4 with the positive and negative mood curve. Interestingly, people tend to evoke higher levels of positive mood in the middle part of the day with no crucial peaks in negative mood. In terms of tendency, the first curve shows a concave up behavior whereas a little fluctuation throughout the day is given by the negative mood one. Thus, positive or negative user reactions vary during the day with specific time instances of intensity more highlighted in the positive mood.

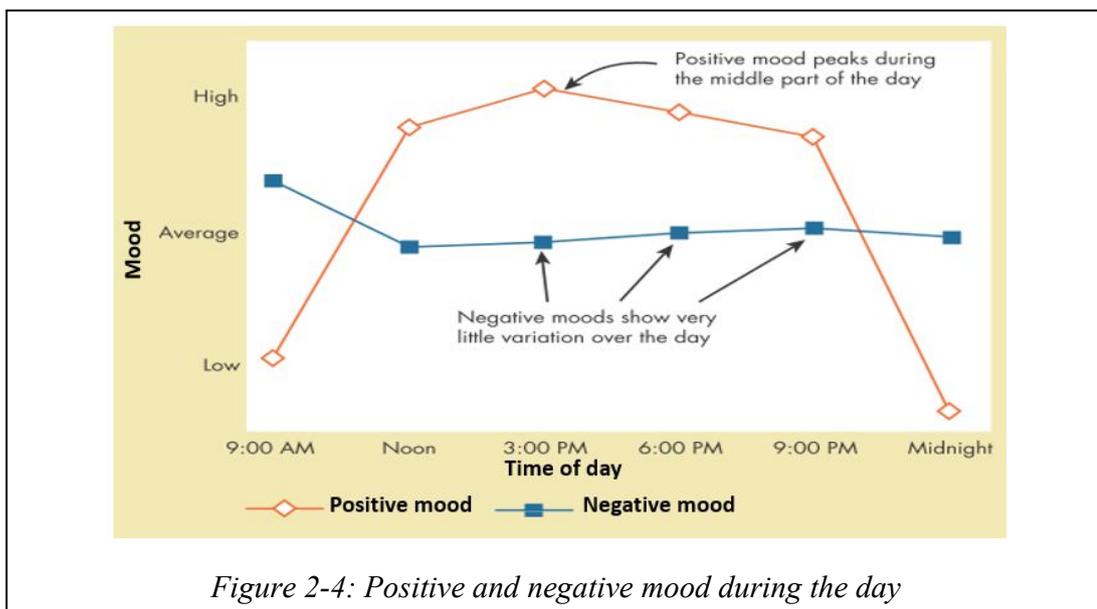


Figure 2-4: Positive and negative mood during the day

These mood distinctions overtime are influenced by *emotions* because intense or repetitive emotional experiences are likely to become themselves into moods (Brave & Nass, 2002, p. 60). Moreover, emotions that have a duration of seconds or minutes can turn into a mood in a gradual process (Steunebrink & others, 2010, p. 6). Brave and Nass explain that a user who is often frustrated will likely be set in a frustrated mood, while a user who is frequently made happy will likely be set in a positive mood. Moreover, the same authors states that mood can also be influenced by anticipated emotion. For example, users may be in a bad mood from the start when they must interact with an application previously associated with a negative emotion like dislike.

### *Age and gender*

We discussed the fact that emotions by definition are related to user characteristics, both of these ones are *age* and *gender*. First, emotional experience tends to improve with *age* so that as people get older, they experience fewer negative emotions as argued by (Hume, 2012, p. 270). In fact, Hume underlines that for people aged between 18 to 94 the frequency of negative emotions is lower as age is increased. Moreover, it is not only about the emotion frequency but also its intensity. For instance, (Diener, Sandvik, & Larsen, 1985) (Larsen & Diener, 1987) argued that there is a pronounced drop between young adult and middle-aged groups in emotional intensity which is mainly caused by biological changes, individual life activities and adaptation or habituation.

There exist also differences in emotional experience based on *gender* at expression emotions particularly in social activities and emotion intensity levels. In the social side, three differences were remarked:

1. women express in a more positive manner their emotions concerning work activities (particularly by smiling) (LaFrance & Banaji, 1992);
2. They better read nonverbal paralinguistic signals (i.e. vocal communication that is distinct to actual language such as tone of voice, loudness and pitch.) (Deutsch, 1990); and
3. They have an inherent ability to read others and evoke their emotions (Hoffman, 1972). A social behavior supported by (Gur, Gunning-Dixon, Bilker, & Gur, 2002) who stated that women have a more active limbic systems (emotions, memories and arousal) evidenced by being more susceptible to depression and engaged with children emotionally.

Thus, the inherent biological distinctions are embodied in how women and men behave in their daily social activities and how they express emotions. Moreover, these expressed emotions are influenced by age as emotions tends to change during time. So, gender and age determine a source of emotion that can be considered as variables that impact emotions.

#### **2.1.4 A basic set of essential emotions**

Even if emotions are expressed differently depending on users, some of them can be considered as universal (Ekman, 1992) (Herbon, Peter, Markert, Van Der Meer, & Voskamp, 2005). In the research community, there have been numerous efforts to limit and define the existing dozens of emotions into a fundamental set of emotions (Shaver, Schwartz, Kirson, & O'connor, 1987). This large quantity of emotions includes happiness, joy, love, pride, anger, disgust, contempt, enthusiasm, fear, frustration, disappointment, embarrassment, disgust, surprise and sadness. As a current debate (Brave & Nass, 2002, p. 61), some researches argue that it is pointless to define a basic group of emotions as universal categories (common to all human) because there are other rarely emotions which have also the potential to impact highly human beings (Solomon, 2002). This is the case of shock (strong emotional response) that can have a powerful effect on people. Despite this exception, the community has built the foundation of emotions in a small group since some measures (e.g. heart rate, blood pressure and skin conductance) have proven reliable at distinguishing among basic emotions (Brave & Nass, 2002, p. 61). This also shows us that there are different points of views for studying emotions (Brave & Nass, 2002, p. 55).

This primary or basic set of building blocks of emotions aims to be recognized by all humans of different cultures (Meudt et al., 2016, p. 4). Contemporary researchers have tried to identify this set by using facial expressions (Ekman, 2007). This approach deals with the complexity of understanding emotions which are not easily represented by facial expressions. For instance, when individuals express fear with their face (Ersche et al., 2015). Furthermore, there exist norms which govern an emotional experience based on culture (Hume, 2012, p. 272). For instance, some Japanese enterprises provide programs to teach people how to contain or even hide their inner feelings into a professional atmosphere (Diaz, 2018).

However, the research community have agreed on a set of six basic emotions also called Universal emotions (Ekman, 1992). These emotions are defined as common or essential emotions to all human. These ones include anger, fear, sadness, happiness, disgust and surprise where most other emotions are subsumed under one of these six categories (Weiss & Cropanzano, 1996, pp. 20–22). For instance, optimism, pride and relief are included into happiness. To remark, contempt was also added posteriorly by Ekman as part of basic emotions (Ekman, 1999). A lack of emotional reaction given by users is known as neutral (Ben-Ze'ev, 2000, p. 94).

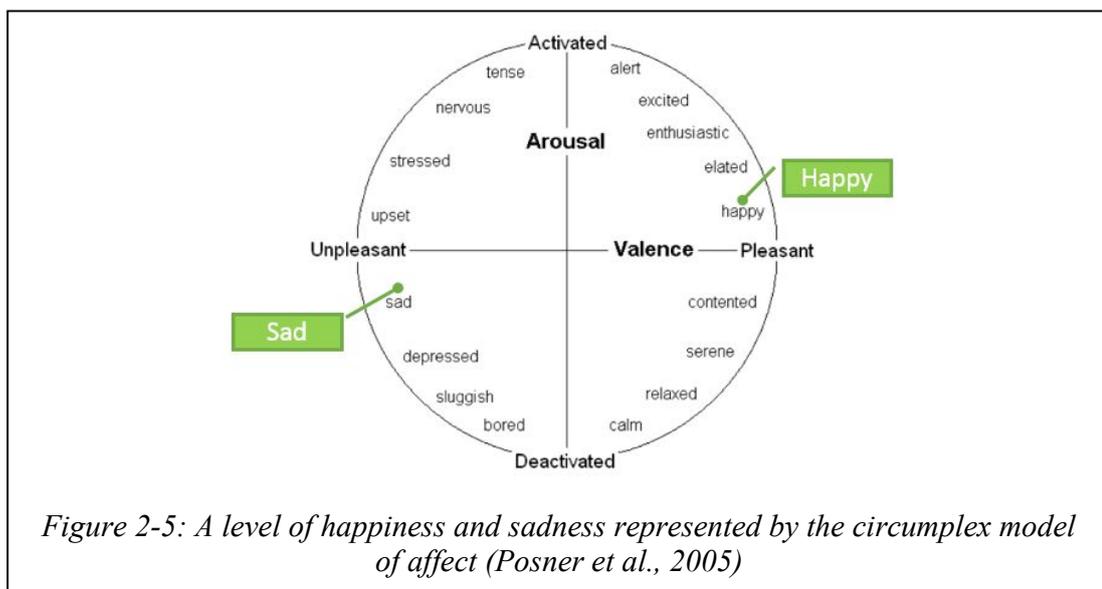
This basic set of emotions can be either positive or negative (Steunebrink, 2010, p. 4). The negative emotions involve anger, fear and sadness and disgust (Steunebrink, 2010, p. 34). while the positive ones only include happiness (Steunebrink, 2010, p. 35). Particularly, there are two special cases: surprise and neutral. Surprise is defined as a completely unexpected occurrence which can be either positive or negative (Steunebrink & others, 2010, p. 119). It means that both pleasant and unpleasant surprise exist as user reactions. Hence, although there are numerous emotions, there is a basic recognized set of emotions including anger, fear, sadness, happiness, disgust and surprise plus neutral.

### **2.1.5 Dimensional emotion model**

For theoretical and practical reasons, the research community defines emotions based on one or more dimensions (Farr, 1983). For instance, the valence dimension to represent whether a user is feeling good or bad (Zhang, 2013). It attempts to conceptualize emotions by defining whether they lie in two or three dimensions by using emotion models. An emotions model is important to group, arrange, represent and analyze user responses in a structured manner. Many different models have been developed to categorize human emotions (Meudt et al., 2016) underlined below.

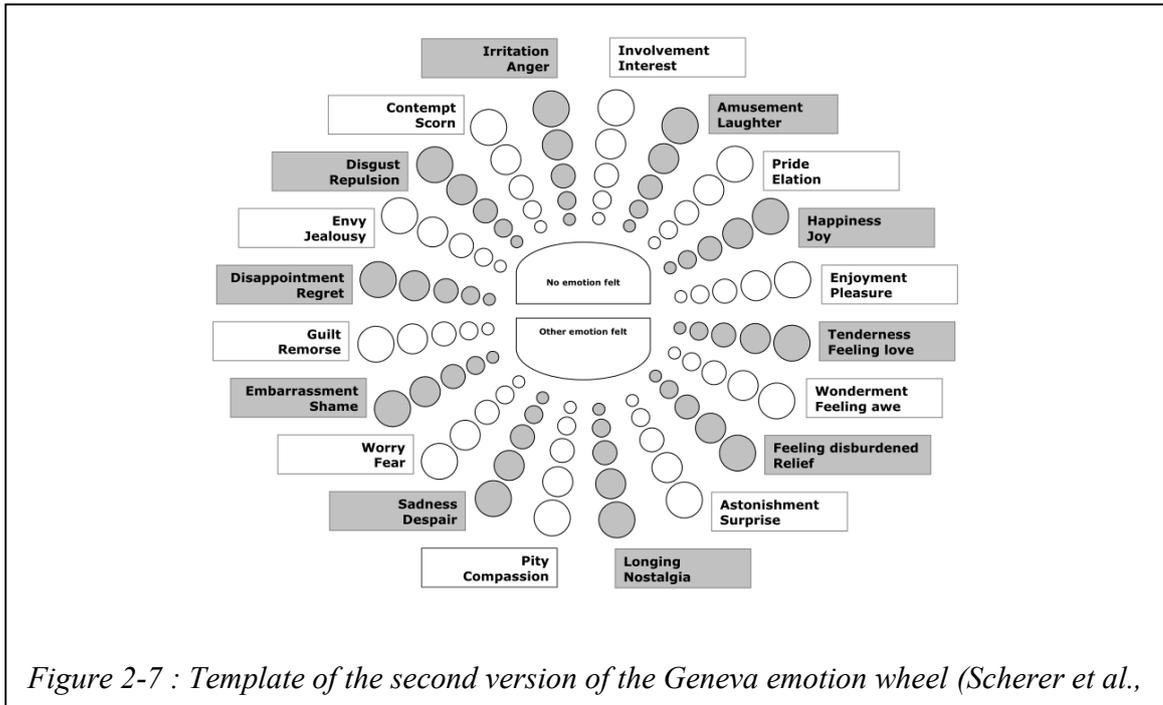
The Circumplex model of affect (Posner, Russell, & Peterson, 2005), a dimensional model with two perpendicular axes: arousal (activation) and valence (pleasant/unpleasant). This model was introduced by (Posner et al., 2005). It represents emotions in a two-dimensional circular space, distributed over **arousal** and **valence** dimensions. **Arousal** represents the vertical axis and **valence** represents the horizontal axis. The vertical one is the extent to which a user is feeling engaged or energized (Russell, 2003) with two intensity limits: active and inactive. While the horizontal axis representing valence is characterized by the extent to which one is generally feeling good or bad (Zhang, 2013) with pleasant and unpleasant limits.

This model is illustrated by Figure 2-5. The arousal is plotted against the valence dimension. There are emotions marked among each dimension limit. For instance, happy is between pleasant (positive side) and activated while sad is into unpleasant (negative side) and deactivated. Thus, the circumplex model of emotions allows researchers to understand the emotion activation (arousal) and the positive or negative response (valence) of users.



The Plutchik's wheel of emotions (Plutchik & Kellerman, 1980) is grounded on the idea of basic emotions (Ekman, 1992) including two more: trust and anticipation. This model is an emotion circle where similar emotions are located together and very different or bipolar emotions on the opposite side (Figure 2-6). It is similar to a color wheel, where the intensities of the different emotions are displayed by color saturation. It is claimed that all other emotions are combinations of these eight primary (Ekman emotions plus trust and anticipation). Figure 2-6 shows the circumplex and opened representation of Plutchik's emotion model. It includes the eight bipolar emotions grouped by their similarity. The color saturation highlights the emotions intensities where the combinations of the basic set of emotions are written in between.





The Self-Assessment Manikin (Bradley & Lang, 1994), which allows integrate persons' experienced emotion very easily in the Valence-Arousal-Dominance space by a self-rating scale. This three-dimensional space includes three continuous axes which allow to arrange emotions in a more flexible subjective manner. Valence and arousal follows the definition used in the Circumplex model of affect. Dominance represents the sense of control or power that the user has of the evaluated situation. Figure 2-8 shows the Self-Assessment Manikin which is used for participants to rate the affective dimensions of valence (top panel), arousal (middle panel), and dominance (bottom panel). The participants can select the manikin in each line aiming to represent best the experienced emotion. Then, the collected values can be transferred in the three-

dimensional space.

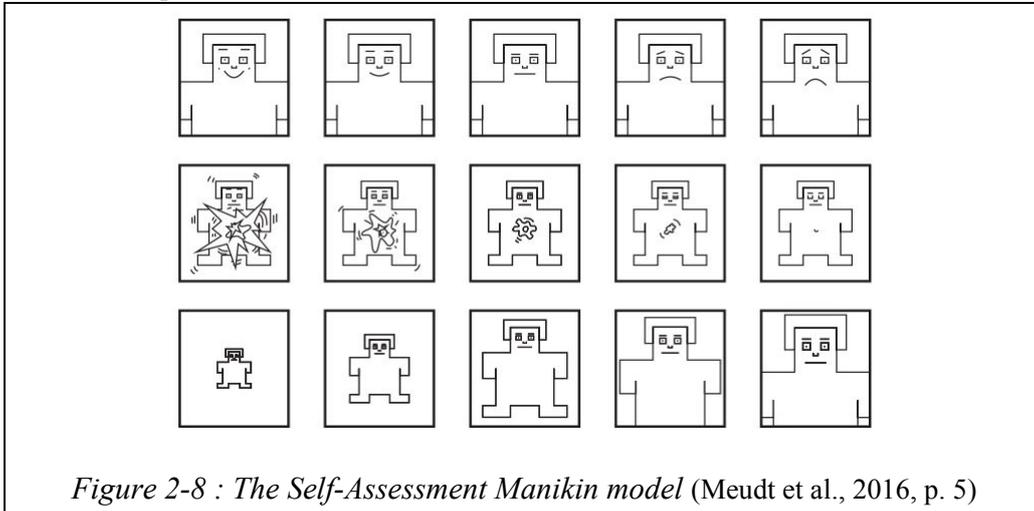


Figure 2-8 : The Self-Assessment Manikin model (Meudt et al., 2016, p. 5)

The Positive Activation & Negative Activation (PANA) model (Watson & Tellegen, 1985) proposes that positive affect and negative affect are two separate systems. It contains these dimensions: positive and negative affect, *engagement* (is characterised by emotions of being quiet or aroused) and also *pleasantness* (is characterised by emotions of being happy or sad). Figure 2-9 shows all dimensions. The vertical axis represents low to high positive affect and the horizontal axis represents low to high negative affect. Engagement and pleasantness are represented in diagonal lines on the positive and negative axes.

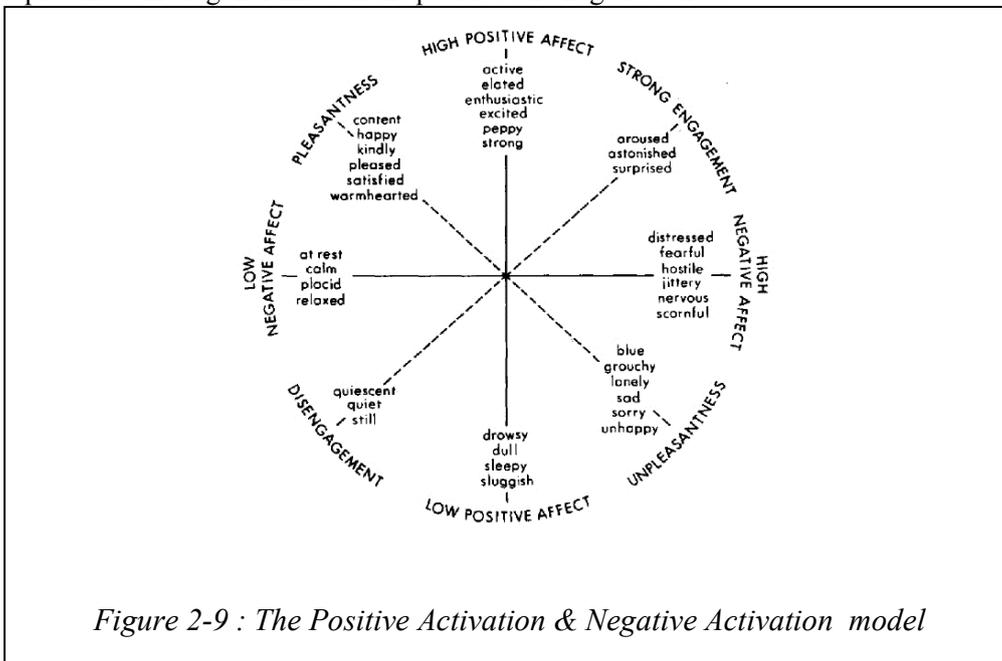


Figure 2-9 : The Positive Activation & Negative Activation model

We decided to focus on one of the most common models (Rubin & Talarico, 2009), the Circumplex model of affect, since the use of its two dimensions: valence and arousal is considered as “nearly sufficient to describe the entire space of conscious emotional experience” in HCI (Brave & Nass, 2002, p. 63). Furthermore, in our case, it provides support for:

1. the basic set of Ekman emotions which are detected by the majority of emotion recognition tools and are defined as common or essential emotions to all human (Ekman, 1992);
2. the motions categorization into pleasant or unpleasant (valence) to help us to discriminate which emotions (user responses) are categorized as positive or negative;
3. the understanding of the activation or deactivation of emotions (arousal) which has the potential to explain the intensity (active/inactive); and
4. the use of emotion recognition in facial expressions (Loijens & Krips, 2008, p. 9) as the studied measure in our work (more details are provided in *section 2.2.2*).

Since these models help us to conceptualize emotions in different manners, we move beyond to know how such emotion values can be gathered by emotion detection.

## **2.2 Emotion detection**

### **2.2.1 Implicit or explicit method**

The characterization of some users’ emotion requires to be able to collect emotions precisely. The emotion detection is based on the collection method of emotions at the interaction. Emotions can be obtained from 2 methods: *implicit (what users do)* or *explicit (what users think they do)* (Redet, Vian, Esposito, & Tijus, 2016). The *explicit* or subjective methods do not evaluate user emotion automatically, they use the interpretation of some emotions given by the user himself or an observer (Redet et al., 2016). The majority are called self-assessment tools as based on the interpretation from the user himself (e.g. The Self-Assessment Manikin (Bradley & Lang, 1994)). This method is characterized by reporting the emotional experience from the users’ point of view (Wallbott & Scherer, 1989).

The *objective* method measures the emotional activity by indicators in an *implicit* manner. These measures can be expressive, behavioral, physiological and neuropsychological with collect the emotion responses without asking the user (e.g. automatic facial analysis).

Many different ways for detecting emotions automatically have been proposed. They can use speech (Cowie et al., 2001, p. 62), vocal expression (Eero, 2016a, p. 19), bio-signals (Guoying, 2016, p. 36) and gestures (Bull, 1987; De Meijer, 1989; Mehrabian, 2017). The most used is based on analysis of facial expressions (Calvo & D’Mello, 2010). These techniques will be developed in the next section with a particular spotlight in *face* as a fundamental mean by which humans recognize emotion (Brave & Nass, 2002, p. 61).

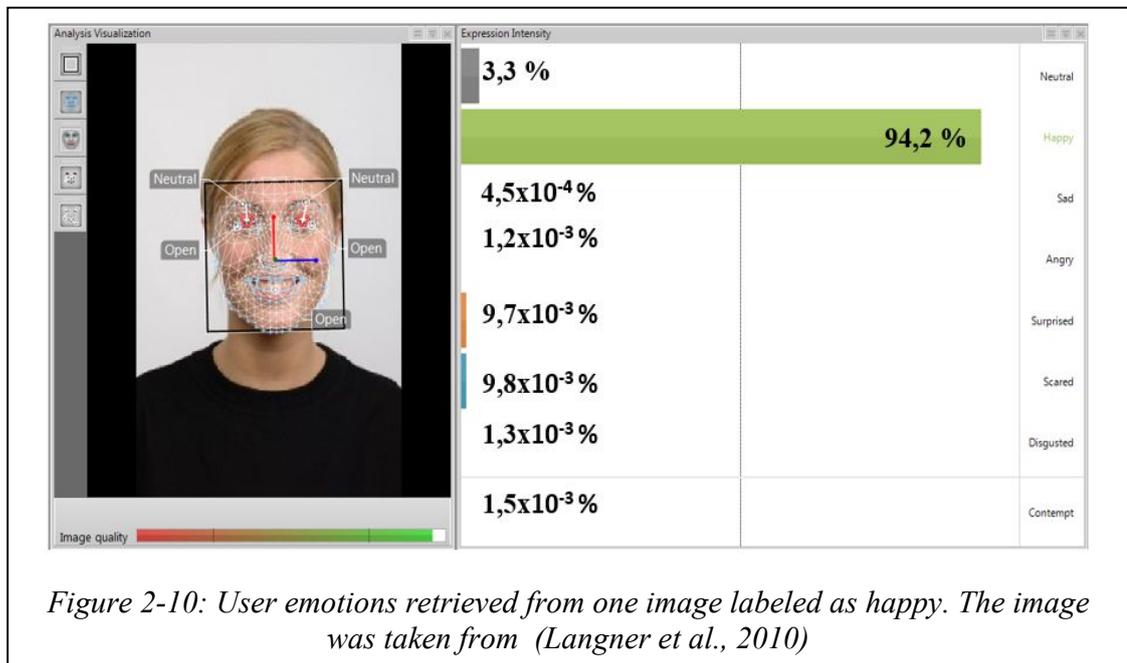
### 2.2.2 Emotion measures

As argued by (Brave & Nass, 2002, p. 60), measuring emotions provides insights into what the user is feeling. In user interface, knowledge about the user emotion, can provide a useful feedback concerning how he achieves his goals in the interface. This knowledge enables different perspectives like the understanding of the user response during interaction to perform a dynamic and intelligent adaptation. Consequently, we explore how to measure emotions by face, speech, biological signals, gestures and text. We start with face as the main mean of communication (Russell & Fernández-Dols, 1997) (Keltner, Ekman, Gonzaga, & Beer, 2003).

#### *Face*

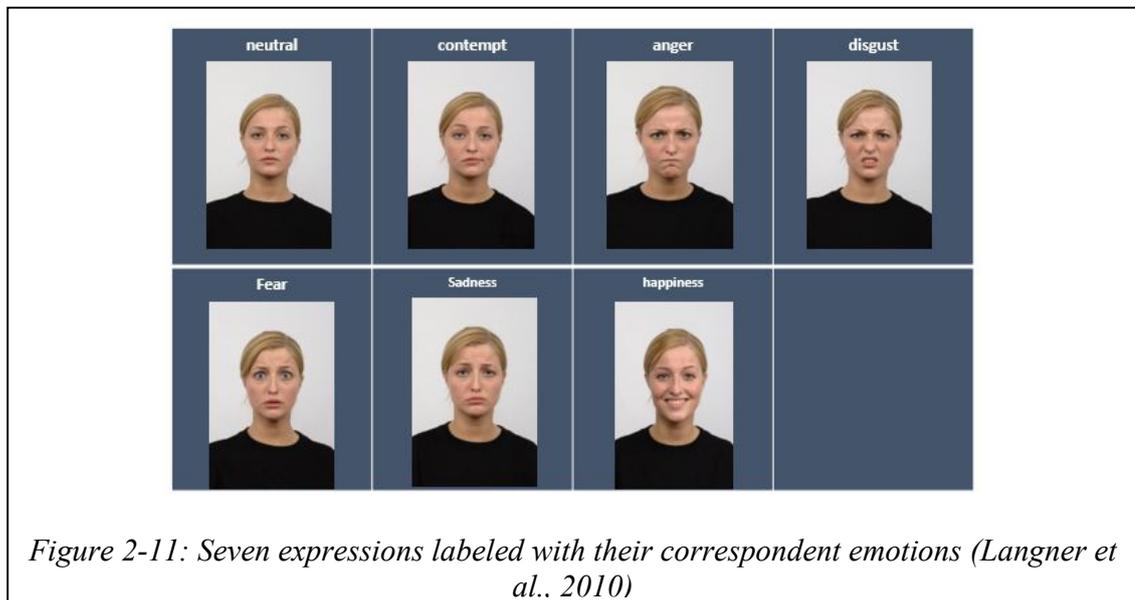
Human face is a direct, natural and dominant mean for communicating emotions (Russell & Fernández-Dols, 1997) (Keltner et al., 2003). Facial expression analysis is known as the most common modality of emotion recognition (Konar & Chakraborty, 2014, p. 3). This recognition of facial expressions involve three steps: (1) the selection of the studied emotions, (2) the facial expression analysis, and (3) the retrieve of numerical emotion values.

To start with the ***emotion selection***, A large research community has focused on basic emotions detection from face (Calvo & D’Mello, 2010). It includes the six basic emotions from Ekman: anger, disgust, fear, joy, sadness, and surprise (Ekman, 1992) plus other added emotions such as contempt (Ekman, 1999) and neutral. These emotions are used by some tools such as FaceReader (Loijens & Krips, 2008), Microsoft Emotion API (Microsoft.com, n.d.) and Affdex SDK (McDuff et al., 2016) to recognize emotions by providing numerical values associated to them. For instance, Figure 2-10 shows the recognition of emotions by analyzing a user image (labeled as happy, 94.2%) extracted from a facial expression databases called Radboud Faces (Langner et al., 2010). The detection was done with FaceReader.



Once the emotions have been selected, *the emotion analysis* involves the observation of subjects’ facial expressions during interaction. While people are experimenting some emotion they trigger a facial expression for a short duration (Calvo & D’Mello, 2010). In consequence, emotions detection can be a matter of analyzing the prototypical facial expression of users during interaction.

One method to measure such facial expressions is called the Facial Action Coding System (FACS) shown by Ekman and Friesen (Friesen & Ekman, 1978). They identify independent motions of the face in a group of action units (AUs). AUs are the fundamental actions of one’s muscles or muscles group (Calvo & D’Mello, 2010). AUs are identified by a number (i.e. AU1, AU2, etc.). If we assumed that “facial expressions are words, AUs are the letters that make up those words” (imotions, 2016). For instance, the following actions units: AU6 (cheek raise), AU25 (lips part) and AU12 (lip corner pull) characterizing the happy facial expression in Figure 2-10. Then, specialized analysts decompose each facial expression into a set of AUs which leads to a classification of facial expressions per emotion, a well-known codification technique in behavioral science. The classification is illustrated by Figure 2-11 where seven expressions were coded to retrieve the correspondent emotions by trained human coders.



Another alternative to measure facial activity is based on coding of video segments. In this technique, specially trained coders may spend approximately one hour for each recording minute to retrieve all emotions from action units (AUs). There are some efforts to detect AUs automatically by video coding (Jiang, Valstar, & Pantic, 2011) (Lucey et al., 2011); however, the recognition accuracy is degraded because the coding system is developed by using static pictures rather than the automatic change of expressions over time.

Once an expression is analyzed either manually (specialists) or automatically (system) releasing a set of categorized emotions (Figure 2-11), each emotion intensity may be also associated with **numerical values** by emotion recognition tools. The accuracy can reach values between 90 and 98% in emotion recognition tools (Brave & Nass, 2002, p. 61). For instance, FaceReader provides emotion intensity values from 0 to 1 by using the Facial Action Coding System with an overall accuracy of 95,61% (Loijens & Krips, 2008, p. 12). Moreover, it is helpful to use the retrieved emotion values as detectors: “while the facial expression or emotion occurs and/or intensifies, the Emotion values rises from 0 (no facial expression) to 100 (facial expression fully present)” (imotions, 2016). Finally, the facial expression most likely represents a highly joyful face with associated numerical values.

Overall, facial expression provides a fundamental resource in which humans communicate emotion and tools recognize them. Measuring face activity involves the analysis of facial expressions to categorize emotions and associate each expression with emotion intensity values. Interestingly, high accuracy levels have been reported in emotion recognition tools at detecting Ekman emotions.

*Text*

Emotion can also be recognized by using Text (Gross, 2013) (Eero, 2016a, p. 19). It involves the detection of text emotional content sourced by written language and transcriptions of oral

communication. People studying emotions through text have identified three dimensions: *evaluation*, *potency* and *activity* (Charles Egerton Osgood, May, Miron, & Miron, 1975), (Charles E. Osgood & Tzeng, 1990). The quantification of how words are pleasant or unpleasant events is addressed by *evaluation*. *Potency* quantifies how a word is linked to an intensity level (strong vs weak) while *activity* refers to whether a word is active or passive.

Many text-based approaches for detecting emotions depend on analyze text using a dictionary-based categorization called linguistic inquiry and word count (Pennebaker, Francis, & Booth, 2001). The main function is to reveal the affective content in the text by identifying precise words. For instance, negative emotions can be recognized by using first person singular pronouns like "I". This pronoun is more frequent in students' essays with high depression scores than those with low depression scores (Chung & Pennebaker, 2007) (Weintraub, 1989).

Three more techniques exist: corpora-based, semantic-analysis, affect-models construction. The first one assumes that subjects with similar languages would have also similar notions for different discrete emotions. For instance, a dictionary which contains emotional terms in English (English lexical database, WordNet) (Miller, Beckwith, Fellbaum, Gross, & Miller, 1990). This database defines terms such as joy, "the emotion of great happiness", or surprise as "a sudden unexpected event" accessible for users by a web browser.

The second one, semantic-analysis, analyzes the meaning of bodies of a text to retrieve their similarity with emotions. For instance, text has been labeled (coded) as expressing fear and joy vs. emotional concept words: "terror" for fear and "paradise" for joy (Gill, French, Gergle, & Oberlander, 2008).

The last technique, affect-models construction, also called sentiment analysis aims to construct emotional models thanks to a large corpora of words knowledge. These models are used to identify affective tones in texts (Liu, Lieberman, & Selker, 2003), e.g. "I lost all my writing as the computer using windows crashed". Here, the word "crashed" is usually related to an undesirable event so that its presence evokes a negative valence of the sentence. Accuracy levels of this technique have been reported from the analysis of the text corpus at comparing three different corpora Wikipedia data, Gutenberg corpus and Wiki-Guten (Agrawal & An, 2012). Particularly, the overall accuracy on detecting Ekman emotions rates from 45 to 57.25% (Agrawal & An, 2012, p. 6).

To summarize, emotion detection of text emotional content is possible thanks to the analysis of written language and transcriptions of oral communication. Three main techniques are identified: corpora-based, semantic-analysis, affect-models construction where a considerable lower detection accuracy than facial expression is reported.

### *Speech*

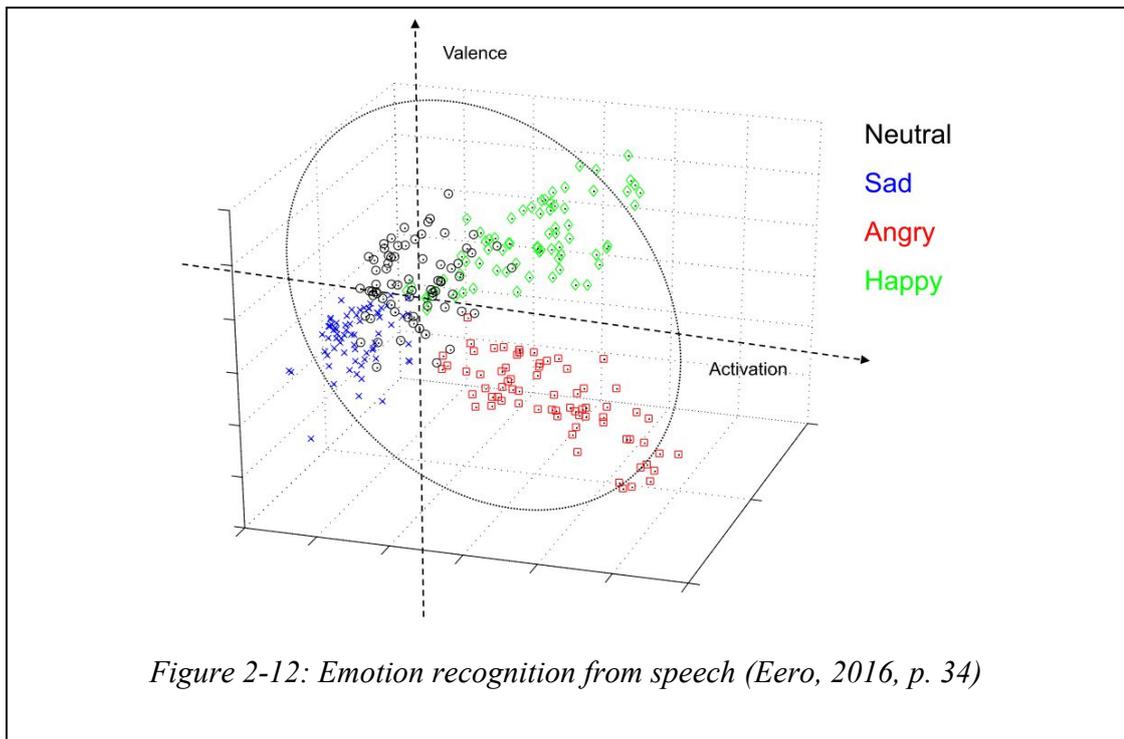
Emotions can also be detected from speech (Cowie et al., 2001, p. 62). This approach relies on the speech transmission by taking into account two elements: *what is said* (explicit linguistic

message) and *how it is said* (implicit paralinguistic features of the expression) (Calvo & D’Mello, 2010).

It involves the use of methods to detect emotion states, mood or stress based on the extraction of vocal cues from speech (Gjoreski, Gjoreski, & Kulakov, n.d.). It relies on the prediction of the speaker emotional state by assuming the existence of objective measurable cues. This assumption underlines that emotional states arouse from physiological reactions which influence the production of user’s speech. To illustrate, a user feeling fear usually expresses physiological activities such as muscle tension, heartbeat, rapid breathing and sweating (Becker-Asano, 2008). As a result, there are changes in the vibration of the vocal cords and how the sound is filtered in the vocal tract. All these vocal features allows the listener to recognize the speaker’s emotion state (Harrigan, Rosenthal, & Scherer, 2008).

In fact, recognition uses four basic speech audio features: fundamental frequency (pitch as human perception of sounds), power, intensity (loudness), duration features and vocal perturbations. The manner of detecting emotions from speech involves generally a five steps process: 1) speech signal input, 2) pre-processing, 3) feature extraction, 4) emotion classification and 5) results of emotions (Pantic, Sebe, Cohn, & Huang, 2005) (Eero, 2016a). First, the audio is captured by using an electronic device (e.g. microphone) usually in an isolated place to avoid noise. Second, there is a signal segmentation to pre-analyze active speech level (energy and frequency measures), voiced and unvoiced features (periodicity) and phonemes (unique set of speech sounds in any given language) (Guoying, 2016, p. 28). Third, acoustic features are extracted such as predictive ones (e.g. Perceptual Linear Predictive coefficients), simple signal measures (e.g. zero-crossings) and prosodic properties to uncover the pitch levels, rhythm or duration, intensity and vocal quality. Fourth, these features are collected in a database and passed through classifiers by using data mining techniques such as linear discriminant analysis, or nonlinear mapping (isomap) to label all instances with the corresponding emotion (Meudt et al., 2016, p. 10). The resulting values have a similar scale than face recognition (from 0 to 1) since they are also based on classifiers but with different reported accuracy from 47 to 93% (Zeng, Pantic, Roisman, & Huang, 2009, p. 49).

Figure 2-12 illustrates the application of a speech technique to recognize basic emotions: neutral, sad, angry and happy. The voices (.wav files) were captured from a user as acted emotions (posed ant not spontaneous voices). It shows the emotions distribution in the valence axis between positive (happy) and negative (sad and angry) emotions with a concentration of neutral along the activation axis.



Overall, vocal communication can be measured to recognize emotions. It is achieved by extracting vocal cues of speech to analyze audio features. The different techniques allow the classification of emotions releasing values in a similar scale to face analysis. Despite this and lower accuracy levels than face analysis, this measure requires user speech production and silence during interaction as main potential limitation in experimentation.

### *Biological*

Emotion is provided by people biology and their reactions to emotional stimuli (*section 2.1.3*). The detection of emotions can be linked to the recognition of physiological or bio signals derived from human body (Central Nervous System or Peripheral Nervous System) (Guoying, 2016, p. 36). It focuses on identifying patterns in physiological activity by using machine learning techniques to uncover the expression of different emotions.

In terms of accuracy, accurate recognition requires models adjusted to each individual person. Moreover, researchers are looking to efficient ways of improving current rates from 10 to 81.25% (Calvo & D’Mello, 2010, p. 27).

The monitoring of user reactions at facing stimuli from biological signals is usually performed by using recording signals produced by brain, heart, muscles, and also skin. These measures are underlined in the following list:

1. electromyogram that tracks muscle activity, the electric energy generated by bodily movements of the face, hands or fingers, etc.;

2. electrodermal activity also referred to as galvanic skin response that measures electrical conductivity which reflects the amount of sweat secretion from sweat glands in the skin surface;
3. electrocardiogram that measures or tracks heart rate to retrieve insights into respondents' physical state, anxiety and stress levels (arousal);
4. electrooculogram measuring eye movement and pupil dilatation with particular insights into visual attention, monitoring where users direct eye movements at a certain point in time; and,
5. electroencephalography measuring brain electrical activity (Guoying, 2016, p. 37).

Hence, emotion detection based on bio signals is derived from human body analysis. It is performed by identifying patterns in physiological activity by using machine learning techniques.

### *Gestures*

The human body express gestures and expressive motions such as head, hands or shoulders postures which can be used for the recognition of emotions (Bull, 1987; De Meijer, 1989; Mehrabian, 2017). It is a challenging task because there is not a generic conception of gestures to represent someone's emotional states. Mainly, there are many elements to analyze such as multiple degrees of freedom of human bodies with many possible configurations (Bernstein, 1967).

These gestures can be static (single pose) or dynamic (continuous poses) (Gheran, Vanderdonck, & Vatavu, 2018) (Gross, 2013, p. 11). These static positions can be combined with a multitude of movements. It creates potential channels for emotional communication through postures (Coulson, 2004). A human posture can extend the information collected by other nonverbal measures like face. It is particularly helpful when the emotion recognition is performed (1) at long distances, e.g. smile perception based on body expressions. This recognition is more easily visible from a distance than delicate changes in the face (Walk & Walters, 1988); and (2) with gross body motions to reflect an ordinary and unconscious behavior, e.g. detecting anger, fear, grief and joy while dancing (Castellano, Villalba, & Camurri, 2007).

Despite many elements to analyze, emotion detection based on human body gestures is maturing in the research community (Calvo & D'Mello, 2010, p. 26). In fact, there are many techniques to recognize emotions relying on gestures such as neural networks, Bayesian trees and fuzzy logic (Eero, 2016b, p. 39). Moreover, gestures and facial expressions are the most common ways to manifest emotion in screen-based characters (e.g. emotion recognition from animated expressions) (Cassell, Sullivan, Prevost, & Churchill, 2000).

Static gestures are recognized by matching some predefined templates while a collection of interchanged time states is used for dynamic ones. These states can be modeled with Hidden Markov Models, Support-Vector machines and Discrete Time Differential Neural Nets and preprocessed by tracking important points or temporal gesture states. Two techniques are relevant for the tracking: particle filtering and level sets. The first one involves the tracking of a geometric-shaped region, circle or rectangle, on the image. The main limitation states that all the points of the reference frame cannot be tracked in subsequent frames in no rigid videos (Konar &

Chakraborty, 2014, p. 12). The second one allows all points enclosed in a frame region being tracked while the shape region may change over the subsequent frames into the region of interest.

(Zeng et al., 2009, p. 47) shows that gesture and body motion information is an important modality for improving accuracy of the emotion recognition. In fact, the combination of face and gesture can be more accurate than facial expression alone with high values between 80 and 100% (images with posed expressions at no real-time) and 75 to 98% (images and video with spontaneous expressions at no real-time) correspondingly.

Overall, emotion recognition by human body gestures is feasible when the detection is performed at long distances with gross body motions. There are many potential techniques to classify emotions. Despite this, it is still a challenge because of a lack of a generic conception of gestures, high variation of human bodies and configurations. Thus, this approach is in continuous evolution to overpass limitations. It can also bring high accuracy levels at being combined with facial expressions in no real-time experiences.

### ***Summary***

This emotion measures section (2.2.2) highlights these key-points:

- There exist many measures to recognized emotions including facial, text, speech, bio-signals, and gestures.
- Detecting emotions from text is possible thanks to the analysis of written language and transcriptions of oral communication with lower accuracy than facial expressions.
- Vocal communication can be measured to recognize emotions by extracting vocal cues of speech with lower accuracy levels than face analysis.
- Bio-signals relies on human body analysis by identifying patterns in physiological activity where the accuracy level relies on model configuration per subject.
- Human body gestures analysis is feasible when the detection is performed at long distances with gross body motions which can be combined with facial expressions to increase accuracy.
- Facial expression provides a central mean of communication being also a key-central element in emotion recognition. Measuring face activity allows the categorization of emotions such as Ekman's ones. This process release emotion intensity values with the highest accuracy level reported by tools.

Hence emotion facial analysis has the potential to uncover UX since it shapes human interaction as a dominant mean of communication. Therefore, the next section will explore how to collect data from facial expressions by using emotion recognition tools.

### **2.2.3 Emotion recognition tools based on facial expressions**

The majority of tools for automatic emotion recognition use the interpretation of facial expressions thanks to the Facial Action Coding System shown before in the section 2.2.2 (Face measure). These tools helps to identify the facial expressions with their corresponding Ekman

emotions. Many tools have been proposed: FaceReader (Loijens & Krips, 2008), Microsoft Emotion API (Microsoft.com, n.d.), Affdex SDK (McDuff et al., 2016), Google Emotion API (google.com, 2015), Kairos emotion API (Kairos, n.d.), et cross platform libraries from OpenCV (Gent, n.d.) (manoelramon, 2016). Although there are many tools in the market, these ones address one important element in our work which is real time analysis allowing user faces images as input during interaction. In fact, there is evidence of the use of these tools in experimentation: FaceReader (Bijlstra & Dotsch, 2011), Microsoft Emotion API (Khanal, Barroso, Lopes, Sampaio, & Filipe, 2018), Affdex SDK (Svoboda, 2018), Google Emotion API (Sridhar, Wang, McAllister, & Zheng, 2018) , Kairos emotion API (Foley & O'Reilly, n.d.), and cross platform libraries (Sanjaya, Anggraeni, Juwardi, & Munawwaroh, 2018). Moreover, they are suitable to be analyzed and compare according to our properties to find their distinctions. These *properties* contain:

- *company*: to know which company the tools belongs to.
- *tool's name*: to identify the tool among others.
- *real-time analysis*: to know whether the tool releases the emotions values during users' interaction or not.
- *web analysis*: to know whether the analysis is mainly performed from the web or not.
- *Emotions*: the detected emotions by the tool.
- *Ekman dimensions*: to know whether the tool consider Ekman emotions or not.
- *input and output data*: to identify the required input and data elements.
- *error rate and accuracy* of the recognition: to know the level of the emotion detection accuracy of the tool.
- *reference*: to identify the academic source of the tool.

Consequently, these tools will be examined deeply: FaceReader, Microsoft Emotion API, Affdex SDK, Google Emotion API, Kairos emotion API, and cross platform libraries from OpenCV. Followed by a comparative of tools *properties* so that the reader can have a global insight.

### *FaceReader*

FaceReader<sup>1</sup> from Noldus is a desktop tool that detects emotions based on facial expressions by analyzing an image, video or camera input data of each participant (Loijens & Krips, 2008) in real-time experiences. These expressions are classified in happy, sad, angry, surprised, scared, disgusted, and neutral by using machine learning (Artificial Neural Network). Similarly, each other tools use a machine learning algorithm to analyze images and retrieve the emotion values. These categories conform the definition of the basic or universal emotions argued by (Ekman & Keltner, 1970) plus contempt (Ekman & Friesen, 1986) and neutral. The output of each emotion detection is a set of real values into [0,1]. The total of all these values are 1. Accuracy levels have been reported with an overall rate of 97.4 among all emotions. Furthermore, FaceReader supports extra classifications such as detection of the gaze direction and whether mouth and eyes are closed or not. It also provides extra information such age and gender. With this, it is possible to analyze the participant's attention. Images with a low quality are not detected (either the illumination or the camera position is not optimal).

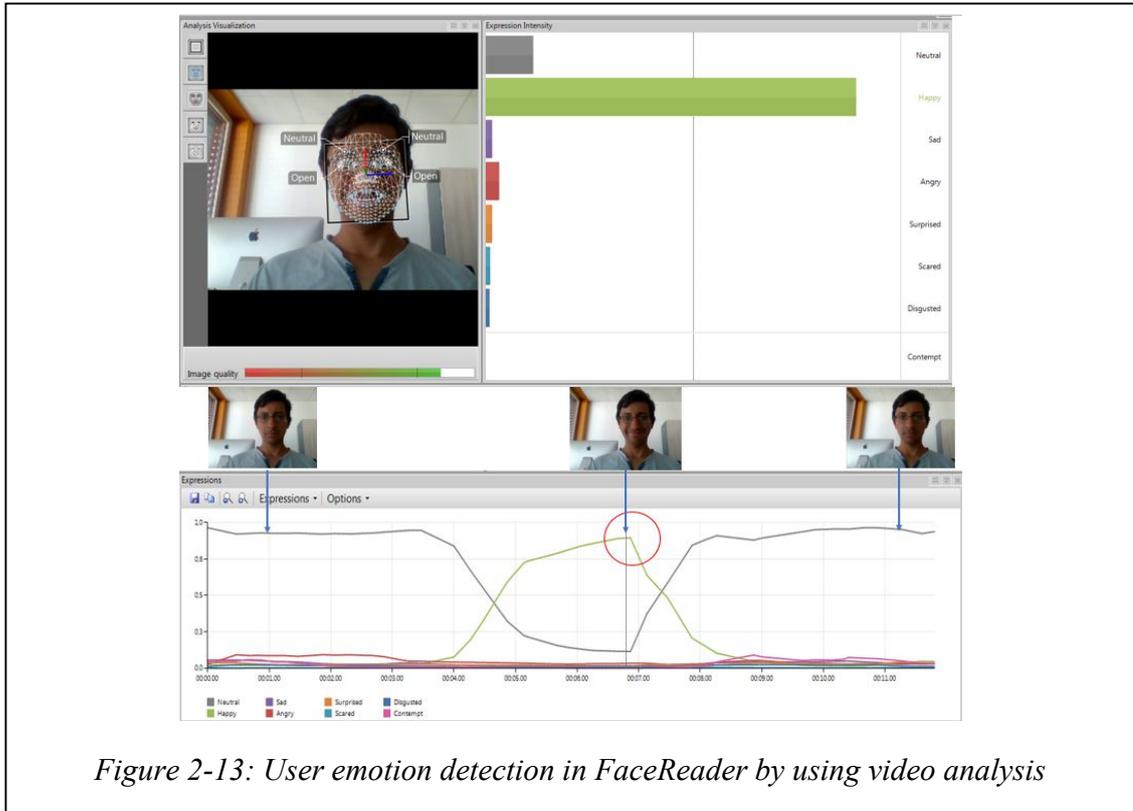


Figure 2-13: User emotion detection in FaceReader by using video analysis

An overview of FaceReader 7.0 interface is provided in Figure 2-13. This image shows the records of a user showing a change of facial expressions mainly from neutral to happiness during almost 11 seconds. While the user was posing at the camera his emotions were detected in a speed of 3 frames per second. The user starts with a neutral emotion (blue line at the top and at the beginning of the chart), then the middle mark (red circle) shows the sharp fluctuation to happiness evidenced with open mouth and eyes. In this point, the correspondent detected emotions are: neutral (0.10), happiness (0.753), sad (0.097), angry (0.018), surprised (0.001), scared (0.007), disgusted (0.019) and contempt (0.005). The total of these values is 1. Lastly, the user gets back to a neutral state with almost 92%. The complete information is saved in a text file including emotion values, time, facial expressions and subject characteristics (e.g. gender equal to male, age between 20 to 30, moustache equal to none and glasses equal to yes).

### Microsoft Emotion API

The emotion API<sup>2</sup> from Microsoft recognizes the emotions expressed by one or more participants in an image or video (input data) in real-time analysis by using Cloud-Based Emotion Recognition Algorithm (Microsoft.com, n.d.) (Deshmukh & Jagtap, 2017, p. 4). The input data can be sent by using web services allowing web interaction analysis to retrieve the emotions. The emotions detected are happiness, sadness, surprise, anger, fear, neutral, and two experimental ones: disgust, and contempt.

No specific accuracy levels are reported by (Microsoft.com, n.d.). To overcome this and to have a better notion, a custom and exploratory analysis was performed by using all user images from the Cohn-kanade database (Kanade, Tian, & Cohn, 2000) and Radboud Faces Database (Langner et al., 2010). The first database reported accuracy rates of 80% (disgust), 99.9 (happiness) and 0% (contempt); similarly, the second one reported 74% (disgust), 99.04% (happiness) and 17.9% (contempt). Since this initial analysis provides us an idea of how this tool performs the emotion detection in terms of input data, detection values and accuracy, no more analysis was needed.

The image data input supports JPEG, PNG, GIF (the first frame), BMP. We can note that the image file size should be no larger than four megabytes. Faces in image and video analysis are not detected in particular cases when: the face is out of the range from [36x36 to 4096x4096 pixels] for images and [24x24 to 2048x2048 pixels] for videos, very large face angles (e.g. head-pose) and large occlusion. The best results are reported in frontal and near-frontal faces for both images and videos. Similarly, to FaceReader, the output of each emotion detection is a set of real values into [0,1]. These values total in 1. Interestingly, developers can connect to the emotion API online by implementing different technologies: Curl, C#, java, JavaScript, PHP, Python and Ruby. It is particularly interesting to send many images or videos for online analysis.

The emotion API can also work with other services such as speech (e.g. real-time translation),

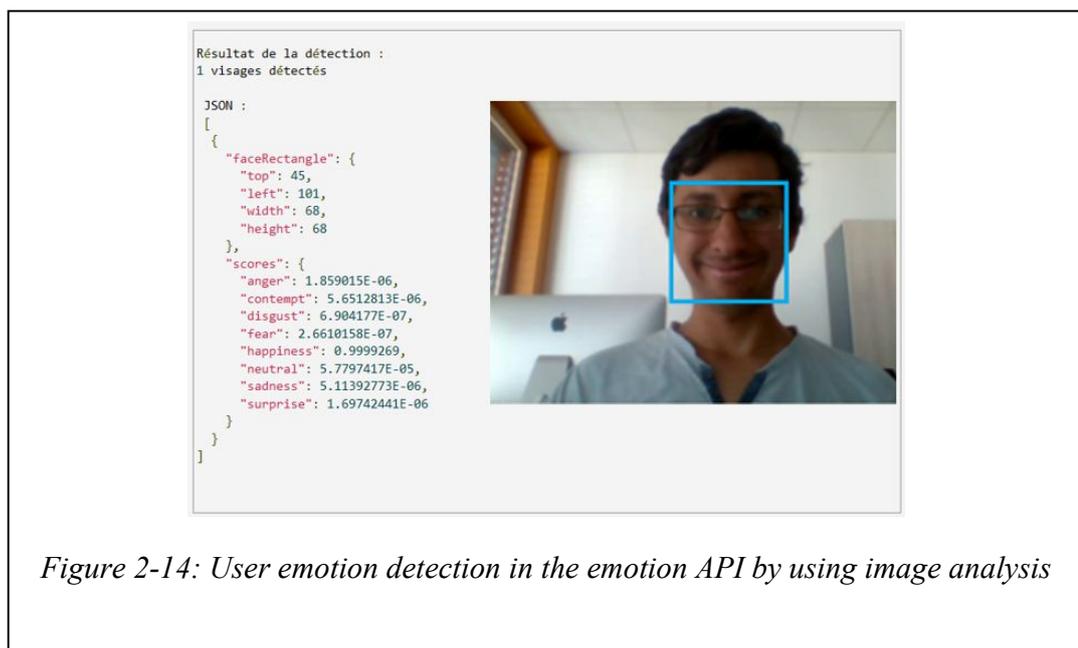


Figure 2-14: User emotion detection in the emotion API by using image analysis

vision (e.g. image activity recognition), language (e.g. text sentiment analysis) and search (e.g. image identification).

For instance, the picture used in Figure 2-13 showing the highest level of happiness (middle mark on the red circle) was sent to the emotion API (online tool) to get back the evaluation of emotions. The results are evidenced in Figure 2-14. The API recognizes the user face returning a blue face rectangle and the scores (emotion values) in a JSON object. The emotions result show anger (1.8e-06), contempt (5.65e-06), disgust (6.9e-07), disgust (6.9e-07), fear (2.66e-7), happiness (0.99), neutral (5.77e-05), sadness (5.11e-06) and surprise (1.69e-06). These values total in 1 similar to FaceReader output values.

### *Affdex SDK*

Affdex SDK<sup>3</sup> is a system for automated facial coding. It analyzes spontaneous facial expressions from images or videos to retrieve emotions automatically by using deep learning (McDuff et al., 2016) (Deshmukh & Jagtap, 2017, p. 4). Generally, the entire face is detected, and individual movements of the face are registered by the position of facial landmarks (facial key-points detections) on the eyes, brows, nose and mouth. Actions units (e.g. nose wrinkle) are derived from these landmarks to provide a likelihood of an emotion. For instance, weighted scores of nose wrinkle and upper lip raise can release a high detected value for disgust. The facial system identifies 7 emotions (anger, sadness, disgust, joy, surprise, fear and contempt.). Differently from the two previous tools, it identifies 13 emojis (small digital images to express an idea or emotion). Although, the Affdex SDK tool is a desktop solution, developers are able to connect to the SDK by implementing new components by using C++, Python and JavaScript (Affectiva, 2018). The overall rate of accuracy states over 90% with anger, sadness, and fear with lower values. This emotion detection system relies on four components: face and facial landmark detection, face texture feature extraction, facial action classification and emotion expression modelling. Finally, emotion detection values range from 0 (absence of emotion) to 100 (presence of emotion). Similarly, to FaceReader and Microsoft Emotion API, the output totals in 100%.

Figure 2-15 shows a user posing in front a computer with a happy face. The Affectiva SDK desktop tool confirms this emotional behavior by detecting the landmarks (white points on the user face) and emotions. It clearly evidences that the user is evoking joy (almost 90%), wearing glasses and a positive valence (green color) represented by a happy emoji. The results are saved in a JPG file. It can be noted that developers need to implement their own connection to the SDK to retrieve other user metrics (e.g. gender, age or ethnicity features) in more appropriate data

outputs (e.g. JSON objects).

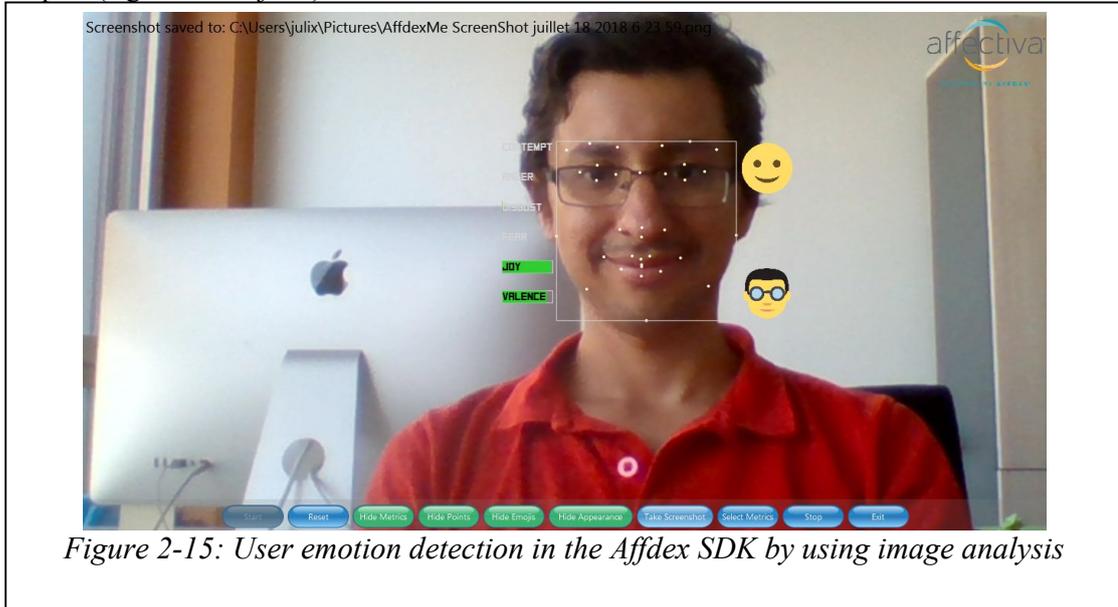


Figure 2-15: User emotion detection in the Affdex SDK by using image analysis

### Google Emotion API

This tool works as a web service which detects one or multiple faces within an image releasing facial attributes like emotions (google.com, 2015). It is based on advanced machine learning techniques (e.g. deep learning) which permit mainly the detection of emotions (happiness, sorrow, surprise) and other image characteristics (exposed, blurred & headwear) from the face. Differently to the previous tools, it releases values in a nominal scale ["VERY\_LIKELY", "VERY\_UNLIKELY", "POSSIBLE", "LIKELY", "UNLIKELY", "UNKNOWN"]. Accuracy levels are not reported by (microsoft.com, 2017). Interestingly, developers can retrieve more information from the image by using other Google services. This information includes image (dominant colors, crop hints), labels (e.g. vision care, chin and hairstyle), web (e.g. pages which include searched images) and safe search or potential offensive content (e.g. adult, violence and racy). This tool also releases the angles of the user position that describe rotations about the z (pan), y (tilt), and x (roll) axis.

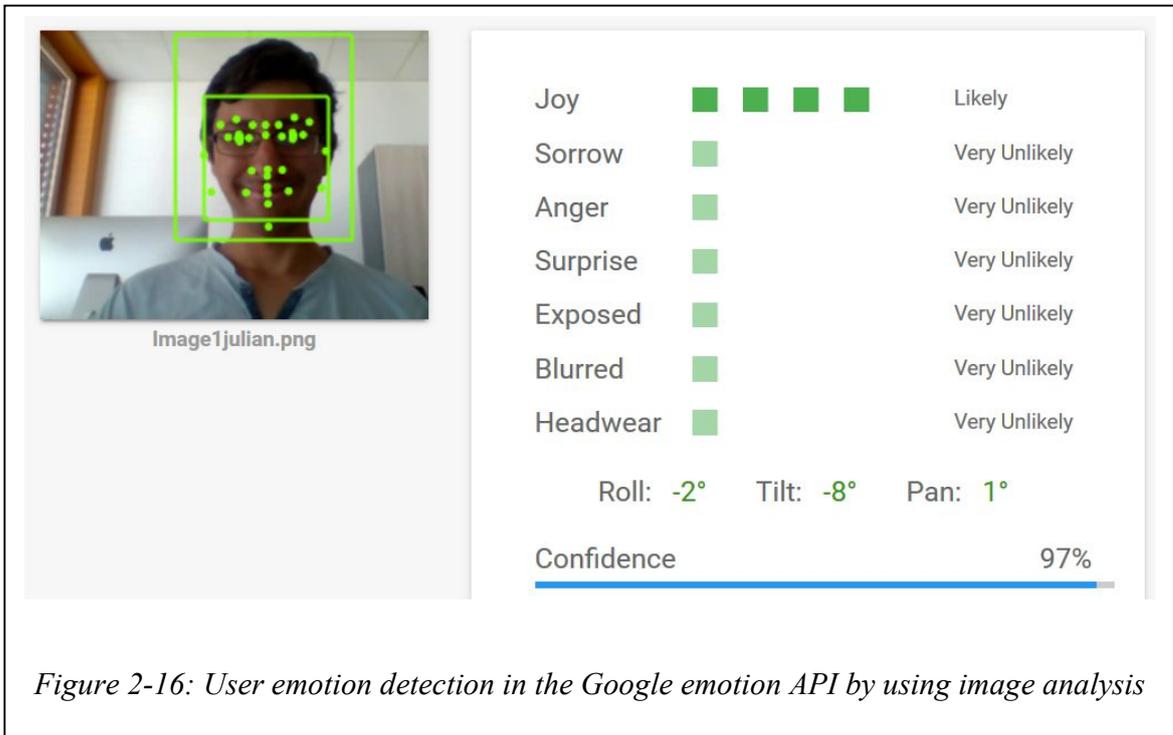
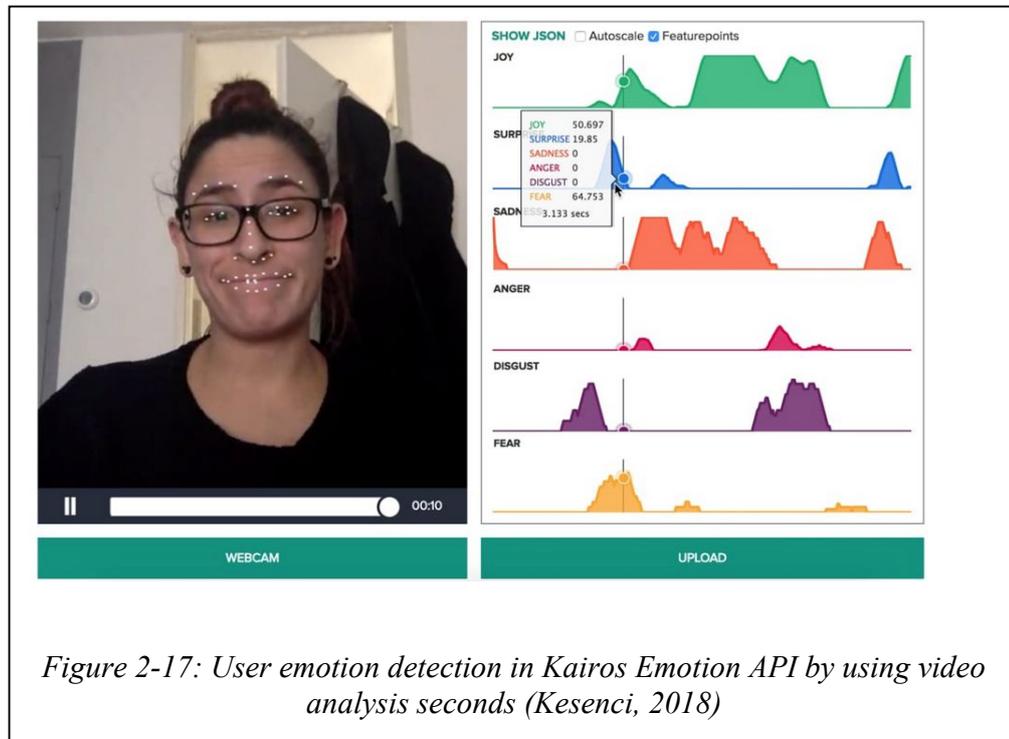


Figure 2-16: User emotion detection in the Google emotion API by using image analysis

For instance, a user image posing a happy face was provided to the google emotion api online. Figure 2-16 shows the detection results validating the acted happy face by proving LIKELY level in joy. The facial expressions of happiness are also evidenced with VERY\_UNLIKELY in sorrow and anger. This detection also releases the confidence of this detection with a 97%. Since the user was with a frontal position, the values from roll, tilt and pan were also retrieved with [-2, -8, 1] degrees accordingly.

#### Kairos emotion API

This tool is defined as a computer vision platform which allows researchers to submit images or videos to its API to analyze faces online thanks to deep learning algorithms (Kairos, n.d.) (Deshmukh & Jagtap, 2017). Similarly, to Affdex SDK, they recognize joy, anger, disgust, sadness, fear, and surprise giving back emotion values from 0 to 100. The values total in 100. The Kairos Emotion API can also detect multiple faces up to 25 in an good lighting condition (Deshmukh & Jagtap, 2017). It is particularly used by developers in identity verification (Virdee-Chapman, 2019).



*Figure 2-17: User emotion detection in Kairos Emotion API by using video analysis seconds (Kesenci, 2018)*

Figure 2-17 shows facial analysis from a video recording (Kesenci, 2018). The emotions were detected during 10 seconds. For instance, the marked point in the chart released joy 64.75 (fear), 50.59 (joy), 19.85 (surprise) and with a zero value for sadness, anger, and disgust. The highest retrieved level of emotion in fear is characterized by expressions such as lips stretched, and brows and lids raised.

### *Cross platform libraries*

It is a particular case because it shows that it is also possible to build a tool to detect emotion from other existing libraries (manoelramon, 2016). (Gent, n.d.) developed a tool to detect emotions by using an Open Source Computer Vision Library (OpenCV), Python and a Face Database containing emotions (Cohn-kanade database) (Kanade et al., 2000). This database was used to train and classify images by discriminant analysis (FisherFaces). This classifier was trained to classify images into the prediction classes (Neutral, happy, surprised, angry, disgusted, afraid & sad). Each image from the Cohn-Kanade database was resized to obtain the same size for all images and to improve the performance of the classifier by using OpenCV. Then, each face was extracted from these images collection, and then each resulting image was converted to grayscale, cropped and saved into dataset. With this organized dataset, a sample was selected randomly for being used in training (80%) and data classification (20%) by the classifier. Emotion detection values were retrieved releasing the best overall accuracy of 69.3% among all

emotions. Then, this accuracy was improved by providing to the classifier only neutral, anger, disgust, happy and surprise. With this, an improvement was evidenced with an 82,5% among such emotions. Although it is a modest accuracy, the classifier used only posed facial expressions from the Cohn-kanade database. A more realistic estimation was done by using natural expressions of images extracted from Google. The accuracy dropped considerably to 61.6%. Figure 2-18 shows three false detections of anger, happy and anger; the tool detected incorrectly happy, neutral and disgust respectively. Although it shows that is possible to build a tool to recognize emotions, it is a complex task and deserves a deeper treatment to increase accuracy levels at using spontaneous expressions (Gent, n.d.).

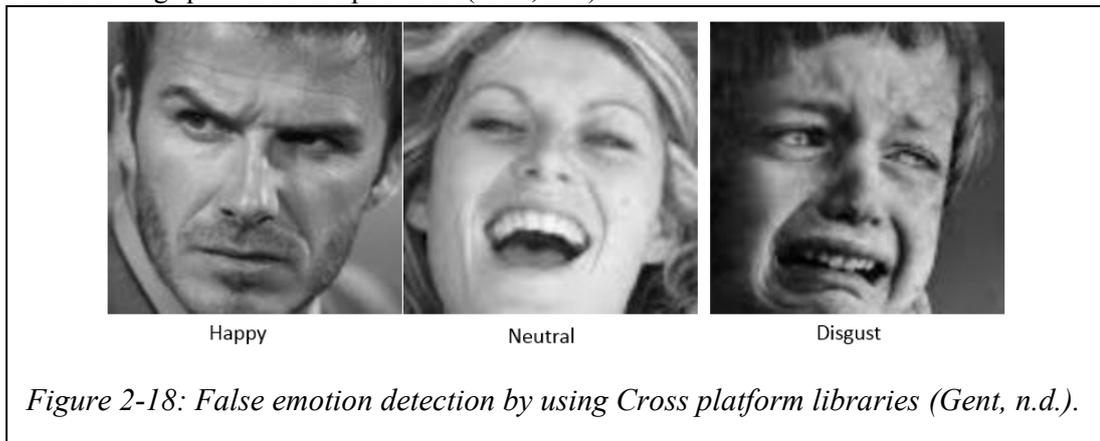


Figure 2-18: False emotion detection by using Cross platform libraries (Gent, n.d.).

### Comparative

The following Table summarizes the characteristics of the tools studied for emotions recognition (Table 2-1). It attempts to compare the theoretical differences among them. The table includes 10 columns or properties previously described at the beginning of this section: *company, tool's name, real-time analysis, web analysis, Ekman dimensions, input and output data, error rate, accuracy and reference.*

In terms of values, “**yes**” signifies that the tool answers to the corresponding property otherwise “**no**” is added. The value “**n.a.**” stands for a not available entry which means that the property is not declared by the author so that it was not found. Moreover, the symbol “**+**” stands for “**more related**” whether the characteristics is more related while “**-**” corresponds to “**the characteristics is less related**” for the studied property.

### Similarities

The majority of tools (FaceReader, Microsoft Emotion API, Affdex SDK, Google Emotion API and Kairos emotion API) share similar input values allowing real-time analysis. The most common input is the use of image or video (*input column*).

The tools (Microsoft Emotion API, Google Emotion API, Kairos emotion API) based on APIs allows real-time and web analysis of emotions; sending image or video to get back the emotions online while user's interaction (*real-time and web columns*).

A similar characteristic is the manner of emotion results is shown where most tools prefer output values into [0,1] or equivalently [0,100] (*output column*). Google emotion API is the only one using nominal values. Since the level of accuracy in the emotion recognition is important for UI adaptation (Carberry & Rosis, 2008), real values ([0,1] or [0,100]) appear to be more appropriate.

Except from Google emotion API, all tools support Ekman emotions detection (*Ekman dimensions column*) which allows studies with emotions that are considered as common or essential to all human (*section 2.1.1*).

### ***Differences***

The exception case in real-time is evidenced with tools where the developer needs to implement extra libraries such as cross platform libraries. Here, tool users do not get the emotion values automatically; instead, they retrieve emotion values by a post analysis of the collected data (*real-time and web columns*).

A particular exception in the output values is given with Google emotion API which releases nominal values (e.g. happiness equal to very-likely) (*output column*).

Not all the accuracy levels are reported (*accuracy column*). FaceReader has the highest level with 97.4% of overall accuracy among all emotions followed by the Affectiva SDK-API with reported values over per cent.

Company	Tool	Real-time analysis	Web analysis	Emotions	Ekman dimensions	Input	Output	Technique	Error rate	Accuracy	Reference
Noldus	FaceReader	yes	n.a.	happiness, sadness, fear, disgust, anger, surprise, contempt & neutral	yes	Image or video Individual face	Real [0,1]	Artificial Neural Network	Overall 2.6%	Overall 97.4 % (RaFD database) Disgusted (84.8%), Surprised (94.4%), fearful (84.8%), Sad (87.1%), Happy (95.9%), Angry (93.0%), Neutral (87.1%) .	(Loijens & Krips, 2008)
Microsoft	Emotion API	yes	+	happiness, sadness, fear, disgust, anger, surprise, contempt & neutral	yes	Image or video	Real [0,1]	Cloud-Based Emotion Recognition Algorithm.	n.a.	(Custom analysis) 1.Cohn-kanade database Disgust (80%, 69 images) Happiness( 99.9%, 68 images) Contempt :0% (17 images)  2.RaFD database Disgust :(74%,117 images) Happiness : (99.04%,117 images) Contempt :(17.9%,117 images)	(Microsoft.com, n.d.)
Affectiva	SDK	yes	-	happiness, sadness, fear, disgust, anger, surprise, contempt & neutral	yes	Image or video Individual/ Multiple faces	Real [0,100]	Deep learning	0,2	bigger than 90% with anger, sadness and fear with lower values.	(McDuff et al., 2016)
Google	Emotion API	yes	+	happiness, sorrow & surprise	no	Image Individual/ Multiple faces	Nominal ["VERY_LIKELY", VERY_UNLIKELY", "POSSIBLE",	n.a.	n.a.	n.a.	(google.com, 2015)

							"LIKELY", "UNLIKELY", "UNKNOWN"				
Kairos	Emotion API	yes	+	Joy, anger, disgust, sadness, fear, & surprise	yes	Image or video	Real [0,100]	Deep learning	n.a.	n.a.	(Kairos, n.d.)
Intel	(Open CV). Cross-platform libraries (Java, Python and C++)	no	-	Neutral, happy, surprised, angry, disgusted, afraid & sad	yes	Image or video	Real [0,100]	Linear Discriminant Analysis (FisherFaces)	almost 30%	1. Cohn-kanade database (Overall 82,5%) 2. Spontaneous faces (Overall 61,56%)	(Gent, n.d.) (manoelramon, 2016)

*Table 2-1: Comparative of objective emotion recognition tools*

Overall, this comparison between emotion detection tools reveals that they are precise enough as indicators. Another interesting features is that they are able to give values (Ekman emotions) at run-time either from images or videos

### 2.3 Summary

This chapter introduces the background concepts related to affect: feelings, emotions and moods. Then it focuses on emotions. It defines the concept and gives two different points of view, philosophical and cognitive. Then some aspects of emotions are underlined: biology and sources of emotions.

Moreover, it presents a basic set of emotions (*Ekman emotion model*) followed by dimensional models to understand and characterize emotions: The Circumplex model of affect, The Plutchik's wheel of emotions, The Geneva emotion wheel, The Self-Assessment Manikin and The Positive Activation & Negative Activation model.

Secondly, it describes approaches to recognize user emotions based on measures from: *face*, speech and vocal expressions, bio-signals, gestures and text. As *face* is the dominant mean of communication, the rest of the chapter focuses on *tools* to recognize emotions facial expression analysis. They share some properties such as real-time and online analysis, similar input and output values and the capacity of detecting Ekman emotions (basic set of emotions).

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**3.1 Introduction**

This chapter presents the state of the art. It takes into roots from two complementary topics: the 1<sup>st</sup> one, Interactive system adaptation to emotions which are directly comparable to our work, the 2<sup>nd</sup> one, study of User Experience, can be useful for understanding how to create systems able to maintain UX during adaptation.

Considering approaches that study interactive system adaptation regarding emotions, adaptations can be triggered either on the functional part of the application (Janssen, Van Den Broek, & Westerink, 2012) – e.g. for changing the content – or on the UI part – e.g. for adapting the design or the interaction modality.

For approaches that study UX and one of its facets, we focus on, i.e. aesthetics or usability and their links with user’s age and/or gender. Particularly, this study explores a) the impact of aesthetics and usability on UX without considering age and gender; b) the impact of age *or* gender on UX; or c) the impact of age *and* gender on UX.

We give an overview of these approaches (adaptation to emotions plus UX) and compare them according to a set of criteria. A table summarizing the presented approaches is provided at the end of each category. We start by describing the Interactive system adaptation approaches by relying on emotions.

## 3.2 Interactive system adaptation based on emotions

In human-computer interaction, users' emotions are recognized as being important in the design and evaluation processes (Brave & Nass, 2002, p. 55). They cannot be ignored while designing for UX (Hook, 2012). In this context, the field of Affective computing stands for « computing that relate to, arise from, or influence emotions» according to (Picard, 1995). From this notion, there are models (Ekman, 1992; Russell & Barrett, 1999) (*section 2.1.2*) and tools such as FaceReader or Affdex (*section 2.2.3*) to measure affects in terms of basic emotions from Ekman's model (surprise, happiness, sadness, disgust, anger, fear) plus neutral (*section 2.1.1*). Moreover, there are also studies to explore the link of emotions with other users' characteristics such as learnability, performance, and communication in some specific domains such as tutoring systems (Forbes-Riley & Litman, 2011; Graesser et al., 2008; Porayska-Pomsta, Mavrikis, & Pain, 2008).

Beyond models, emotions can be used at runtime in closed-loop applications (Van Gerven et al., 2009): emotions are measured and interpreted in terms of responses to stimuli (“something that rouses or incites to activity” (merriam-webster, 2006) ; then, based on the measurements, a decision is made concerning the applicable actions; these actions are executed; and the loop starts again with new emotions measures. In this way, the decision about applicable action may concern either the functional part of the application (Janssen et al., 2012) – e.g. for changing the content – or the UI part – e.g. for adapting the design or the interaction modality. In our work, we focus on interactive system adaptation.

Only few works (Hudlicka & Mcneese, 2002; Nasoz, 2004a; Meudt et al., 2016; Märtin et al., 2017) studies Interactive system adaptation based on emotions even if the user's emotional state is cited as one of the elements of the context of use for Interactive system adaptation (Paterno, 2013). To clarify, a finer grained analysis was performed by comparing each Interactive system adaptation approach not only according to their theoretical characteristics but also in their prototype implementation. The theoretical analysis will provide the main features in terms of how to use the detected user emotion to drive a Interactive system adaptation, while the prototype will show the feasibility and results of each approach implementation. Both aspects are examined concerning a set of properties: detected emotion, emotion measure, emotion detection method, adaptation technique, interactive system adaptation (content, aesthetics, usability), user characteristics (gender and age), Adaptation type (design-time or run-time) and UI type (e.g. GUI or website). These properties are detailed into the *analysis criteria* exposed in the following section.

### 3.2.1 Analysis criteria

The analysis criterion aims to clarify the approach and prototype comparison of Interactive system adaptation thanks to emotions. It includes the following properties, which are defined in *Chapter 2*, the references indicated below refer to the specific section where explanations can be found:

- *Emotion*: studies which emotions are considered for the adaptation (*Chapter 2, section 2.1.1*).

- *Emotion measure*: refers to which measure is used to recognize emotions during UI interaction such as facial, speech and vocal expressions, bio-signals, gestures and text (Chapter 2, section 2.2.2).
- *Emotion detection method*: studies whether the emotion is recognized in an implicit (what users do) or explicit (what users think they do) manner (Chapter 2, section 2.2.1).
- *Adaptation technique*: corresponds to the adaptation technique used for driving the interactive system adaptation.
- *Interactive system adaptation*: corresponds to the type of changes performed in the interactive system involving content (C), aesthetics (A) or usability (U).
- *Gender*: explores whether the interactive system adaptation considers gender.
- *Age*: studies whether the interactive system adaptation considers age.
- *Adaptation type*: determines whether the Interactive system adaptation is conceived either in design or run-time (Becker, Canal, Murillo, Poizat, & Tivoli, 2005, p. 5,8).
- *UI type*: refers to the type of UI used to apply the adaptation such as Desktop or website.

Remarkably, some properties can be aligned with 5 of the key adaptation questions argued by (Knutov et al., 2009). It is underlined below.

1. what can we adapt? - *content (C), aesthetics (A) or usability (U)*.
2. what can we adapt to? - *emotions, gender and age*.
3. where can we apply adaptation? - *UI type (desktop or website applications)*
4. when can we apply adaptation? - *Adaptation type (design or run-time)*
5. how do we adapt? - *Adaptation technique*

Then, this analysis criterion is used to describe and compare each approach as well as its implementation.

### 3.2.2 Approaches and prototypes analysis

#### a) ABAIS approach (Hudlicka & Mcneese, 2002)

The ABAIS approach (Affect and Belief Adaptive Interface System) (Hudlicka & Mcneese, 2002) in the aircraft driving domain implements an adaptive methodology framework capable of adapting: the UI format (e.g. changes in the background color) and content to the user affective state (e.g. anxiety level), selected key personality behaviours (e.g. aggressiveness level), and to situation-specific beliefs (e.g. an aircraft under attack) that might influence user performance (Deckert, Entin, Entin, MacMillan, & Serfaty, 1994). This methodology is implemented by the ABAIS system architecture shown in Figure 3-1. It includes four modules: *User State Assessment*, *Impact Prediction*, *Strategy Selection*, and *GUI Adaptation* to perform the adaptation in design-time.

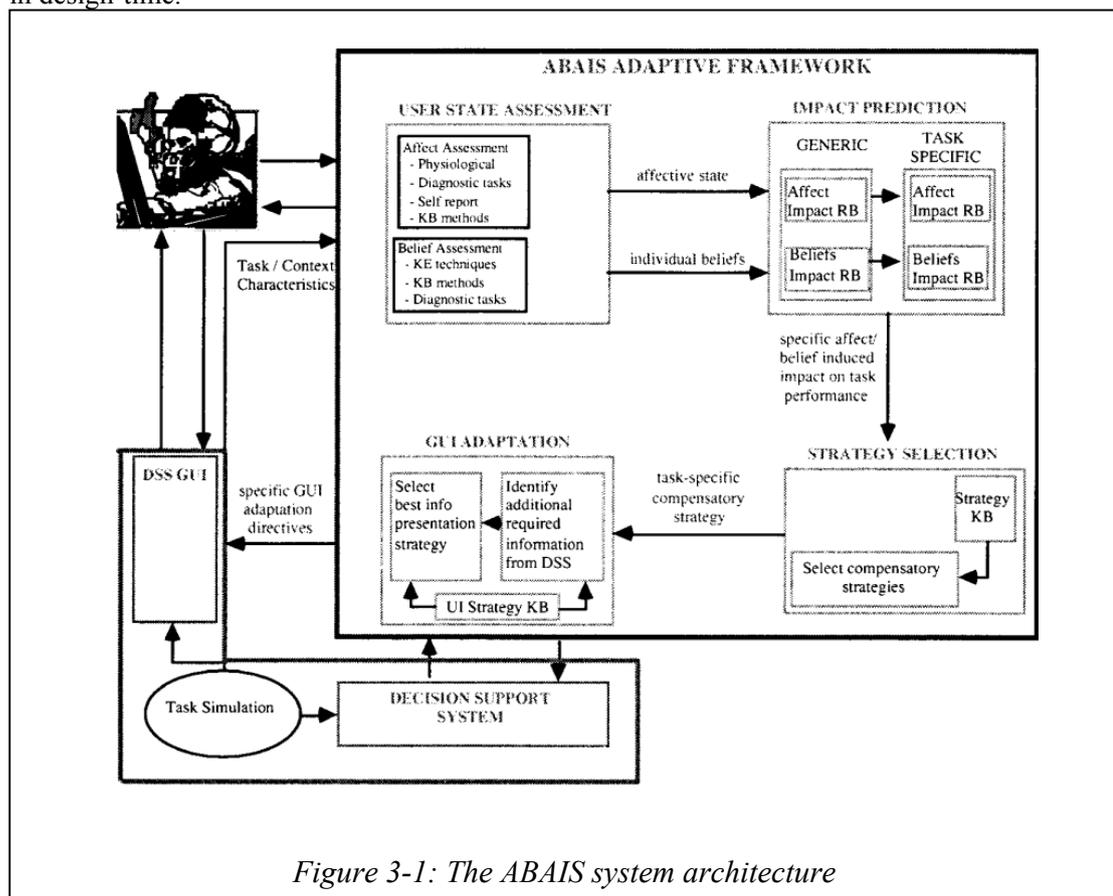


Figure 3-1: The ABAIS system architecture

The process lies on several steps. First, the input data (e.g. physiological signals like hear rate) is collected and interpreted releasing: the user's predominant *affective state* (e.g. high level of anxiety) and situation-relevant beliefs (e.g. interpretation of a threat). They are determined thanks to the *User State Assessment Module*. This module performs this task by receiving different user data (e.g. hear rate) and the user task context. The emotion is *measured* by collecting data from Physiological signals through implicit and explicit *methods*. The implicit methods include sensors for arousal and valence detection (e.g. heart rate sensor); while the explicit ones use knowledge-based, self-reports, and user diagnostic tasks. The selection of these emotion detection methods and measures is highly task-and-interface dependent. For instance, the measure of anxiety by a heart rate sensor when the user is interacting with the radar and performing the task "under attack detection of hostile activity on the radar". In this case, anxiety is the most relevant emotion under such situation while the user is using his hands to drive the aircraft to perform the task so that the use of a sensor is appropriate given the nature of the task.

The collected data serve to predict the influence of a particular affective state (e.g. high/low anxiety) or belief state (e.g. 'hostile aircraft approaching') in the *Impact Prediction Module*. This module uses rule-based reasoning to determines knowledge derived from a Cognitive Affective Personality Task Analysis which predicts the effects of different affective and belief states on user performance within the current task context.

The predicted effects of the affective and belief states are passed to the *Strategy Selection Module* which selects a Interactive system adaptation *technique* named compensatory strategy. This technique follows a rule-based reasoning to map specific performance biases (e.g. task neglect) onto the associated compensatory strategies. These rules are defined by the designer. For instance, a failure-estimation of a threat at evaluating the present evidence incorrectly. Consequently, this module depends on a detailed analysis of context task (e.g. determination of a threat) and predefined compensatory rules that identifies specific strategies available to counteract the possible biases.

Finally, the Interactive system adaptation is performed by the *GUI Adaptation Module*. It is in charge of adapting the interactive system *content* and *aesthetic* by implementing the selected compensatory strategy given in the previous module. *Usability* changes are not considered. A decision support system helps to map the specific compensatory strategies against the necessary GUI adaptations. Specific GUI modifications consider individual user preferences stored and customized by the user into a user profile. For instance, different user preferences to highlight information such as blinking vs. colour change of the relevant icon or display). Although user's characteristics (e.g. user personality by self-reports) are considered, *age* and *gender* are not considered by the compensatory strategy so that the adaptation process uses emotion (affective state) excluding age and gender. The architecture is designed to perform the interactive system changes at *run-time* as changes happened at run-time.

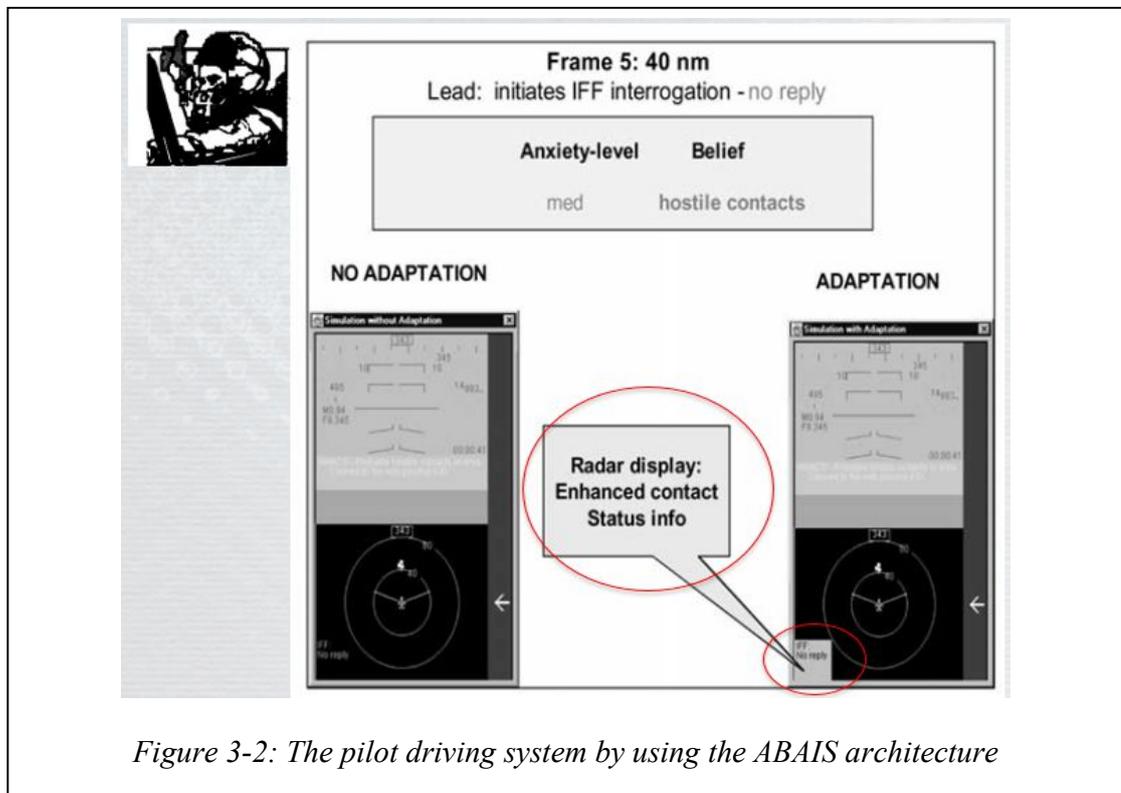


Figure 3-2: The pilot driving system by using the ABAIS architecture

In terms of the ABAIS implementation, Figure 3-2 shows the ABAIS prototype in a pilot driving system. The *affective state* is detected thanks to two *sources*: a heart rate sensor and anxiety self-reports (collecting before using the driving system). The *adaptation technique* (what-if) received the data input (medium anxiety level and hostile contact belief) to perform an interactive system adaptation. In this case, the compensatory strategy implies a radar display (marked in red circles) with two adaptations: the display of a UI message (*content*), and a change of the display size (*aesthetics*) in *run-time*. No other user features were considered.

### Limitations

The ABAIS approach (Affect and Belief Adaptive Interface System) implements an adaptive methodology framework to adapt the UI format and content based on many parameters like the user affective state. Despite the use of emotion in this architecture at run-time, there are some limitations to highlight. First, the approach does not show how to use more than one *emotion* such as the ones states by Ekman (Ekman, 1992). It means that the collected affective state can not work with multiple emotions to conduct the adaptation. It is only one emotion at a time. It limits the adaptation possibilities to only one emotion per UI. Second, the approach relies on *explicit methods (questionnaires)* to recognize personality changes (obsessiveness level) at design-time; however, this level can change as individuals regulate their emotions based on

variable elements such as precepts, concerns and individual parameters to adapt to the situation (procedural view of emotions, *section 2.1.3*). Consequently, the predefined compensatory strategies may become useless. It will impact the GUI adaptation module by implementing incorrect adaptation rules and changes in the UI. For instance, if  $\langle \text{goal}=\text{highlight-radar-display and color-preference}=\text{red} \rangle$  then the action  $\langle \text{highlight-radar-display with red} \rangle$  could not work when the user changes his color preference without reporting it.

The Interactive system adaptation includes only content and format changes (*aesthetics*) excluding *usability* (e.g. a widget changes like a radio buttons group modified into a select list). So, the distinction between usability and aesthetics problems is not realized as the goal is not to improve UX. Fourth, the emotion level (e.g. high anxiety or depression) can be influenced by gender and age (Cleland, Lee, & Hall, 2007) (age and gender in *section 2.1.3*), a point which is not considered in the ABAIS architecture. For instance, the pilot driving system could use the mentioned link to adjust the compensatory strategies according to different gender and age values. Finally, the prototype results cannot be reused in other contexts for more widespread UIs since it is highly dependent on the driving experience (detected anxiety and self-reports about believes).

*b) Adaptive intelligent approach (Nasoz, 2004a)*

(Nasoz, 2004a) proposed a general approach for interactive system adaptation to emotions. It consists in an adaptive intelligent system relying on the recognition of affective states from

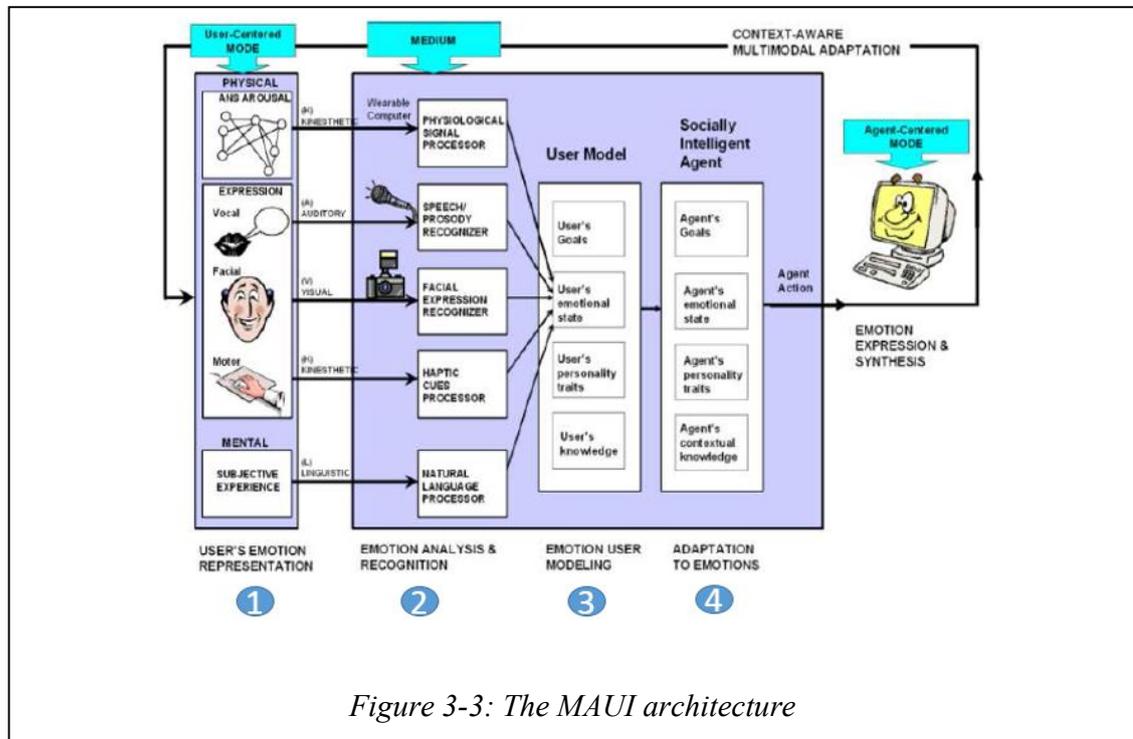
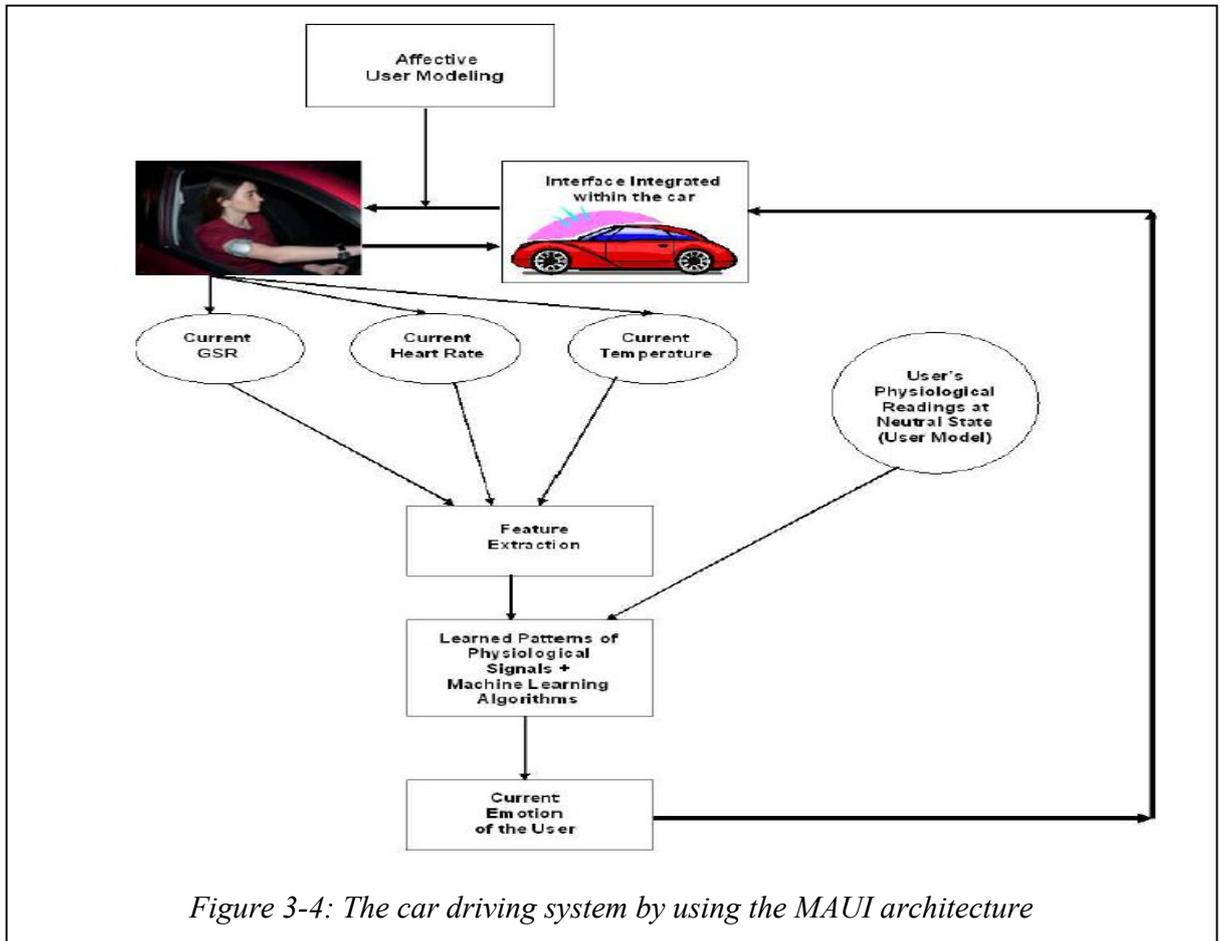


Figure 3-3: The MAUI architecture

physiological signals (Galvanic Skin Response, Heart Rate, and Temperature), speech, facial expressions and motor movements. It includes a user model with the following features: personality, age, gender, recognized emotion (sadness, anger, surprise, fear, frustration, and amusement) and frequency of experiencing a specific emotion. Non-invasive wearable sensors are proposed to collect the physiological data from users. This data is analysed thanks to machine learning techniques to enable the intelligent system to adapt to the user model by using agents. An agent aims to recognize the user's emotional states and respond accordingly (adapting the system) at run-time. For instance, sleepiness can be detected by an armband sensor during a car driving experience to change the volume of the radio station (agent task) through a Bayesian belief network analysis.

The intelligent system follows an existing architecture called multimodal affective user interface (MAUI, (Lisetti & Nasoz, 2002)) illustrated in Figure 3-3. It is composed of four modules: *user emotion representation*, *emotion analysis and recognition*, *emotion user modelling*, and *adaptation to emotions*.

First, the data input involves both elements (emotion measures): physiological and mental of a particular user emotion (*user emotion representation* ①). The physiological elements are identified and collected from observing the user through sensors (*implicit method*) in the *emotion analysis and recognition module* ②). These elements include physiological signals (galvanic skin response, temperature, and heart rate), speech (vocal intonation and natural language), facial expressions and motor movements (hand movements). The mental element represents an *explicit* experience by receiving linguistic terms for emotion concepts from users by questionnaires. Once these two pieces of data are collected and analysed by the *emotion analysis and recognition component*, this data is stored in an emotion user model including user goals, emotional state and user knowledge (*emotion user modelling* ③). Then, the *adaptation module* ④ receives the user model and executes interface actions through an agent. The agent aims to recognize and adapt to user's emotional state by executing actions to change the interactive system. For instance, displaying "make a joke" when anger and personality trait are both equal to neurotic in a 90% level.



To go beyond, (Nasoz, 2004a) implemented MAUI by developing a prototype of a car driving system to adapt the interactive system by providing multi-modal feedback to users based on their current affective state at real-time.

Figure 3-4 shows the link between emotion recognition and the interface integrated within the car. The first part collects psychological data (e.g. armband sensor) during the experience (*implicit method*). Then, a post-analysis reveals the user emotional state as input to apply a Bayesian belief network (*adaptation technique*) to find some adaptation actions in content at run-time. In this prototype, the detected emotions are not related to the UI but to the driving situation (e.g. panic or fear detection while driving downhill in an accident scene).

Particularly, three psychological signals were collected through an armband sensor (galvanic skin response and temperature) and a polar chest strap (heart rate) while users were driving the car simulation system. This system provides many stimuli (traffic events during the driving) to users for eliciting the four mentioned emotions during the UX. As mention above, the post-analysis which aims to reveal the user emotion state involves a feature extraction process that analysis the

questionnaires to derivate user data such as the emotions experienced by users associated also with time slots.

This analysis uses machine learning algorithms (k-nearest neighbour and marquardt backpropagation) mainly to analyse the gathered data signals and to find unique physiological patterns of emotions. This analysis releases a user model including: the recognized emotion, personality trait, age, gender and emotion frequency. This user model is sent to a Bayesian belief Network which finds 1000 potential adaptation actions by combining the information into the such model. A Bayesian belief Network is a probabilistic causal network , normally used for taking an event and predicting the likelihood of several possible known causes (Nasoz, 2004b, p. 75). Due to the high combinations number and to evaluate the applicability of the user model, the Bayesian belief network was created with a small set of user data releasing 32 combinations. The adaptation actions impact the *content* and not the *aesthetics* or *usability*. For instance, the action to display “Suggest a relaxation technique” or “Change the Radio Station”. The retrieved actions at run-time are calculated with the Bayesian network during the system execution so that it is an adaptation at-run-time.

In order to address individual differences in user preferences (e.g. skin color, hair, make-up or accessories), the recognized emotions were used to design a Multimodal Affective User Interface to mirror the user emotional state by a personalized avatar during future experiences with the car driving simulation system. The avatar (skin colours, voices, hair, make-up, accessories) and a background are proposed based on user’s preferences. Then adaptation mirrors the user’s current emotional state with the avatar design (face shape and orientation changes).

### ***Limitations***

The adaptive intelligent approach involves interactive system adaptation to emotions. There are some limitations that can be underlined. Adaptation details are not provided to drive an adaptation that considers *aesthetics/usability*. Although age and gender are considered individually to define adaptation actions, there is not an association between *aesthetics/usability* and the collected user characteristics (*age* and/or *gender*). As shown by the Bayesian belief network (Nasoz, 2004b, p. 82), age and gender values are not associated among them to understand whether age intervals need to be defined for women or men to drive the Interactive system adaptation. The use of different *adaptation techniques* (machine learning) with *aesthetics/usability* at run-time is undescribed. Consequently, some key points about adaptation are presented as future work (Lisetti & Nasoz, 2002, p. 72): 1) implicit Interactive system adaptation using multi-modal devices (expression, posture, vocal inflection) to provide adaptive feedback; and 2) explicit changes in UI agents depending on user state.

Moreover, this approach does not provide enough details related to the adaptation process. First, since agents depend on each user model element, each new change may imply a new agent implementation to understand the full functionality of MAUI architecture. Thus, agents dependency to one user’s characteristic implies that changes cannot be fully considered. Second, the adaptation actions mainly cover *content* without considering UI. Third, although user

characteristics (*age* and *gender*) are into the user model for UI content adaptations, they are not related with UI quality factors. Fourth, the emotions were detected in a post analysis through a explicit method. Based on this, the adaptation actions were defined at *design-time* analysis. So, it may cause unappropriated adaptations when there is a lack of accuracy (e.g. error at processing paper questionnaires) in the emotion detection. Lastly, the Interactive system adaptation *technique* relies on machine learning where the complexity of the rules prediction is not explored. Mainly, the designers needs to deal either with a high quantity of retrieved rules combinations (1000 in Bayesian Believe network) or the criteria to select appropriate ones.

c) *Companion approach* (Meudt et al., 2016)

(Meudt et al., 2016) proposes an approach which aims at identifying the cause of an emotion from the history of interactions and then at proposing an appropriate adaptation at run-time. Emotion recognition is expected to be made at run-time to provide hints about expected user reactions (e.g. recognize dislike levels when increasing the volume in a car driving system). Although, the approach does not seem to have been implemented in systems, it presents a generic architecture called Companion-System based on interconnected layers.

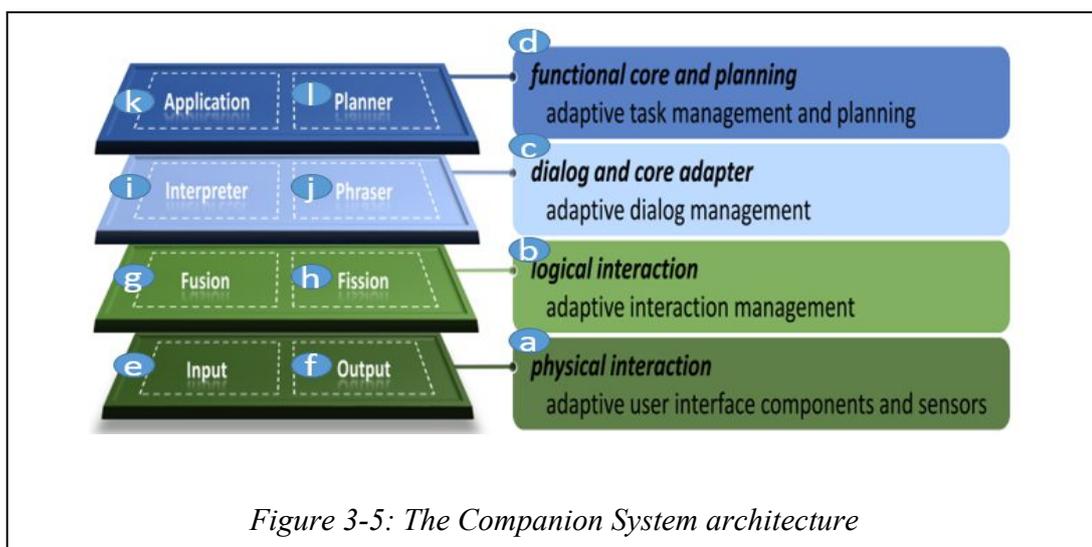


Figure 3-5: *The Companion System architecture*

Figure 3-5 shows this architecture which includes many layers and components: four *layers* (right side) and eight components (left side). A layers is a level starting from a physical interaction (the highest level) to the functional core and planning. Each layer contains two components. These layers are (a) *physical interaction* with input (e) and output (f) components; (b) *logical interaction* with fusion (g) and fission (h) components; *dialog and core adapter* (c) with interpreter (i) and phraser (j) component; and (d) *functional core and planning* with application (k) and planner (l) components. An intercommunication among all these components attempts to provide a sequence of tasks (set of steps in the system) to perform an adaptation.

Since this architecture is complex to understand and not implemented yet, we provide first an example (not implemented) of its use before going deeper into the architecture details. There are some scenarios to show how the Companion-system could behave to drive an adaptation. For instance, one is based on an automatic volume control (*functional core and planning*) in a car driving experience. Nowadays, cars offer the functionality to adjust the volume control (*functional core and planning*) relying on the current car speed recognized by sensors (*physical interaction*). In this manner, drivers are not required to adjust the volume manually. So, if the car speed decreases abruptly then the volume may drop dramatically. Consequently, some users may not be able to fine-tune the settings for this adaptation process. Thus, it is feasible that the automatic volume adjustment does not match the driver criteria in some driving experiences. This inconsistency can lead to a negative emotion expression detected in an implicit manner by facial expressions through a camera. Another potential input may be trough skin conductance (e.g. body activation as a strong predictor of attention and memory.) as the driver is in continuous contact with the steering wheel. Therefore, the decision level fusion can combine the facial and skink conductance data to estimate the appearance of a negative emotion. This finding as user feedback may be passed to an automatic volume controller so that an adaptation can be performed to re-adjust the volume at run-time in a more appropriate manner.

Four points are introduced to understand this architecture functionality. First, the lowest level, *the physical interaction (a)*, contains two components (input (e) and output (f)) to collect user information thanks to sensors (*implicit method*). Input sensors are provided with specific configuration data which allow to recognize possible implicit (e.g. user *emotional* state or location) and explicit user inputs or *emotion measures* (e.g. speech, facial expressions, or gestures). Similarly, the output component (f) renders the output in a multimodal manner (e.g. emotion data collected by microphones and cameras).

Second, the *logical interaction* component allows the fission component (h) to refine the output of a dialog management interpreter. This element manages and communicates the content of each necessary adaptation task sequence seen as the *adaptation technique*. There are no provided details whether this content affects *aesthetics* and/or *usability* in the UI. Thus, the fission component decides about the use of the components and sensors in the previous layer. The fusion component (g) is able to fuse multimodal inputs as a single input for the dialog management interpreter. No more details are provided about the fuse multimodal inputs.

Third, *the dialog and core adapter (c)* has two functions: 1) to provide a modality-independent interface to the *functional core* and 2) to communicate the content of each necessary task step. A task signifies a set of steps in the system to perform an adaptation. The phraser (j) aims at providing a dialog structure (speech interface for communication between the user and the system) for each user as the system intended output. Moreover, the user input interpretation is performed by the interpreter (i), for instance, the understanding of voice commands during the interaction.

Finally, the highest level contains the *functional core (d)* of an application (e.g. a car driving system). It also includes a component for *planning (l)* the adaptation actions. In the case of a user needs to solve a complex problem, the *planner* is able to infer a sequence of tasks to find a potential solution (adaptation) in the UI. As an example, if a user dislikes the volume in a car

driving system then it is possible either to change the volume (action) inside task1 or to provide a new task (stop radio or change radio station) in the *planning* layer.

The system also defines an interaction history of all actions accomplished by the layers so that they can be reused in future adaptations thanks to an emotion action rating. To clarify, the components' layers provide their action items (potential UI change). The items are stored in an interaction history for future use. The current emotion recognition is configured by analysing previous detected user reactions (e.g. the analysis of the user speech "hmm" which can be considered as a reaction of impatient). This emotion is sent to the component to update their status to know whether a user likes or dislikes a particular action. The manner of rating actions associated with this detected emotion is not detailed.

### ***Limitations***

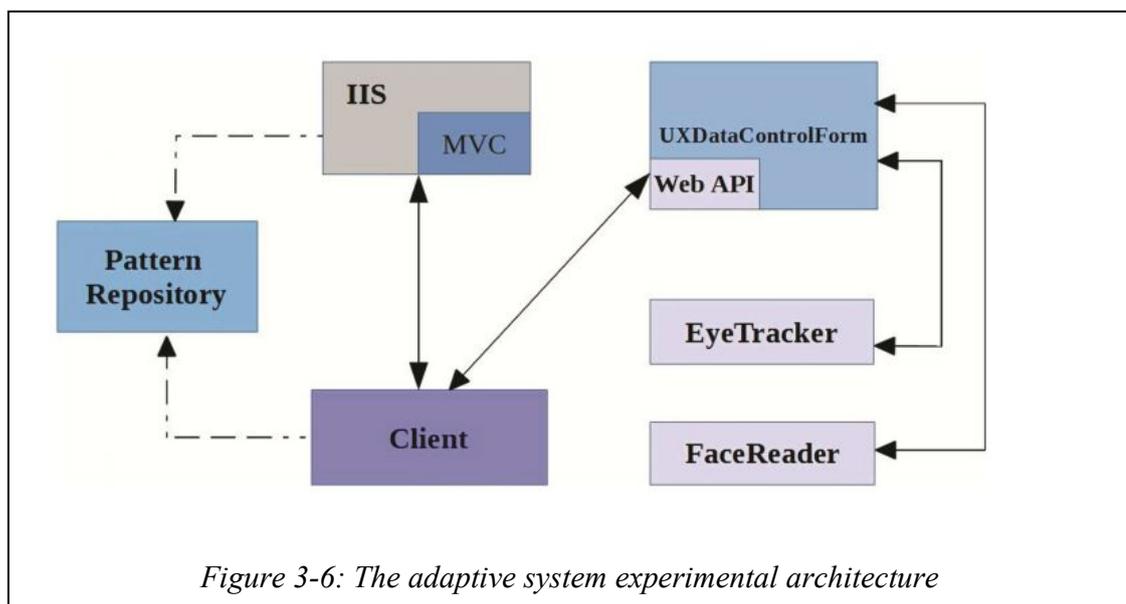
The companion approach aims at identifying the cause of an emotion relying on the history of interactions to propose an appropriate adaptation at run-time. Some limitations can be highlighted. First, the approach is designed to work with only one emotion at the time. Each ***emotion*** is related with an action such as a dislike level during an automatic volume adjustment. However, in a HCI context, a UI object with different colours may evoke multiple emotions since colours themselves can evoke many user emotions as shown in the Plutchick's wheel of emotions (Plutchik, 1991). Thus, there is a potential lack of user emotional behaviour which may lead to an inappropriate adaptation. Second, there is potential inaccuracy results in the ***adaptation technique*** based on the interaction history. Particularly, the approach cannot identify with precision the referenced object which causes a particular emotion since it analyses an interaction history to deduce later such emotion-object relation. Moreover, this imprecise analysis is an input data for all the *layers* which can affect future Interactive system adaptations. Third, there is not details about how to implement the ***adaptation technique*** based on a set of sequential tasks. It limits the understanding of this technique and its consequences in the adaptation process. Fourth, while content adaptation is considered, ***aesthetics*** is partially mentioned in the adaptation process so that the following elements: ***usability*** or user characteristics (***gender*** and ***age***) are not considered to drive the adaptation. ***Adaptation technique*** thus depends only on the sensors information to define proper adaptations. Finally, since there is up to now no demonstrator implementing this approach, it is difficult to understand how the adaptation process should be executed at ***run-time*** as well as the user implications when facing incorrect Interactive system adaptations.

#### *d) Pattern-based approach (Märting et al., 2017)*

Finally, (Märting et al., 2017) proposes an experimental architecture where automatically detected emotions can trigger Interactive system adaptation based on patterns expressed as XML specifications of the UI (e.g. an xml definition of a panel with its colours). Interactive system adaptation can be related to colours or structure and is performed at run-time. The approach considers an adaptation of UI aesthetics and usability based on emotions detected at run-time. The adaptation follows predefined rules decided at design time to perform changes in the UI at run-time. It has very similar goals to ours. The feasibility of this approach is demonstrated by a prototypical interactive application. This implementation provides an architecture for building

adaptive interactive systems which serves as an experimental platform for testing an existing framework called PaMGIS. It stands for Pattern-based Modeling, Generation and usability evaluation of Interactive Systems (Engel & Martin, 2009) (Engel, Martin, & Forbrig, 2015).

Figure 3-6 shows this architecture which contains four modules (Meudt et al., 2016): *UXDataControlForm* (Windows form application), *client*, *Internet information Server or IIS (server)*, and *pattern repository*, and. First, The *UXDataControlForm* represents the *Windows Form application* which aims to retrieve user experience data (emotion and gaze points). These data are captured in an implicit manner by accessing dynamically to the input elements to measure eye movements and facial expressions. It is achieved thanks to an eye tracker and face analysis tool (FaceReader). This access is performed by requiring data to each corresponding input APIs [15]. Once there is a connection between the application and FaceReader, the application is able to control it by calling actions such as start and stop facial analysis. These



actions are stored in a detailed log. It contains all the classifications (detected emotion values, e.g. 77% of happiness and 5% of disgust). Similarly, the user dominant expressions are stored in the state log (e.g. only 77% of happiness). Conversely, the application automatically detects the tracker and a connection can be established when an eye tracker is connected. The application also enables the user to start/stop tracking and run the eye-tracker calibration.

Once the data are collected, the central part of the prototype architecture, the *Client*, which accesses user data and sends it to the server. To achieve this, a connection needs to be established with the *UXDataControlForm*. Once the application is listening to the <http://localhost:8080/> address then the Web API Controller “*UXDataController*” sends a GET HTTP request to return the data coming from the *FaceReader* and *Eye tracker* via a UI.

The *server* is implemented by following a *model view controller* architecture (*MVC*). It handles a component analyzing the user experience state which is implemented as a client-side application

by using AngularJS<sup>4</sup>. Its views are based on JavaScript, HTML and CSS. It allows dynamic changes in the page, and thus avoids loading the whole Webpage again.

Through the Web API, the system requests the data and evaluates them in a directive. A directive is basically a function executed on the client-side to define an adaptation in the UI. For instance, the directive `show-input-button` which displays an input text button in the UI. Each web page is linked with a directive and also a *controller*. The *controller* is in charge of executing the main functions in services (e.g. getting input data from facial recognition) associated with directives. For instance, the service fetches sensor data from the eye-tracker and Face Reader. The *model* manages the data of the web application; it includes the link maps and user events data (e.g. how often the user looked at a given UI panel).

Finally, the analysis of these user's events data is matter of the *pattern repository* (PaMGIS). It uses the pattern specification language for describe HCI patterns for all abstraction levels (Engel et al., 2015). These patterns may be defined in the *client* or the *server* acting as XML specification of the UI. They include definitions of colors (e.g. “<Panel1:timeTableInformationColor = blue />”) or page layout structure. These patterns allow adding the related user emotion state, i.e. “<Panel1:timeTableInformationColor.Neutral/>” as initial state. Thus, if the user emotion changes to angry then the pattern is modified to “Panel1:timeTableInformationColor.Angry”. No details are provided to understand the use of user emotions variations (angry level from low to high into Panel1) into the HCI patterns or the association of UI quality factors (e.g. low aesthetics) with such emotion variations. The Webpages are modeled following these XML specifications. The Webpages' code uses a deployment element which contains aspects such as concrete code definitions and model fragments which may be used for automated user interface generation.

Furthermore, the Interactive system adaptation needs a decision-making process related to a dominant emotion which is selected by the system designer . In fact, the automated UI generation depends on the final dominant user emotion on a UI element, which is figured out by a statistical calculation. It means that over a specific time period, the resulting dominant emotion is assigned to, for instance, a Webpage panel by calculating how often the user has looked at this panel. So, this dominant emotion is analyzed by the system designer which can decide (at design-time) which adaptation action an update-method should do. These actions include “change a Webpage color dynamically” or may have some other extra features. It is the font-size change of a page element when the user is aged. There are no details about the kind of statistical methods can be applied or specific variations in aesthetics and/or usability relying on user characteristics (age or gender). Furthermore, no definition of the use of age (or age intervals) associated with UI changes is given.

Figure 3-7 shows a screenshot of the web application as an example. It shows five panels released by one directive on one template (pre-built HTML page). When the user is looking at one specific panel (marked by a red rectangle on the figure), the *client* gets the user data (emotion from FaceReader and gaze points from the eye Tracker) which is passed to the model into the MVC architecture. Here, the patterns defined in the *server* relates the detected emotions with panel1 (“Panel1:timeTableInformationColor.Neutral” as first state). To provoke anger in the user on purpose at filling a timetable, the panel does not include a UI element (no destination field) to

allow the user to add information about the desired destination. It may update the pattern to “Panel1:timeTableInformationColor.Angry” which will change the color to a predefined enjoyable one.

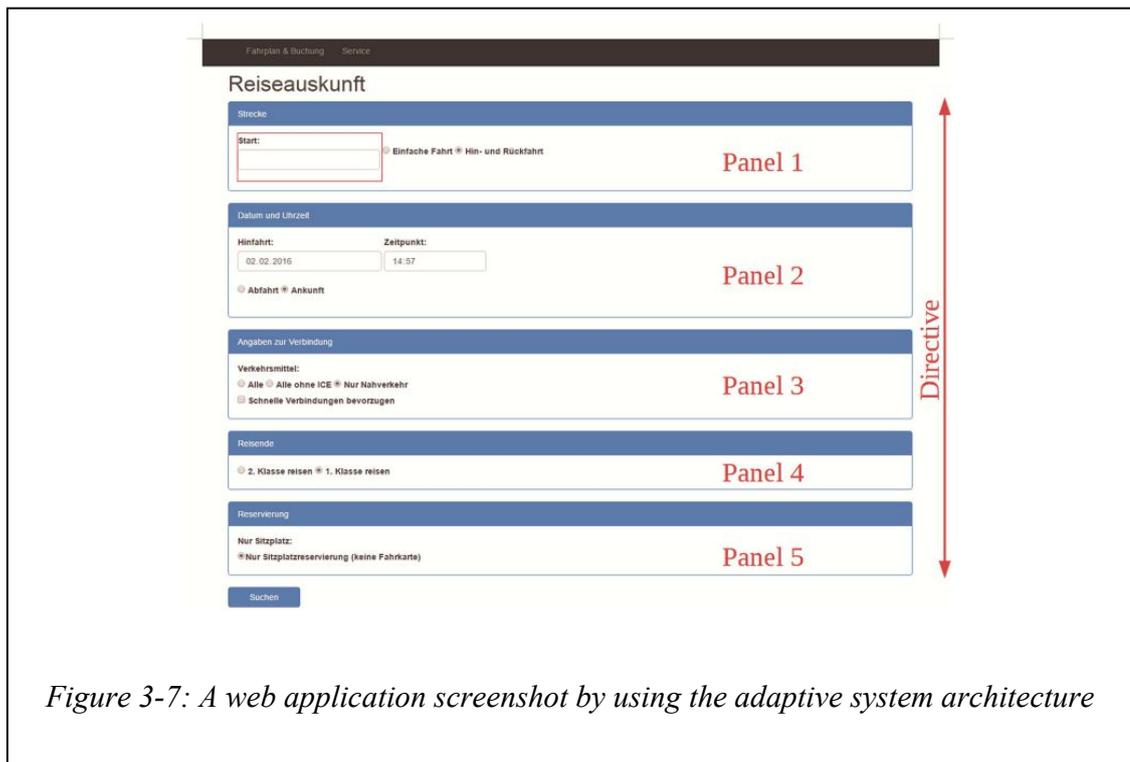


Figure 3-7: A web application screenshot by using the adaptive system architecture

The system designer will use the dominant emotion found it in a period of time to define a Interactive system adaptation action (e.g. if dominant emotion is present then change panel color). Moreover, the system designer needs to define which template is given to the directive by passing a parameter, i.e. `template1-path = template1.html`. Then, the update-method calls an object inside the model to say which template has to be loaded for a directive. Finally, this directive interprets and includes the template in the final HTML page.

### **Limitations**

The pattern-based approach shows an experimental architecture in which detected emotions can generate interactive system adaptations based on patterns. Although the approach has similar goals with us, there are some concerns that we can underline. First, adaptations are based on one dominant **emotion** over a period of time. This emotion is compared with a dominant emotion determined at design-time for each UI element. The manner this comparison is realized is not made precise: the period of time and the threshold that triggers **adaptation** are not specified.

Second, there is also no evidence about how to identify the cause of non-expected emotions and then proposing appropriate modifications.

Third, there are many different types of stimuli in a web page (e.g. colors, images, animations and drop-down menus) so that designers need to define as many HCI patterns per page as they need (e.g. 10 patterns for supporting 10 different colors of panel1). Hence, this notion rises to multiple patterns, leading in turn to a huge work for defining all of them and limiting the approach to the patterns that have been identified.

Fourth, positive and negative affects change in a period of time (Watson, 2000), but the authors do not detail how to consider this variation if it is not predefined in the patterns, i.e. how to take into account the change of an angry level from low to medium or high. Five, although emotion detection is made by automatic recognition tools (e.g. FaceReader), the Interactive system adaptation at runtime could be affected w facing unexpected emotions since the designer needs to make decisions each time about a new dominant emotion and also the *adaptation* actions to call an update-method.

Finally, there are different sources of emotions such us personality, day time, age and gender which can affect emotions (Hume, 2012) that are not formally defined to drive the Interactive system adaptation. Moreover, these sources are not related explicitly to UI quality factors (aesthetics and/or usability) above all in the HCI patterns.

### 3.2.3 Approaches Comparison

To facilitate the comparison of approaches presented previously, Table 3-1 summarized their characteristics, where “+” stands for “yes” whether the characteristics is explicitly studied in the related work, “-” for “**the characteristics is somehow related**”, and **blank** when nothing was related to the characteristics. The columns correspond to the analysis criteria identified in the previous section.

	TO WHAT?			WHEN ?	WHAT?			TO WHAT?		HOW?	WHERE?
Reference	Emotion	Emotion source	Emotion detection Method	Adaptation Technique	Content	Aesthetics	Usability	Gender	Age	Adaptation type	UI Type
(Hudlicka & Mcneese, 2002)	Affective state	Physiological signals	Implicit (sensors) & Explicit (diagnostic tasks)	Compensatory strategy	+	+				Run time	Desktop
<b>Prototype implementation</b>	Anxiety	Heart rate	Heart rate sensor & anxiety self-reports	What-if rules	UI messages	Format-based				Run time	Pilot driving system
(Nasoz, 2004)	Experimented emotions	-Physiological signals (galvanic skin response, temperature, and heart rate) -Speech (vocal intonation and natural language) - Facial expressions -Motor movements	Implicit (sensors) & Explicit (linguistic terms)	Machine learning	+			-	-	Run time	Desktop
<b>Prototype implementation</b>	Anger, panic, sleepiness, frustration	Physiological signals	Armband sensor & polar chest strap	Bayesian belief Network	UI messages			No specific associations between them		Run time	Car driving system
(Meudt et al., 2016) Potential implementations section 4	Experimented emotion	-Speech - Facial expressions -Gestures	Implicit (sensors) & Explicit (dialogs with the user)	Adaptation rating strategy	+	-				Run time	Desktop
<b>Prototype design (not implemented yet)</b>	Dislike	Facial expressions	Camera		Volume control and UI messages					Run time	Car driving system
(Märtn et al., 2017)	Experimented emotion	-Eye movements -Facial expressions -body temperature	Implicit (sensors)	HCI patterns & designer analysis	+	+	+		-	Run time	Website
<b>Prototype implementation</b>	Anger	-Eye movements -Facial expressions	Camera and Eye tracking sensor	Panel pattern & designer analysis		Panel colors			No details	Run time	Booking system

Table 3-1: A comparative study of Interactive system adaptation approaches and prototypes

Overall, Table 3-1 synthesizes and compares the studied approaches about adaptation driven by user emotions. It can be summarized per *Analysis criteria property*:

- *Emotion*: The detected emotions are mostly related with the experimented emotion during the interaction excluding other emotions such as Ekman emotions. Therefore, adaptation is normally conducted by following one user experimented emotion regarding the domain of the involved system. For instance, anxiety for the pilot driving system. Thus, designers need to define a relevant emotion regarding the domain at design-time.
- *Emotion source*: Describes how emotions are captured. In general, the approaches support facial expressions being considered as the main key element of human communication.
- *Emotion detection method*: Besides implicit methods to recognize emotion, some approaches rely on explicit methods to collect user data. However, it can be disturbing for the user when the interaction is interrupted as it is the case for user dialogs in (Meudt et al., 2016). Moreover, emotions change during time so that a collected set of emotions by paper-based methods after the experimented event can be useless, releasing inaccurate adaptations. Conversely, automatic emotion recognition can provide a history of emotion-objects events to be analyzed for a suitable adaptation. (Meudt et al., 2016) underlines this characteristic; however, his approach has been not implemented yet so the impact of emotion recognition to define adaptation actions or rules is unclear.
- *Adaptation technique*: there are different techniques with precise limitations: what-if rules and Bayesian belief networks without the definition of how to deal with a big number or combination of potential rules; the adaptation rating strategy with a lack of precision of the referenced object (e.g. widget) which causes a particular emotion; and the HCI patterns with no clear explanations about variations of UI quality factors and emotion values. Particularly, the period of time and the emotion thresholds that triggers adaptation are not specified. Moreover, the patterns depend on decisions done by the designer to determine precise adaptations.
- *Interactive system adaptation: Content, Aesthetics, Usability*: the majority of the approaches focus on modifying the content and aesthetics of the interactive system. Mainly, the modifications involve the display of text as messages to inform the user about the interaction. (Hudlicka & Mcneese, 2002) covers also aesthetics focusing on format-based changes. Only one approach is designed to adapt the UI (websites) concerning aesthetics and usability. It has the potential to modify specific properties inside aesthetics elements based on one dominant emotion (e.g. change the color of panels by analyzing the main detected emotion) and HCI patterns. Besides panel change colors, usability and other aesthetics adaptations were not described, but could be imagined. The Interactive system adaptation needs to follow system designer decisions to select appropriate adaptation actions and UI templates. Thus, the majority of approaches focus on Interactive system adaptation for functional changes (content) following one particular emotion rather than the potential use of multiple emotions to define better UI quality factors (aesthetics and/or usability)
- *User characteristics factor (age and gender)*: Aesthetics and usability adaptations are not related with other factors of emotions such as age or gender. Thus, there is a lack of formal definition of Interactive system adaptations depending on different user characteristics (age intervals, gender distinctions) and emotion levels (high/low emotions levels).

- *Adaptation type*: All approaches are designed to adapt UIs at runtime; however, the adaptation process relies on a post-analysis of the detected emotion and the UI element which evokes such emotion. This post-analysis should be accurate enough to drive a proper adaptation. Besides (Meudt et al., 2016), all other approaches use an explicit method to detect emotions which can be disruptive for users. (Märting et al., 2017) needs designer decisions to define proper Interactive system adaptation actions based on one dominant emotion. It may lead to a run-time adaptation attached to only one emotion arousing potential issues with unexpected emotions in run-time.
- *UI type*: Almost all approaches focus on GUI adaptations since the focus is on the domain understanding rather than UI quality factors adaptation. A web proposition is given by (Märting et al., 2017) where these UI quality factors are not described in detail (e.g. low/high levels of aesthetics or usability).

Beyond this the study of approaches about adaptation driven thanks to emotions, we move to understand deeply user experience. Mainly, a system able to adapt UIs for maintaining UX, requires to have a fine grained understanding of UX and its impacting factors.

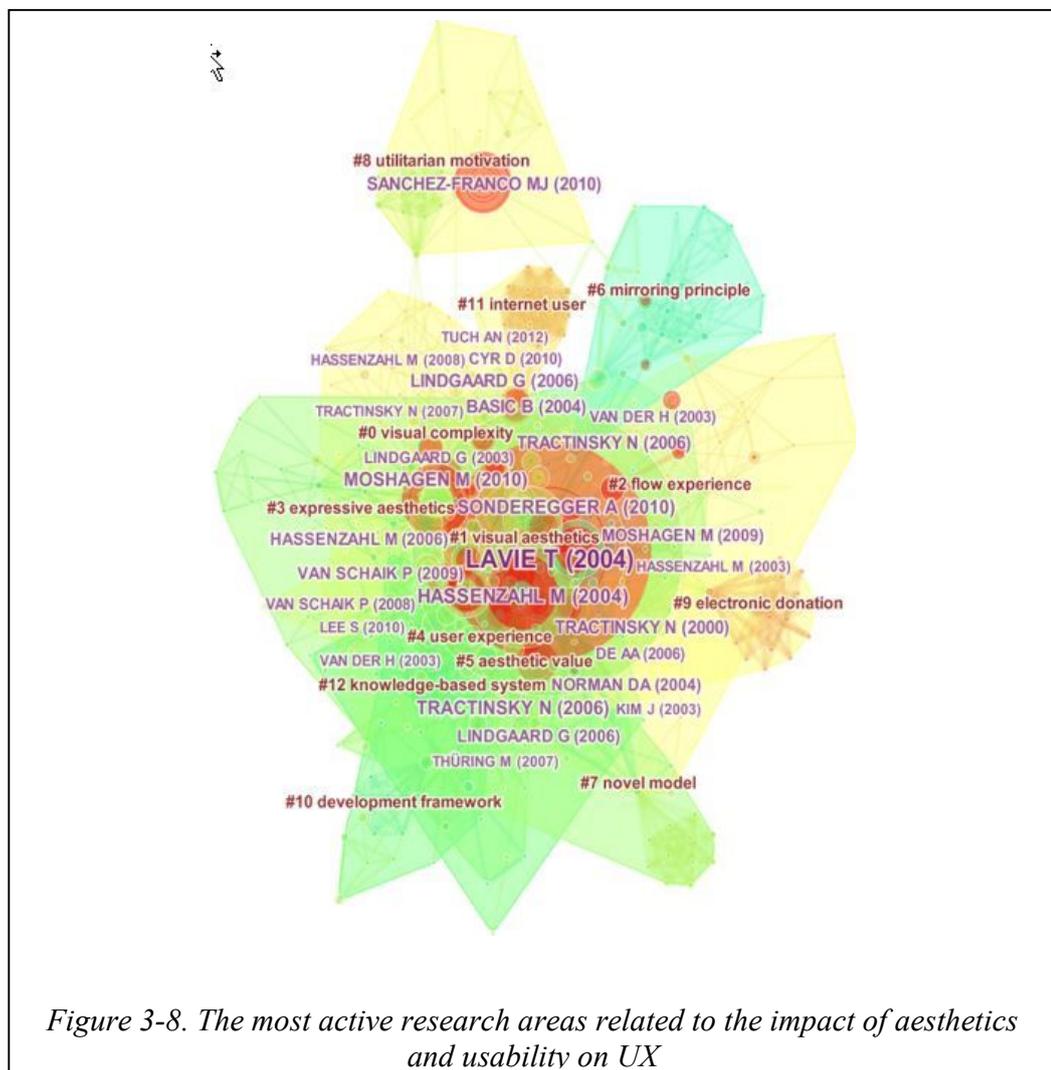
### 3.3 User experience

Papers studying UX and one of its facets through emotions are numerous. They study a) the impact of aesthetics and usability on UX without considering age and gender; b) the impact of age *or* gender on UX; or c) the impact of age *and* gender on UX. To **identify key papers**, we conducted a quantitative analysis called Bibliometrics (De Bellis, 2009), then proposed a qualitative analysis (manual content analysis per contribution).

The quantitative analysis included three main steps: citation data collection, citation analysis and report results (Ishag, Ryu, Lee, & Ryu, 2018). First, contributions were collected by this query string: “usability OR aesthetics AND emotions OR (gender OR age)” from Scopus web platform. It is important to note that the contributions are also indexed in other academic databases (e.g. ScienceDirect). We used the Scopus web interface since it provides an easier manner to extract results from queries for a quantitative analysis in tools like CiteSpace (Chen, 2014, p. 5). The query released 6077 contributions distributed in medicine (1730), computer science (1582), social sciences (1432), arts and humanities (1374), Engineering (696), Mathematics (433), Psychology (425), Dentistry (325), Health professions (255) and Business (200). We only selected the computer science contributions (1582) as the most relevant domain. Then, papers were distributed in each UX facets by title, keywords and summary - excluding the ones not matching the facets with precision: 878 papers on usability and aesthetics without consideration of age or gender, 411 papers studying the impact of age or gender, and 250 papers considering both age and gender. A published thesis in archives-ouvertes was added (Bataoui, 2017) to that last category, considered as recent and not indexed work.

Second, the total number of papers identified (1539) was sent (Scopus file) to a bibliometric tool (CiteSpace by (Chen, 2014, p. 5)). The citation burst indicator identified the most active research areas (set of related papers) per facet by releasing 12 **central papers** (*clusters*) per area automatically. To clarify, Figure 3-8 shows the applied process for the first facet. It shows 878 papers distributed in a citation network. All papers are associated by their references so that if a

paper is cited by another one then the network visualizes a link between them. Mainly, 12 clusters were retrieved and identified by a hash tag (e.g. #0 visual complexity, #1 visual aesthetics, #2 flow experience, #3 expressive aesthetics, #4 user experience, etc.) where the most active areas are marked by red circles in the network. It clearly shows that there are active areas which highlights key papers in each one such as (Lavie & Tractinsky, 2004) for #visual aesthetics at the center and (Sanchez-Franco & Rondan-Cataluña, 2010) for #utilitarian motivation at the top. Therefore, the quantitative analysis released a total number of 36 *key papers* retrieved from the most active areas for all facets.



A qualitative human analysis then discriminated these papers further according to this criteria: (1) the selection of the ones that included clear (explicit) results about aesthetics and/or usability through emotions and which also (2) involve websites experimental studies: eight papers

concerning usability and aesthetics without any consideration of age or gender, six papers on either age *or* gender and four papers for age *and* gender.

Although there are other papers in each active research areas, these **gathered ones** (18) are valuable as they (1) are central papers from active areas, (2) include clear explicit results about aesthetics and/or usability thanks to emotions and (3) involve websites experimental studies. This sample allow us to perform a sharp content examination by an *Analysis Criteria* shown below.

### 3.3.1 Analysis criteria

This analysis used the retrieved papers related to each UX facets where emotions are declared or detected with the following criteria:

- *Aesthetics and Emotions*: refer to aesthetics thanks to emotions.
- *Usability and Emotions*: discuss usability thanks to emotions.
- *Emotions and Gender*: consider UI impact on emotion and gender.
- *Emotions and Age (AG)*: study UI impact on emotion and age.
- *Emotion/s*: study emotions, declared or detected.
- *Analysis technique*: studies the techniques to analyze emotions.
- *Emotion recognition method*: to know whether emotions are detected or declared.
- *Website domain*: represents the domain.

First, we study the relation between UI quality factors: aesthetics and usability.

### 3.3.2 Aesthetics-usability relation

Many works studied the impact of aesthetics and usability thanks to emotions. In this section, we focus on those that do not consider users' characteristics. They are all based on different kinds of emotions with statistical techniques to examine the impact of aesthetics and usability.

A first combined study of aesthetics, usability and affect was given by Tuch et al. (Tuch et al., 2012). They worked on the relationship between perceived usability and affective response (valence) by using declared emotions. The results suggested that a low usability level causes a negative emotion (frustration), implying a decrease in aesthetics perception. (Harrison, 2008, p. 101) evidenced more noteworthy differences in the negative affective responses in aesthetics rather than usability measured by valence in e-commerce and e-government websites. Valence stands for the extent to which one is generally feeling good or bad (*section 2.1.2*).

Some works used a common analysis technique, correlations, to study the relation between aesthetics and usability with emotions. (Lavie & Tractinsky, 2004) argued that the correlation between aesthetics and pleasure was more significant than the usability-pleasure one. It demonstrated a higher frequency in choosing attractiveness over functional aspects within websites. (Porat & Tractinsky, 2012) highlighted a more substantial correlation between usability-pleasure than aesthetics-pleasure when interacting with a different UI's type (book and apparel store websites). Similarly, dominance correlations (user control degree) were found of lower value in aesthetics than in usability while the opposite was true for arousal. Commercial

UIs influence an user emotions such as trust and satisfaction (Sanchez-Franco & Rondan-Cataluña, 2010). In their online survey study, the correlation in satisfaction-aesthetics was bigger than satisfaction-usability; whereas lower in aesthetics rather than usability at considering trust. Then (Seo, Lee, Chung, & Park, 2015) studied the same analysis technique but with different variables: valence, arousal and engagement in an online survey. They argued that both perceived usability and perceived aesthetics were positively correlated with emotional valence and negatively correlated with emotional engagement. There was no relationship between perceived usability/aesthetics and arousal. Perceived aesthetics evidences potentially a higher impact on valence than perceived usability. Conversely, perceived usability may influence more engagement rather than the influence given by aesthetics. Moreover, the interaction with hedonic (virtual travelling) and utilitarian (e-banking) online services also evidences a different impact on user emotions by using correlations (Sánchez-Franco & Martín-Velicia, 2011). It studied commitment which reflects feelings such as loyalty, belonging and affiliation. The banking website reported a more significant correlation in commitment-usability than commitment-aesthetics while an opposite effect was found at interacting with the travelling one. Thus, these works shows that there are differences in how aesthetics and usability are related with some emotions thanks to a study of correlations.

Lastly, an empirical investigation given by (Coursaris et al., 2010) shows a set of emotions (Pleasant, Terrible, Delighted, Frustrated, Contented, Unhappy, Gratified, Sad and Joyful) in the case of hotel bookings websites. Three measures were used (means, standard deviations and loading) and all user emotions were collected by a paper-based method. Aesthetics influences only pleasantness while usability impacts all remaining emotions such as terrible-delighted or unhappy-gratified.

To facilitate the comparison of work presented previously, Table 3-2 summarized their characteristics, where “+” stands for “**yes**” whether the characteristics are studied as an explicit variable in the related work, “-” for “**the characteristics is somehow related**”, and **blank** when nothing was related to the characteristics. The columns correspond to the analysis criteria identified in the previous section.

Reference	Emotion	Analysis Technique	Aesthetics and Emotions	Usability and Emotions	Emotions and Gender	Emotions and Age	Emotion recognition Method	Website domain
(Tuch et al., 2012)	Affective response	Valence values and parametric tests	+	+			Paper-based survey (SAM)	Shopping
(Harrison, 2008, p. 101)	Affective response	valence values	+	+			Online survey and eye tracking.	E-commerce and e-government
(Lavie & Tractinsky, 2004)	Pleasure	Correlations	+	+			Online survey	Food and wine site.
(Porat & Tractinsky, 2012)	Pleasure, arousal and dominance	Correlations	+	+			Paper-based survey	Bookstores and apparel stores.
(Sanchez-Franco & Rondan-Cataluña, 2010)	Trust and satisfaction	Correlations	+	+			Online survey	E-commerce
(Seo et al., 2015)	Valence, arousal, Engagement	Correlations	+	+			Online survey	Various domains
(Sánchez-Franco & Martín-Velicia, 2011)	Affective commitment	Correlations	+	+			Online survey	Travelling and Banking services
(Coursaris et al., 2010)	Pleasant, Terrible, Delighted Frustrated, Contented Unhappy, Gratified Sad, Joyful	Means, standard deviations. and loadings	+	+			Paper-based survey	Hotel bookings

*Table 3-2. A comparative study of the impact of aesthetics and usability on UX*

Overall, these related works prove of the influence of aesthetics and usability on emotions. However, the elements used to characterize emotions such as valence or arousal are few. A fine-grain understanding of the impact of UI quality factors is limited. Moreover, these works only studied verbally-declared emotions. Thus, emotion interpretation remained subjective without an automatic emotion evaluation and which can provoke a bias in the studies (Isomursu, Tähti, Väinämö, & Kuutti, 2007).

### 3.3.3 User experience by age or gender

Few research studies investigated the impact of age or gender on UX. First, we present the ones related to gender and then concerning age.

Some of studies related with gender use a parametric test technique to analysis emotions: (Simon, 2000), (Cyr & Bonanni, 2005) and (Ozdemir & Kilic, 2011). (Simon, 2000) explored commercial websites satisfaction within various cultures gender groups: Asia, Europe, Latin & South America, and North America. Women were found to prefer less disordered sites, composed of few images and avoiding multiple levels of navigation with sub-pages to drill through. Contrarily, men's preference went towards sites with extensive graphics and animations. (Cyr & Bonanni, 2005) focused on the relationship between gender and web site design preferences by studying trust, satisfaction and loyalty. They collected user's impressions of e-business websites by using a paper-based survey trough t-tests. Interestingly, they argued that men indicated more favorable impressions of the visual design of products information. While women were more attracted by web sites colors, men by animations and the interactive, "flashy" elements. Then there is one study that addresses gender while considering a category of age (18-24 years). (Ozdemir & Kilic, 2011) investigates whether there are differences in website visualization according to the gender of young consumers (aged 18-24 years). The parametric tests evidenced that six website visualization features evoked different likeness in participants. These gender-based differences involve different color preferences using rounded lines and shapes, 4 to 6 colors in typeface, female figures in photos and expert language in the websites. No distinctions were reported regarding age and visual elements.

Another group of papers analyze emotions by sample distribution measures such as mean or standard deviations. (Bakaev et al., 2007) studied the aesthetics preferences of the elderly and the design factors for e-business web sites by using means and standard deviations. Two age groups were identified: elderly (from 60 to 75) and non-elder (from 25 to 42) in two nationalities (Korean and Russian). By a descriptive analysis, elder Korean participants reported a higher pleasure level than non-elder ones; while there was not a significant pleasure difference for Russian participants. In terms of design elements influence, elder participants from both nationalities reported a negative influence on aesthetics impressions in design factors related to "expressive aesthetic dimension" such as sophisticated, original, fascinating, creative and special effects. (Djamasbi et al., 2010) also proposed a study based on distribution measures related with age focused on the Y generation. Remarkably the emotion recognition method used participants' eye-movements that were tracked while users browsed informative websites. Mainly, it showed by an online survey how users in generation Y (from 18 to 31) liked more some web pages than others. Here, the preferred pages included aesthetics (main large image, images of celebrities,) and usability elements (search feature and little text) where the main difference was shown in pages with images of celebrities rather than images of people.

Independence tests was used only by (Moss et al., 2006). It explored the gender differences in design. Independence tests reported that women were more likely to use some design elements than male users. These design elements include rounded shapes rather than straight ones, a horizontal layout, more colors in the typeface (font-family), and informal images. No likeness distinctions were found in visual elements such as 3D or 2D design and colors' mixture (black and blue).

Following the same criteria given in Table 3-2, Table 3-3 compiles and compares work related to age or gender. It can be summarized into five highlights:

1. most papers studied the aesthetical aspects of UI while studying users' characteristics;
2. the impact of aesthetics is more pronounced on gender than on age,
3. the affective elements studied here were limited to satisfaction, trust, loyalty, likeness and pleasure, thus they do not refer to Ekman's universal emotions (Ekman & Keltner, 1970);
4. with the exception of the last approach, all studies gather users' impressions using explicit feedback methods (e.g. paper surveys), sometimes subjective;
5. the statistical analysis does not cover multivariable analysis with seven or more outcome variables to explore Ekman emotions in UX associated with gender and age.

Ref.	Emotion	Analysis technique	Aesthetics and Emotions	Usability and Emotions	Emotions and Gender	Emotions and Age	Emotion recognition Method	Website domain
(Simon, 2000)	Satisfaction	Parametric tests	-	-	+		Paper-based survey	Commercial
(Cyr & Bonanni, 2005)	Trust, satisfaction and loyalty	Parametric tests	+		+		Paper-based survey	E-business
(Ozdemir & Kilic, 2011)	Likeness	Parametric tests	+		+	- [18-24]	Paper-based survey	Marketing
(Bakaev, Lee, & Cheng, 2007)	Pleasure	Means and stds.	+			+ [25-42] & [60-75]	Online survey	E-business
(Djamasbi, Siegel, & Tullis, 2010)	Likeness	Means, stds. and error	+	+		- [18-31] Y generation.	Online survey and eye tracking.	Informative
(Moss et al., 2006)	Likeness	Independence test	+		+		Not reported.	Commercial

Table 3-3. A comparative study of the impact of UX depending on age or gender

### 3.3.4 User experience by gender and age

Unlike the previous section, there are a few studies which explored the UI impact on *both* gender and age. (Bataoui, 2017) studied the affective reactions by interacting with welcoming websites. It studied emotions by age and gender separately. These reactions were measured by positive valence (plenitude, pleasure, relaxation, calm, stimulation, surprise) and negative valence (oppression and irritation). The results showed more significant gender rating in positive (plenitude, relaxation and stimulation) rather than negative valence (irritation). Two age groups were identified: from 18 to 40 and since 41 years old. Although there were no significant differences based on age, differences were found in the average of each emotion belonging to positive and negative valence within the age groups.

(Steenkamp & Geyskens, 2006) studied the perceived value and utilitarian experience of 30 commercial websites in a multicultural approach. The perceived value measured aspects such as usefulness, user matched expectations, and global UX while clarity, simplicity, learnability, efficiency and consistency were evaluated in the utilitarian experience. This study found a correlation of users' characteristics (gender and age separately) between pleasure and arousal in an online survey where men proves a higher level of arousal than women as previously argued by (Zuckerman, 1994). Moreover, positive correlations were found in gender across both perceived value and utilitarian experience. In terms of age, older people seemed to attach less importance to pleasure felt during web navigation than during customization as the results showed only negative correlations in perceived value.

(Lee & Kozar, 2009) conducted cognitive usability evaluations based on emotions for three travelling and one electronic websites. These evaluations known as user affective appraisals show significant differences in how the legibility (easy navigation), mystery (curiosity by features stimulation) and variety (enjoy vivid and dynamic images) of websites impact users' perceptions across age and gender independently. Age and gender results were reported independently. In fact, Women revealed a higher level of affective appraisals (user emotion evaluation) than men in legibility and mystery while the websites differences influenced more men than women. Concerning age, two groups were studied: group A (30 or below) and B (over 30). Here, group A evidenced higher appraisal levels in legibility and coherence while B had higher appraisal levels in website's variety.

Finally, (Faiola, Ho, Tarrant, & MacDorman, 2011)(Dittmar, 2001) explored the potential of regression and factor analysis in a general and cross-cultural comparison of web home pages. Gender and age as regression factors were reported independently where users were 41.7% male and 93.5% were older than 31. Mainly, after collecting user impressions online, the second and third regression equations reported that the factor age-gender is important to uncover the UI impact. To clarify, the second equation examined the relation between home page design elements and gender-age. It shows that participants preferred (liked) icons, frames, and margins while a less preference was given for navigation, bars and typography. To extend this, the third equation evidenced the preference on home pages with a higher color's contrast. In the same manner as previous tables, Table 3-4 groups and summarizes the exposed approaches.

Overall, this section determines that:

1. few studies focused on UI influence for both gender and age;
2. there was some evidence of a different UI impact related to gender and preliminary results towards age;
3. no research studies both usability and aesthetics as separate variables, depending on gender and age.

Moreover, all the studies were based on surveys, which can have some limits or biases as discussed earlier.

Ref.	Emotion	Analysis technique	Aesthetics and Emotions	Usability and Emotions	Emotions and Gender	Emotions and Age	Emotion recognition Method	Website domain
(Bataoui, 2017)	Plenitude, pleasure, Relaxation, Calm, stimulation, surprise, closeness, oppression, avoidance, nervousness	Means' scores of positive and negative affective reactions			+	+ [18-40 & >41]	Online survey	Welcoming
(Steenkamp & Geyskens, 2006)	Pleasure and arousal	Correlations	-	+	+	+ [not reported]	Online survey	Commercial (brand manufacturer)
(Lee & Kozar, 2009)	Affective appraisal (Dull, exiting, pleasant, unpleasant, enjoyable, unenjoyable)	factor loadings	-	-	+	+ [<=30 & >30]	Paper-based Survey	Travelling and electronics
(Faiola et al., 2011)	Likeness and calm	Regression analysis and factor loadings	+		+	+ [>31]	Online survey	Cultural (Korean home pages)

*Table 3-4. A comparative study of the impact of UX depending on age and gender*

To conclude, research in this field does not include any detailed study on the impact of both UI quality factors (aesthetics & usability) depending on the age and gender users' characteristics (summary tables). Only three papers looked into age and gender as variables influencing UX perception. Furthermore, they did not explore the influence of UI quality factors. Most related research only used declared emotions which introduced some bias in the emotion measurement (Isomursu et al., 2007) and generally limited the number of emotional elements studied.

These limits underline the need for a more precise evaluation of emotions (use of detected emotions) and a broader set of emotional elements to foster more advanced statistical analyses, in order to obtain a more precise understanding of the impact of usability and aesthetics on UX depending on gender and age.

### 3.4 Summary

This chapter presents the state of the art for UI adaptation based on emotions by focusing on 2 axes: (1) interactive system adaptation approaches, in which a set of properties related to the use of emotion recognition to drive the adaptation is analyzed and (2) approaches to study UX and each one of its facets (aesthetics/usability, age/gender).

For the first axis, we present and compare a few approaches that mainly represent systems using detected emotions to trigger adaptation. Despite the interesting features of each one, no approach focuses on UI adaptation associating UI quality factors (aesthetics and/or usability) with user characteristics (Ekman emotions, age and gender) at run-time. Particularly, only one approach (Märting et al., 2017) considers UI quality factors with emotions; however, adaptations are based on only one dominant emotion. The time period and emotion thresholds that trigger adaptation are not specified, the impact of UI quality factors levels (e.g. high) on different emotion levels (e.g. high level of disgust) is not considered, and the use of gender and age is not shown explicitly.

For the second axis related to the study of UX, we present and compare several approaches that study a) the impact of aesthetics and usability on UX without considering age and gender; b) the impact of age *or* gender on UX; and c) the impact of age *and* gender on UX. None of them proposes an analysis of the UI impact of usability and aesthetics on UX depending on gender and age.

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**4.1 Introduction**

We learned from the previous chapter that no work goes deeply to uncover UI adaptation by relating UI quality factors (aesthetics and/or usability) with user characteristics (Ekman emotions, age and gender) at run-time. Thus, we propose in this chapter an approach, *Perso2U*, for UI adaptation to emotions at run-time. This proposal allows users to interact with the UI where his/her emotions are detected by facial emotion recognition at real-time. This emotion detection is planned to be used to trigger UI adaptation thanks to the articulation of three components: Inferring Engine, Adaptation Engine and Interactive system.

The angular stone of *Perso2U* is an architecture. In this architecture, we focus on the component in charge of inferring UI problems from emotions to trigger adaptation. To define an appropriate functioning of this component, called Inferring engine, we conducted an experiment, from which we performed several analyses.

This chapter starts by describing the global approach relying on an architecture. Then, the experimental protocol used is presented. A first analysis of this experiment was realized to study the independence of the inferring Engine from facial emotion detection tools.

## 4.2 Global approach

Our approach aims to personalize user interfaces with user emotions at run-time (Galindo, Dupuy-Chessa, et al., 2017). In the user point of view, an important element for a suitable UI adaptation is to model users (Carberry & Rosis, 2008, p. 5). It should take into account a large variety of users' characteristics (Browne, 1990), profiles and preferences (Biswas, Bhattacharya, & Samanta, 2005) from interactive systems. As explored in section 2.2, emotions can be detected as user responses to some stimuli (e.g. anger detection at interacting with a pilot driving system (Nasoz, 2004a)). Moreover, emotion detection by using facial expression analysis is considered as the most common modality of emotion recognition (see section 2.2.2). In our approach, we use facial emotion recognition as user responses to interaction with web sites to upgrade the contextual information. This information can include age, gender, detected emotions values, and negative/positive inferred emotion associated with an aesthetics/usability problem. Then, this information is used to improve the user interface by a UI adaptation process.

From a tool point of view, our long term goal is to provide a tool that can adapt UIs to users' emotions taking into account characteristics such as gender and age (Hume, 2012). The tool is used to allow users to interact with web interfaces. While users interact with the UI, the tool recognizes the user emotions thanks to facial emotion recognition. The tool finds the best changes in the UI parameters (e.g. a change in the background color) based on the inferred emotions. The computation of these changes releases a modified UI to the user at run-time. There is currently a simplified version of this tool which acts as a prototype which allows our experimentation.

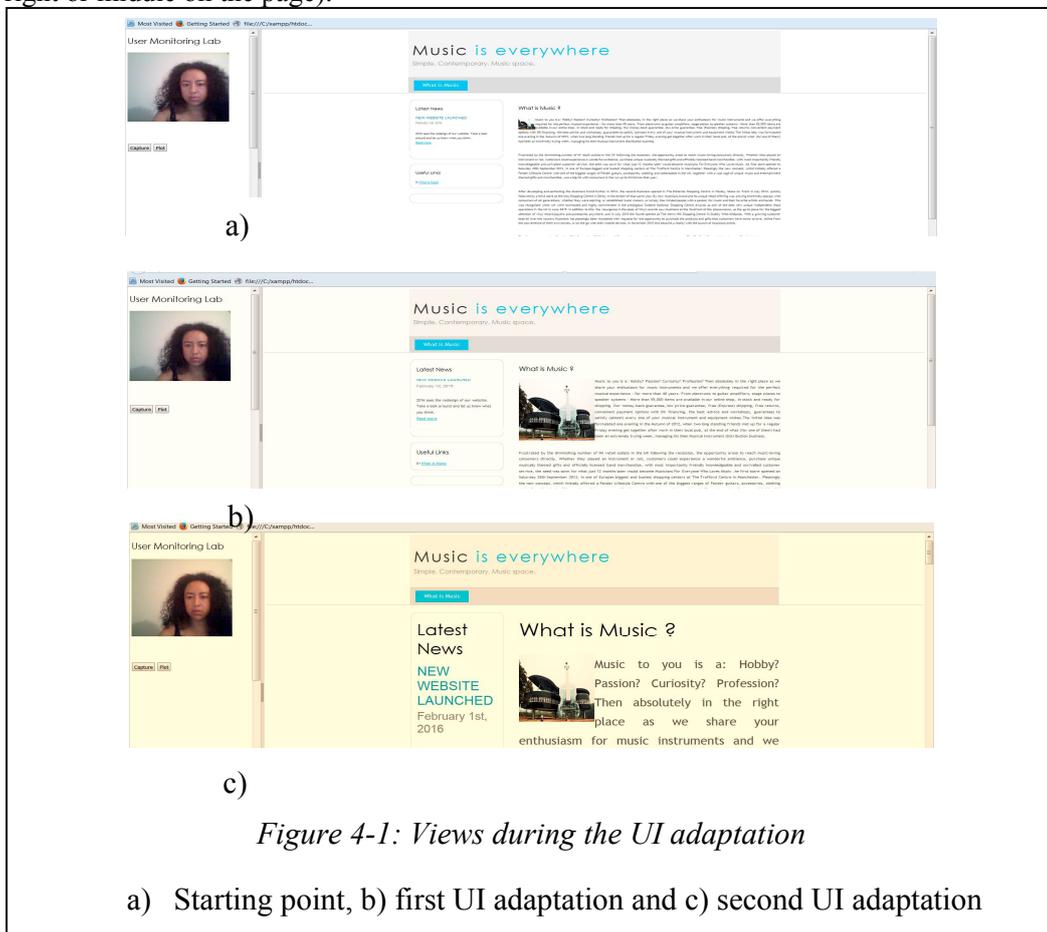
A first step toward such tool is an architecture called *Perso2U* "**Personalize to You**".

*Perso2U* aims at personalizing thanks to user emotions at run-time. It was designed based on the principles stated in a patent by (Céret, Dupuy-Chessa, Calvary, & Bittar, 2016). The proposed approach of this patent, Magnetic UI, considers the UI adaptation based on any contextual characteristics, such as the screen size or the brightness. The *patent* defines "an architecture based on an inferring engine and an adaptation engine, using distance calculation for eliciting a variant that defines the UI's spatial organization and then computing UI parameters for deciding and applying other adaptations". Since this, I reused the principles of Magnetic UI to extend the patent's architecture for considering emotions mainly in the inferring engine. Some common principles of both proposals are explained by key definitions exposed below.

### *Definitions*

**The Context of Use:** is a triplet <users, platforms and environment> representing the users who are intended to use the system, their hardware and software platform(s), and their physical and sociological environment while the interaction takes place in practice (Gaëlle Calvary et al., 2003). Consequently, our approach will deal with this context of use by adding the user emotions in this manner: user model <user with their *emotions*>.

**A UI variant:** is a variation of structures of a UI created for a specific context of use (Céret, Dupuy-Chessa, Calvary, & Bittar, 2016) (Figure 4-1 in a, b and c). Moreover, a UI variant consists of “an alternative being tested by assigning values to the factors: it is either the *control* or one of the *treatments*. The *control* designates the existing variant being compared against the new *treatments*. When there is no *control*, all variants are simply considered as *treatments*” (Vanderdonckt, Zen, & Vatavu, 2019). For instance, there can be two different structures for a laptop and a smartphone, leading to two variants of the same UI. A UI variant is modelled by the following elements: ui-name (the name of UI variation), variant-id (its identifier), path (the path to the source code embodying this variant), and context-of-use (the subset of characteristics of the context of use this variant is dedicated to). The UI variation is not limited to the layout page but also it can include UI changes such as the location of UI elements (e.g. search box on the top right or middle on the page).



**Parameters:** Define a set of variables which personalize UI elements (e.g. font-size, widgets, audio, display and dialogues) regarding with identified context values (Céret, Dupuy-Chessa, Calvary, & Bittar, 2016). User emotions could be used to trigger some changes in these *parameters*; but this would be managed by the inferring engine to infer the relevant emotions to

trigger adaptation. Then, the adaptation engine is in charge of conduct the adaptation process into the UI.

To illustrate previous definitions with a simplistic example, let's consider the UI variant shown in Figure 4-1 (c). In this example, there is only one variant. This variant of the Home page of a website is adapted to window-width which is bigger than 900 (pixels). We underline here that, considering the user's emotions, the adaptation system has decided that the background of the UI should be yellow. It sets the UI parameter (background-color) to the chosen color (light-yellow) and sends it to the variant after it is displayed.

Thus, all these theoretical elements allow the emerging of our architecture based on emotions to perform UI adaptation shown in the following section.

### **4.3 Architecture**

#### **4.3.1 General process**

The *Perso2U* architecture allows users to interact with the UI thanks to a cyclical process composed by three steps: (1) emotion recognition, (2) selection of UI structure and parameters and (3) execution of UI changes in run-time.

First, the architecture recognizes the user's situation and in particular him/her emotions (happiness, anger, disgust, sadness, surprise, fear, contempt) plus neutral which are into Ekman emotion model (*see Section 2.1.1*). This emotion recognition is performed cyclically by following a fixed time period defined by the designer (e.g. the emotions are detected each 10 seconds).

Second, after emotion recognition, the best suitable UI structure is chosen and the set of UI parameters (audio, Font-size, Widgets, UI layout, etc.) is computed based on such detected emotions.

Third, this computation of a suitable UI structure and parameters allows the UI to execute run-time changes aiming to provide a better UI. Since the emotion recognition is performed cyclically then it allows UI adaptation at run-time.

This process is achieved by the implementation of three components (Inferring Engine, Adaptation Engine and Interactive System) described below.

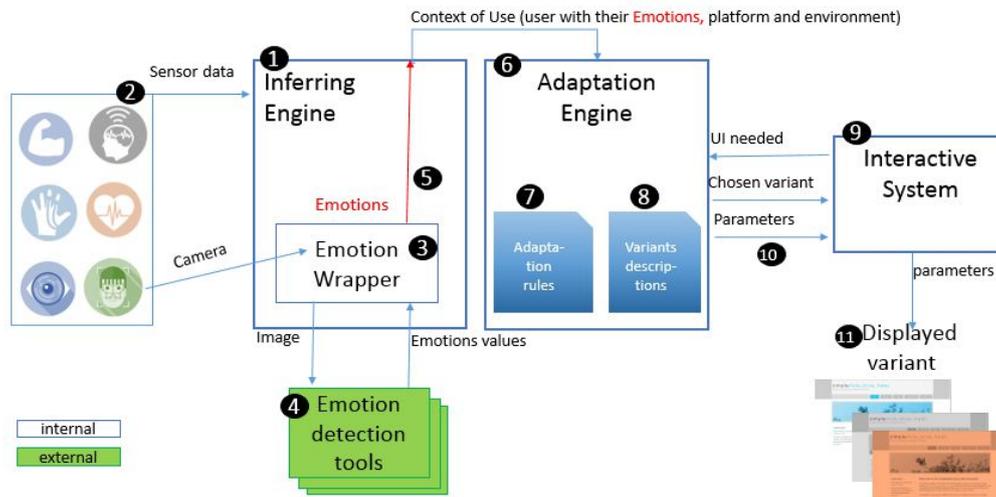


Figure 4-2: Global schema of the architecture.

### 4.3.2 Components

The *Perso2U* architecture (Figure 4-2) articulates three components: the Inferring Engine ❶, the Adaptation Engine ❷ and the Interactive System ❸. An adaptation process might start from either (a) a need for a new UI to display or (b) a change in the context of use. (a) can be exemplified by the user entering a web site: the home page has to be displayed. An example of (b) is the detection of a negative user emotion: when sadness is bigger than 90%, the background color corresponds to a royal blue). In the (b) situation, the overall process is the following: the Inferring Engine ❶ monitors sensors ❷ to detect changes in the context of use. From these values, it deduces the new context of use dynamically. It includes an Emotion Wrapper ❸ which makes it possible to include emotion values in the user model. The Inferring Engine ❶ sends ❹ the computed context of use to the Adaptation Engine ❷, which elicits accordingly a suitable UI variant and the UI parameters ❺. Finally, the Interactive System ❸ displays the variant and executes the changes related to the parameters. The whole process runs cyclically by following a time period parameter defined by the designer.

There are two additional definitions that are useful to filter emotions and to personalize the UI: *filtering emotions* and *personalizing function*.

**Filtering emotions:** Removes unneeded emotions during the interaction. This usefulness of emotions is defined by the designer. This definition is not included in the *patent*. To clarify, the designer can choose which emotions need to be detected by the inferring engine regarding a particular study so that the context of use will pass only the selected emotion to the adaptation engine. For instance, the designer can perform an experiment for studying UX in video games interaction by analysing how joyful is the experience for the user. In this case, the designer can

select only happiness to be detected. It means that the context of use (happiness, platform and environment) will be sent to the adaptation engine to drive a proper UI adaptation.

**Personalizing function** executes a UI personalization thanks to the values of the UI parameters (*a set of variables* which personalize UI elements) decided by the adaptation system Use (Céret, Dupuy-Chessa, Calvary, & Bittar, 2016). This function avoids selecting a UI variant that would have to suit all the characteristics of the context of use. Thus, variants can be reduced to only the variations that cannot be (or hardly be) modified at runtime.

Let's consider the UI variant shown previously in Figure 4-1 (c). Since the adaptation system has decided that the background of the UI should be yellow then background-color (UI parameter) is set to light-yellow. Then the Personalizing function check that background-color=light-yellow so that it executes this change in the current UI variant. With this, the UI variant is modified after it is displayed.

Thus, the use of this function makes possible to deal with repetition and maintenance. It is done by avoiding the designing of multiple UI variants by adapting some UI parameters. The **personalizing function** executes a UI personalization of UI parameters. It means that the designer does not need to develop a UI variant each time there is a change in the context of use. Instead, the **personalizing function** personalizes the UI based only in the needed UI parameters decided by the adaptation system (e.g. the change of the background color from yellow to white).

Conversely, if the designer doesn't not use this **personalizing function** then some potential issues needs to be faced. If designers need to design as many UI variants as possible context of use, the combinations may lead to a complex design task to support <user emotions\*platform\*environment> combinations. Even when designers deal with all designs diversity, there would be many UI repeated features across all variants (e.g., the same font-size across all different background colors). Designers would need to maintain all variants to have consistent UIs, which may be a tedious and ineffective task (e.g., change font-size=small for all UI variants).

The following sections describe the three main components of our global architecture with more details particularly in the inferring engine.

### *Inferring Engine*

This component is in charge of dynamically deducing the value of the context of Use (**user** with their emotions, platform, environment) by executing inference rules (e.g., conversion, aggregation). The key word "**user**" corresponds to user features such as age, gender, and other possible user variables defined in the General User Model Ontology (Heckmann et al., 2005). An Emotion Wrapper ❸ takes sensor input data ❷ (e.g., user's face image) and sends it to an emotion detection tool ❹ such as FaceReader or Affdex that returns the set of detected emotions. These values are returned to the Inferring Engine, which includes it in the context of use (user with emotions, platform, environment) and in turn sends it ❺ to the Adaptation Engine ❻. An example is given after detailing how this component works with emotions.

Figure 4-3 shows how the inferring Engine deduces the context of use. While the user is interacting with the UI, two possible events allow the upgrade of the context of use: a new time instance in a time period (e.g. each 10 seconds) or when the user provides a click on the UI. If

one of these conditions are true, then the context of use is updated. In the example provided, while the user is interacting with UI variant1 in a PC and 10 seconds have passed, then this contextual information is stored: *context-of-use* ([age, gender, happiness, contempt, anger, disgust, sadness, fear, surprise, neutral], platform=[PC], environment=[light-condition]).

```
while UI focus (user is using a web page)
  do if <new-time-instance or user click> then <define context-of-use (user with
emotion, platform, environment)>.
```

```
For instance, if <time=10-seconds> then <context-of-use ([age, gender,
happiness, contempt, anger, disgust, sadness, fear, neutral], platform, environment)>
```

*Figure 4-3: Inferring engine algorithm in Perso2U architecture*

As underlined before, the Inferring Engines is able to include a basic set of emotions (happiness, anger, disgust, sadness, fear, surprise, contempt) (Ekman, 1992) (Ekman, 1999) plus neutral in the context of use. In this case, the set of detected emotions from the emotion recognition tool are sent by the Emotion Wrapper ③ part of the Inferring Engine ⑤. It sends contextual information in this manner: context of use (user with happiness, contempt, anger, disgust, sadness, fear, neutral, platform, environment) to the adaptation engine ⑥. Each emotion is treated as a variable which contains the value of the detected emotion. For instance, we can reuse the emotion detection values (user photo) from *section 2.2.3 in Figure 2-13*. In this case, The Emotion wrapper sends these detected emotion values to the Inferring Engine: happiness (0.753), contempt (0.005), anger (0.018), disgusted (0.019), sadness (0.097), fear (0.007) and neutral (0.10) Consequently, this context of use is sent to the adaptation engine: context of use (user model [0.753, 0.005, 0.018, 0.019, 0.097, 0.007, 0.10], platform, environment).

The use of the basic set of emotions (happiness, anger, disgust, sadness, fear, surprise, contempt) (Ekman, 1992) (Ekman, 1999) plus neutral (Ben-Ze'ev, 2000, p. 94) (*see section 2.2.2*) in our approach.

*Why the use of a basic set of emotions into the architecture?*

Despite the categorization of emotions into a basic set of emotions is an ongoing discussion in a HCI context argued by (Brave & Nass, 2002, p. 55). These authors clarify that the use of discrete emotions (Ekman basic set of emotions) have two main implications in interaction design: (1) unique and measurable categories of emotions for emotion recognition systems and interaction evaluation, and that (2) these emotions have less variation from culture to culture to be more easily understood for a more reliable emotion prediction.

“First, the basic categories would likely be the most distinguishable, and therefore measurable, emotional states (both in emotion recognition systems as well as in post interaction evaluations).” (Brave & Nass, 2002, p. 55). This implication is significant for our architecture characterized by an interactive system which attempts to adapt the UI based on user responses (emotions). If those responses are represented by unique categories (emotions) then the designer can decide or discriminate which emotions need to be detected regarding a particular study. For instance, the selection of only anger to study the UI interaction in a booking system (Märting et al., 2017).

“Further, the basic emotions would be less likely to vary significantly from culture to culture; facilitating the accurate translation and generalizability of questionnaires intended to assess such emotions. Lower variability also enables more reliable prediction of emotional reactions to interface content, both across cultures and across individuals.” (Brave & Nass, 2002, p. 55). Since these basic emotions are universal and can therefore, be found in all cultures as argued by (Herbon et al., 2005) (*see section 2.1.1*), it allows our architecture to be used for participants for different cultures and to preserve a more consistent prediction accuracy. This is important to drive a more appropriate adaptation to user emotions as stated in the adaptation-emotion context (Carberry & Rosis, 2008, p. 7).

Besides a basic set of emotions (happiness, anger, disgust, sadness, fear, surprise, contempt), the research community also included neutral as argued by (Calvo & D’Mello, 2010). It is added to the inferring engine since it evokes a lack of emotional reaction given by users (Ben-Ze’ev, 2000, p. 94) which is important to see whether the UI is making some reaction to users or not. Moreover, neutral is also included in the set of detected emotions of face emotion recognition tools (*section 2.2.3*).

To clarify the Inferring Engine functionality, let’s imagine the case where the Inferring Engine works with a basic set of emotions. Figure 4-4 illustrates this case. While the user is interacting with UI (top left) a user photo is taken and sent by the Emotion Wrapper ⑤ to the emotion recognition tool (MicrosoftApi). This tool gets back the set of emotions (happiness, anger, disgust, sadness, fear, contempt, surprise) plus neutral to the Emotion Wrapper where we can see that the neutral is the biggest emotion value (green colour) which corresponds to the lack of user emotion reaction (*See section 2.1.1 and Figure 8*). This set of emotions are sent by the Emotion Wrapper ③ part of the Inferring Engine ⑤ to the context of use (user model [0.0, 0.0, 0.0, 0.0, 0.002, 0.0, 0.013, 0.985,], platform, environment). Lastly, this context of use is sent to the adaptation engine ⑥.

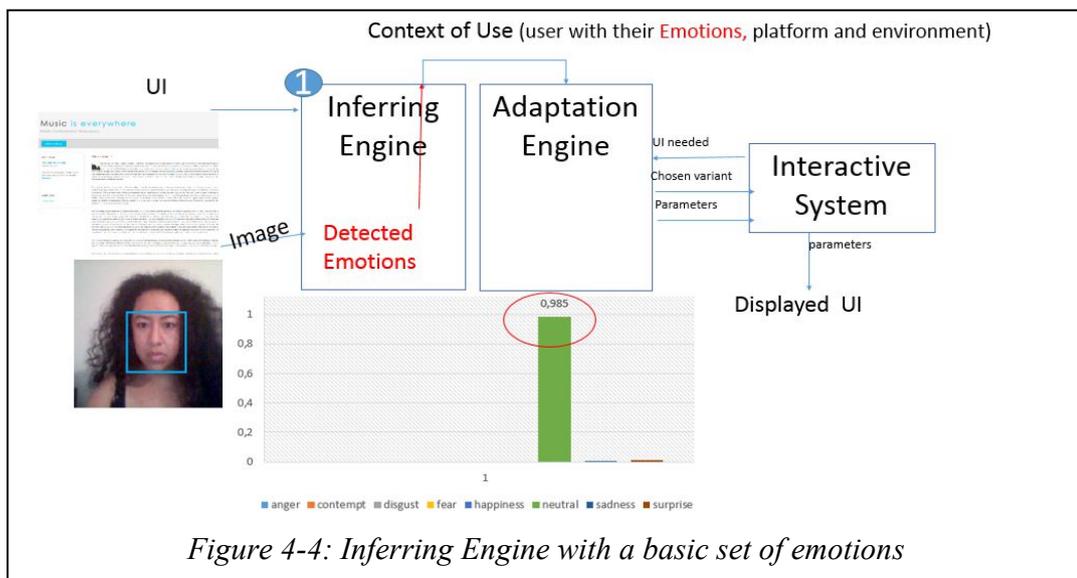


Figure 4-4: Inferring Engine with a basic set of emotions

### *Adaptation Engine*

The Adaptation Engine (AE) aims at (a) selecting the UI variant among all available variants for the UI and (b) computing the UI parameters for even better adapting the chosen variant to the context of use (Céret et al., 2016). First, the Adaptation Engines receives ⑤ the current context of use from the Inferring Engine ① and the needed UI name from the Interactive System ⑨. From the variants description ③, it computes which variant of the needed UI suits best the context of use, for instance a UI variant1 made for a screen width of 400px when the current screen is 450px width. Then it computes if some changes can be or have to be applied to the parameters of this variant1 for making it better, using rules that respect this algorithm (Figure 4-5):

```
for every context-variable  
do if <context-use-conditions> then <define UI-parameters>.  
  
For instance, if (happiness > 90%) then (background-color=light-yellow and  
font-size=normal)
```

*Figure 4-5: Adaptation engine algorithm in Perso2U architecture*

In this (fanciful) example, when the user is considered having an emotion (e.g. 90% of happiness), two parameters are defined for changing the variant: the background-color is set to light yellow and the font size is switched to normal. Adaptation rules might need a continuous observation process to identify the suitable (1) context-use-conditions and (2) the UI-parameters.

### *Interactive System*

The last component of the *Perso2U* architecture is the Interactive System ⑩. When needed, it sends the required UI name to the Adaptation Engine ⑥, receives the chosen UI variant path and the UI parameters to apply, displays the UI variant and applies the UI parameters. This last action is made thanks to the following algorithm (Figure 4-6)

```
for every ui-parameter do  
if <ui-parameter-condition> then <modify UI>.  
  
For instance, if <background-color=light-yellow> then <addClass background-  
light-yellow to UI>.
```

*Figure 4-6: Interactive system algorithm in Perso2U architecture*

As already mentioned, a change in the context of use may occur during interaction and induce the need of changing the displayed variant (e.g., the user has reduced the window size and a variant designed for a Smartphone would be more relevant) or applying new UI parameters (e.g., user's emotion has changed and the Adaptation Engine has decided that another color palette has to be used). The Interactive System is thus also in charge of watching for such updates and applying them dynamically by using the previous definition of the *personalizing function* (<modify UI>).

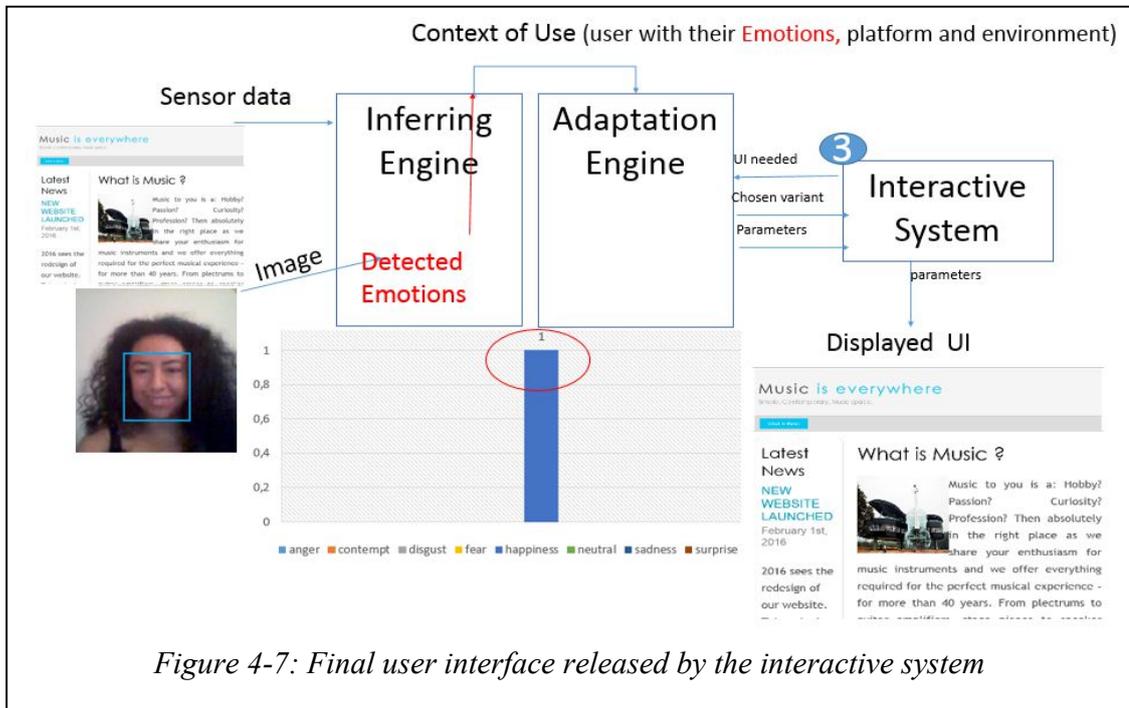


Figure 4-7 illustrates the final UI version released by the Interactive system. Once the Interactive System applies the **personalizing function** displaying a new UI, the user can interact with it. There are some differences between this new UI and the previous one shown in Figure 4-4. In fact, the font-size of the left menu and body content have been increased to 140% as well as the size image from 24x24 to 180x180 pixels as an attempt to improve UI readability. In this example, all UI elements inside the header has not been modified. Since the *Perso2U* architecture works cyclically, we can see the new emotions detection where happiness (blue color) is inferred by the Inferring Engine. The new context of use (user with happiness, contempt, anger, disgust, sadness, fear, neutral, platform, environment) is sent to the adaptation engine.

### 4.3.3 Prototype

The architecture has been implemented for web interaction. From the software perspective, all components rely on JavaScript and jQuery<sup>5</sup> to execute all steps in the adaptation process. Where the Interactive System uses also HTML and CSS. This prototype involves run-time adaptation in UI parameters (color, font-size, image-size) and variants based on with happiness, contempt, anger, disgust, sadness, fear, surprise and neutral emotions. Simplistic generic adaptation rules were implemented by following the components description shown in the architecture section to adapt the color, font-size and image-size according to user emotions (e.g., image-size=large when a high negative emotion is evoked). Their implementation allows to show the feasibility of the approach even if their relevance is questionable.

To conclude, *section 4.3* introduced the *Perso2U* architecture and its prototype for UI adaptation based on emotions at run-time. The reminder of this PHD focuses on the study of the inferring engine. This study is based on an experiment whose protocol is described in the following section.

#### 4.4 Experimental Protocol

This section underlines the main elements of the experiment protocol used all the following chapters. Our goal is to explore the manner of inferring emotions inside the *Perso2U* prototype. We will use this protocol to explore three key points: (1) the inferring engine independence from emotion detection tools since there is a risk of divergence between them because of the accuracy differences in face detection algorithms (Brodny et al., 2016), (2) the UI influence on detected emotions based on user characteristics (age and gender) and UI quality factors (aesthetics/usability) as they can influence UX (Hassenzahl & Tractinsky, 2006b), and (3) how to use the inferred emotions to trigger UI adaptation as an interesting challenge (Carberry & Rosis, 2008, p. 7) .

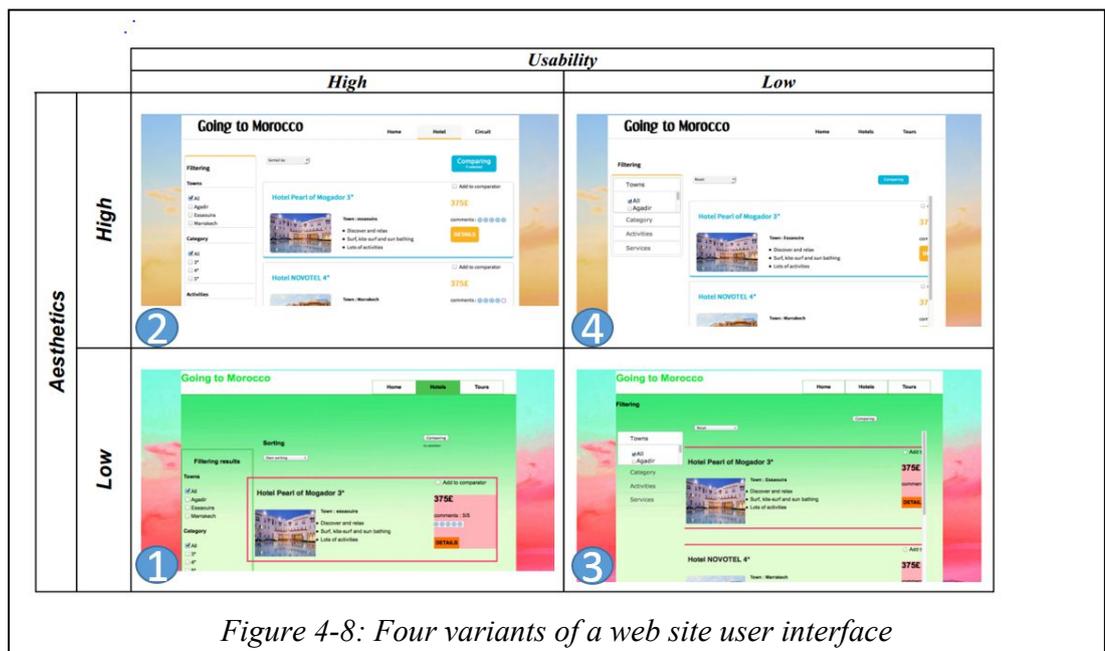


Figure 4-8: Four variants of a web site user interface

##### 4.4.1 Artefact

The main experimental artefact included a website where aesthetics and usability were combined. Usability and aesthetics of these websites were manipulated as independently as possible recommended by (Tuch et al., 2012). This variation of aesthetics/usability aims to explore different inferred emotions in front of different UIs by using the same functional core (inferring engine, adaptation engine and interactive system). It means that the web versions differ in aesthetics and usability aspects but not in the core of the *Perso2U prototype*. Hence, different UIs are conceived to trigger different emotions.

With this, four versions of the same website, advertising travels, were developed to obtain a combination (low vs. high) of the quality factors (Figure 4-8) (Dupuy-Chessa, Laurillau, & Céret, 2016):

- w1 (low aesthetics, high usability),
- w2 (high aesthetics, high usability),
- w3 (low aesthetics, low usability), and
- w4 (high aesthetics, low usability).

Usability and aesthetics of these websites were manipulated as independently as possible recommended by (Tuch et al., 2012). Usability was first considered at the task level (i.e. interaction distance and workload) and also in terms of concrete user interface. For website versions with low usability, the workload was increased by redesigning the concrete user interface, i.e. by using the navigational factors in relation with the ease access to information (e.g. interaction distance). Figure 4-9 shows how the hotels list can be filtered by using a filtering criteria (on the left side of the website) designed with high usability w1 (low aesthetics, high usability) and w2 (high aesthetics, high usability). Conversely, the low usable version w3 (low aesthetics, low usability) and w4 (high aesthetics, low usability) presents one criterion at a time through the use of a dynamic menu. Moreover, other navigation elements were removed like redundant hyperlinks.



Figure 4-9: Filtering criterion for usability versions: expanded list (left: high usability) vs. cumbersome dynamic menu (right: low usability)

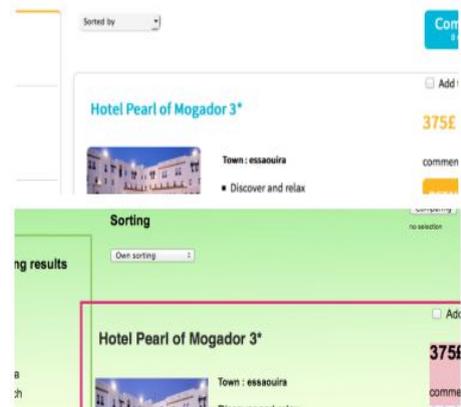


Figure 4-10: High (top) vs. low (bottom) aesthetic versions

For the creation of high vs. low aesthetics versions, only the manipulation of the graphic factors was performed. Figure 4-10 shows the differences including:

- bright background colour, square framework shape and non-aligned format (low aesthetics in w1 and w3 at the bottom).

- light background colour, round framework shape and aligned format (high aesthetics in w2 and w4 at the top).

In terms of website content, each website contained the same content within three webpages called Home, Hotel and Circuit. Precisely, the web elements distributed along web pages contained text and images with widgets such as radio buttons, select lists, scroll bars and JavaScript menus.

#### **4.4.2 Procedure, tasks, participants**

As we learned in *section 2.1.3*, there are different **reactions** to emotional stimuli based on personality, day time, age and gender which can affect emotions (Hume, 2012). Particularly, we are interested in user characteristics such as age and gender as sources of emotions (Hume, 2012, p. 270). Thus, the protocol also considers a variety of participants in terms of age and gender to have a potential spectrum of emotions.

In terms of the procedure, first, each participant was assigned to one version of the travel website. While he/she was interacting with the website, his/her emotions were detected automatically based on user taken photos in a time period of ten seconds as illustrated by Figure 4-11. This shows five timestamps of the seven user emotions detected during the manipulation of one page in w1 (low aesthetics, high usability). The three photos shown correspond to the first, third and fifth timestamps. There was no constraint on user behaviour: participants were asked to have a not predefined position (e.g. immobile hands) during UI interaction.

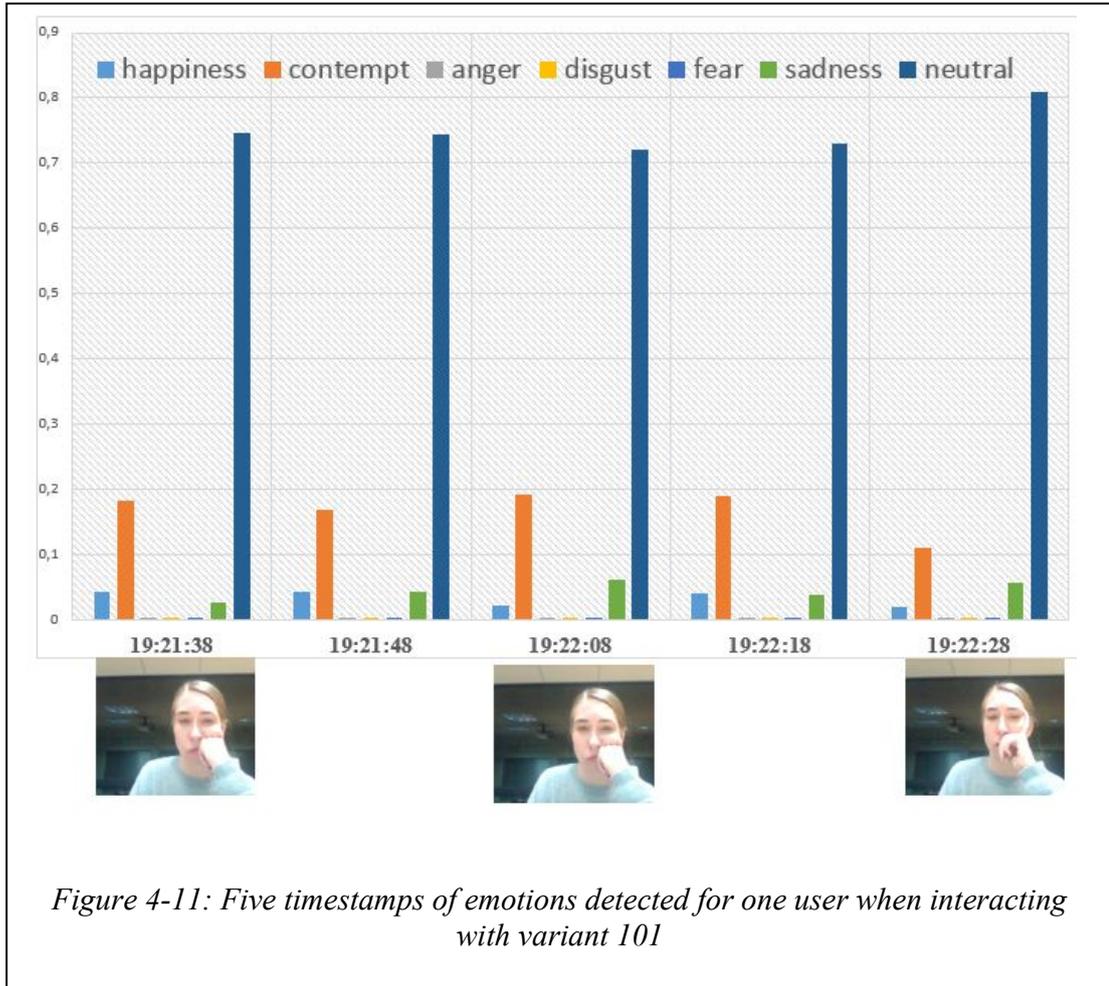


Figure 4-11: Five timestamps of emotions detected for one user when interacting with variant 101

Second, to ensure that participants are involved enough in the web interaction, they had to answer an online questionnaire. It collected participant's information such as gender and age. Then, participants answered questions according to three tasks to achieve: (1) look for a 5-stars hotel which offers a visit in the desert, (2) look for a specific hotel with must include a breakfast plan and (3) look for a hotel circuit in a specific given location.

A total of 45 people participated to the study with an average of approximately 11 participants per website (w1=13, w2=10, w3=12, and w4=10). The sample included 24 males (53%,  $\mu=34$ ,  $\sigma=11.66$ , [19,67] years) and 21 females (47%,  $\mu=27$ ,  $\sigma=12.25$ , [23,63] years) participants.

#### 4.4.3 Interaction data

User pictures were sent to the 3 emotions detection tools for getting the recognized emotions values: Microsoft emotion API, FaceReader, and Affectiva.

In terms of interaction data, participants' head shots were taken every 10 seconds in real-time (one user's observation), as illustrated previously by Figure 4-11. Average time of user interaction with the website approximated 6.51 minutes. Any emotion detection tool provided seven emotion values for each head shot. As some images were found unclassifiable (more details in *section 4.5.2*), the emotion detection tool can only analyse 1730 images (an average of 38 images by user). Table 4-1 shows the interaction time average (in minutes) and the number of images analysed for each website (different levels of usability and aesthetics).

Moreover, one user's observation represents a data tuple with an observation number (sequential index) and 11 data columns: timestamp, seven emotions (happiness, contempt, anger, disgust, fear, sadness, surprise, neutral), UI variant (website version + current page), age and gender. As an observation corresponds to an image, the tool retrieved 1730 observations releasing a total of 19030 data (1730x11).

	<i># images</i>	<i>interaction time avg. (minutes)</i>
<i>High Usability Low Aesthetics (w1)</i>	342	4.47
<i>High Usability High Aesthetics (w2)</i>	293	4.98
<i>Low Usability Low Aesthetics (w3)</i>	718	10.17
<i>Low Usability High Aesthetics (w4)</i>	377	6.41
<i>Total</i>	1730	288
<i>Avg.</i>	433	6.51

*Table 4-1: User interaction data collected by images and interaction time*

#### 4.4.4 Variables

The independent variables (UI quality factors) are usability and aesthetics, each one with two possible levels: low or high. The dependent variables are the set of Ekman's emotions values detected by the tool: happiness, contempt, anger, disgust, fear, sadness, surprise plus neutral, using continuous values [0,1]. Finally, user characteristics act as moderator variables: age and gender (women and men). To go further into the inferring engine examination, we performed a first analysis about the genericity of the inferring engine at detecting emotions.

#### 4.4.5 Discussion

All emotion recognition tools used in experimentation rely on the same emotion detection method (user face image) without considering others such as eye tracking, heart rate or video trace analysis. Measures which may provide more insights to complement or validate our results.

Our UI adaptation architecture based on emotions advocates all elements of the context of use (user, environment, platform), which are not fully considered. For instance, environment changes such as noisy and light variations, day timeline or the user device (e.g. tablet or mobile) are not taken into account in the experiment.

Despite there are other useful emotions (e.g. satisfaction), Ekman ones ensures that the majority of users evoke them culturally independent. A further analysis based on this emotions foundation could release more relevant emotions associated with hotel travelling.

#### 4.5 Inferring Engine independence from emotion detection tools

Nowadays, there are many emotion recognition tools such as Microsoft<sup>2</sup>, FaceReader<sup>1</sup> and Affdex<sup>3</sup> (see section 2.2.3). These tools were selected as they share some features needed in our study: Ekman emotions support, input (image) and output (real values). Although, they provide seven basic emotions with some uncertainty, there is clearly a risk of divergence between them because of the accuracy differences in face detection algorithms (Brodny et al., 2016). These divergences could lead to erratic emotion identification and thus to unreliable and unstable adaptations in *Perso2U*.

Since this approach relies on emotion recognition tools, it is possible to go further to show the similarity of detecting emotions to understand whether this detection is independent from the emotion recognition tool or not (Galindo, Céret, et al., 2017).

The following paragraphs address this point through an experimental analysis by showing these elements: hypothesis, analysis method, results, and discussion. The analysis follows the experimental protocol underlined previously in section 4.4.

##### 4.5.1 Hypothesis

To test the independence from the manner of detecting emotions from facial expressions, the inferring engine must be able to send the same emotions (happiness, contempt, anger, disgust, fear, sadness, surprise and neutral) to the adaptation engine whatever the detection tool is. We will show that from three different detection tools, the inferring engine can infer similar results as emotion detection tools from facial expressions provide similar results. Hence, our hypothesis is:

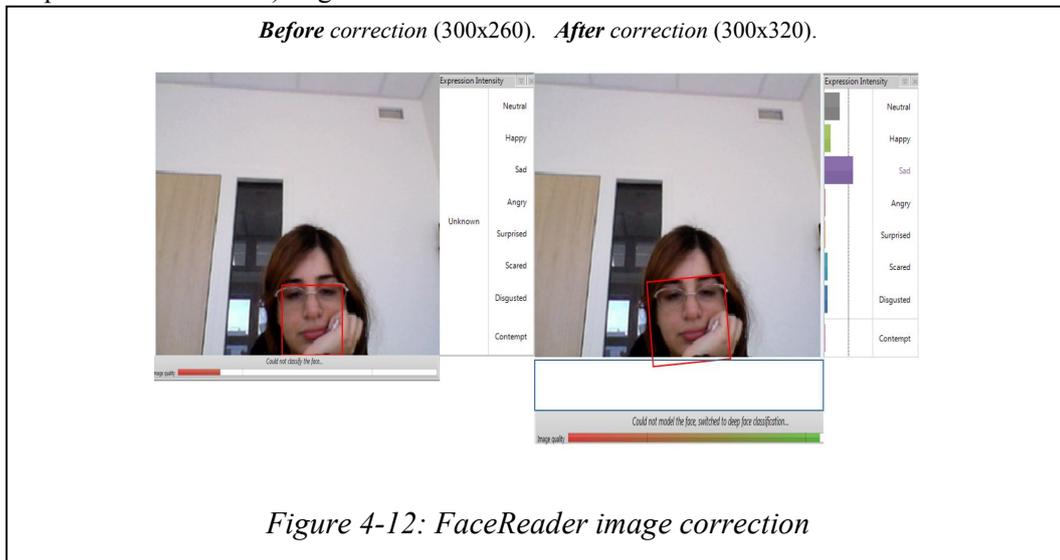
*H1: the emotions detected by Affectiva, FaceReader and Microsoft emotion API provide similar emotion values.*

##### 4.5.2 Images correction

Before being able to study emotions detected by tools, we had to make some corrections. As a matter of fact, to get realistic values from tools during the interaction, participants were not required to have a predefined position (rigid head or hand positions). But some images were not good enough for an interpretation with FaceReader. Thus, a face image correction was done for FaceReader for every image.

The correction was done by adding a white rectangle at the bottom of the image without affecting the user face as illustrated in Figure 4-12. This rectangle allows FaceReader to apply deep face

classification be able to classify the face. As a benefit (Figure 4-12, *After correction*), it was possible to improve the image detection and quality (from an unknown face classification to a deep face classification) to gather emotion values.



### 4.5.3 Experimental method

It uses the basic emotions (happiness, contempt, disgust, sadness, fear, anger, surprise) plus neutral previously discussed in the Inferring Engine component (*section 4.3.2*). To validate our hypothesis, each tool produced for each picture (facial expressions) a vector of emotion variables: happiness, fear, sadness, anger, disgust, surprise, contempt, and neutral from Microsoft API and FaceReader. Microsoft API and Affdex releases values from 0 to 1 while FaceReader releases percentage values in an equivalent scale from 0 to 100. Consequently, [0,100] is treated as [0,1]. As the facial expression or user emotion occurs and/or intensifies, the emotion values rise from 0 (no expression) to 1 (expression fully present).

Then distances between each emotion variables across all tools were computed by using Euclidean distances to compare how similar they are (Kalita & Das, 2013). As suggested by (Frey & Dueck, 2007), a *similarity measure* is a squared euclidean distance seen as a real function that quantifies the similarity between two objects. Particularly, “if two pieces of data have close x, y coordinates, then their similarity score, the likelihood that they are similar, will be much higher than two data points with more space between them.”(deepai, 2017). Thus, a low Euclidean distance in emotion values of (tool1, tool2) represents a high similarity at detecting emotion from the same user picture.

Consequently, this process relies on a distance function called *dist* implemented in R (rdocumentation.org, 2015) (Mardia, Kent, & Bibby, 1979). It computes and returns the distance computed by using the specified distance measure (euclidean) to compute the distances between

the items of vectors. There, the **distance** of one emotion between tool x and y is expressed in this form:  $d(\overrightarrow{X_e}, \overrightarrow{Y_e}) = \text{dist}(\overrightarrow{X_e}, \overrightarrow{Y_e}, \text{method} = \text{euclidean})/n$  where:

- **e** takes a value from {h, c, d, s, f, a, su, n} corresponding to {happiness, contempt, disgust, sadness, fear, anger, surprise, neutral},
- $\overrightarrow{X_e}, \overrightarrow{Y_e}, \overrightarrow{Z_e}$  are emotions vectors corresponding to (Affdex, FaceReader or Microsoft API)

of one particular emotion **e**, e.g.  $\overrightarrow{X_h}$  represents the detected emotions values of happiness in tool1,

- **n** refers to the number of items in each vector (equal to 1730 pictures). This division was necessary to obtain a central value among tools. Since each emotion recognition tool releases a positive value ([0,1]) then the **emotionDistance** range is also from 0 to 1.

For instance, **happiness distance** between tool 1 and tool 2 is equal to  $d(\overrightarrow{X_h}, \overrightarrow{Y_h}) = \text{dist}(\overrightarrow{X_h}, \overrightarrow{Y_h}, \text{method} = \text{euclidean})/1730$ .

#### 4.5.4 Results

This sub section reports the results of the analysis. It describes the distances computation among emotion recognition tools including the equations used in the analysis, the retrieving distances values per emotion and results final remark.

##### *Feasibility of a generic architecture*

To explain the computation per emotion, the distances between FaceReader and Microsoft API are exposed below.

- **happiness distance** is equal to  $d(\overrightarrow{Y_h}, \overrightarrow{Z_h}) = \text{dist}(\overrightarrow{Y_h}, \overrightarrow{Z_h}, \text{method} = \text{euclidean})/1730 = 0,0081$
- **contempt distance** is equal to  $d(\overrightarrow{Y_c}, \overrightarrow{Z_c}) = \text{dist}(\overrightarrow{Y_c}, \overrightarrow{Z_c}, \text{method} = \text{euclidean})/1730 = 0,0070$
- **disgust distance** is equal to  $d(\overrightarrow{Y_d}, \overrightarrow{Z_d}) = \text{dist}(\overrightarrow{Y_d}, \overrightarrow{Z_d}, \text{method} = \text{euclidean})/1730 = 0,0035$
- **sadness distance** is equal to  $d(\overrightarrow{Y_s}, \overrightarrow{Z_s}) = \text{dist}(\overrightarrow{Y_s}, \overrightarrow{Z_s}, \text{method} = \text{euclidean})/1730 = 0,0115$
- **fear distance** is equal to  $d(\overrightarrow{Y_f}, \overrightarrow{Z_f}) = \text{dist}(\overrightarrow{Y_f}, \overrightarrow{Z_f}, \text{method} = \text{euclidean})/1730 = 0,0061$
- **anger distance** is equal to  $d(\overrightarrow{Y_a}, \overrightarrow{Z_a}) = \text{dist}(\overrightarrow{Y_a}, \overrightarrow{Z_a}, \text{method} = \text{euclidean})/1730 = 0,0067$
- **surprise distance** is equal to  $d(\overrightarrow{Y_{su}}, \overrightarrow{Z_{su}}) = \text{dist}(\overrightarrow{Y_{su}}, \overrightarrow{Z_{su}}, \text{method} = \text{euclidean})/1730 = 0,0069$

- **neutral distance** is equal to  $d(\vec{Y}_n, \vec{Z}_n) = \text{dist}(\vec{Y}_n, \vec{Z}_n, \text{method} = \text{euclidean}) / 1730 = 0,0162$

The results computation confirms that there are similar recognized emotions among the three tools: **low distances** were found with values **under 2%** for all emotions (happiness, contempt, disgust, sadness, fear, anger, surprise and neutral) as shown in Figure 4-13 and Table 4-2. Table 4-2 shows the resulting average distances per emotion recognition tool after applying the **emotion-distance** calculus described above. It reports values under 2% starting from 0.003 (disgust between FaceReader and Microsoft) to 0.020 (contempt between Affdex and FaceReader).

tools	happiness	contempt	disgust	sadness	fear	anger	surprise	neutral
Affdex - faceReader	0,0094	<b>0,0204</b>	0,0092	0,0151	0,0070	0,0085	0,0096	n.a.
Affdex - Microsoft API	0,0079	0,0190	0,0102	0,0119	0,0036	0,0045	0,0075	n.a.
faceReader - Microsoft API	0,0081	0,0070	0,0035	0,0115	0,0061	0,0067	0,0069	0,0162

Table 4-2: Distances among emotion recognition tools including the average per emotion

These distance values per emotion are also illustrated in Figure 4-13. Mainly, contempt and sadness were found with the biggest distances differences in contrast to disgust, fear and anger with the lowest distance values among the tools.

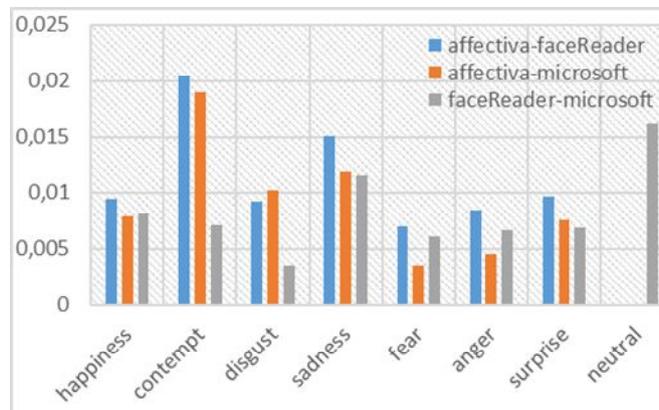


Figure 4-13: Distances among emotion recognition tools

Overall, a **high similarity** is evidenced at detecting emotion values among tools due to the retrieved **low distances** with values **under 2%** for all emotions.

#### 4.5.5 Discussion

Overall, the experiment allows us to validate that: **H1) the emotions detected by Affectiva, FaceReader and Microsoft emotion API provide similar emotion values** with a high emotion detection similarity. It validates that it is feasible to have similar emotion values with different tools as first step (inferring) in a generic architecture to drive UI adaptation based on emotions (happiness, contempt, anger, disgust, fear and sadness, surprise and neutral).

Figure 4-14 shows the detection of happiness for one user and each tool. It evidences that there are cases where the emotion recognition fails for a specific time slot releasing an error as response (e.g. happiness = null). In fact, during this user interaction, there were 2, 4, and 2 failed emotion detections for Affectiva, FaceReader or Microsoft in different time slots and UI versions. In such case, more technical control would be needed to monitor internet, emotion recognition tools' connection and code debugging to find potential implementation issues.

The context of use is updated with user emotions detected by emotion recognition tools with similar accuracy. It means that if one tool fails at detecting emotions then inferring engine can use the emotion values from another tool to keep upgrading the context of use (emotions). Thus, the comparison between tools helps to understand that the inferring engine can use different tools to recognize emotions with similar detected values.

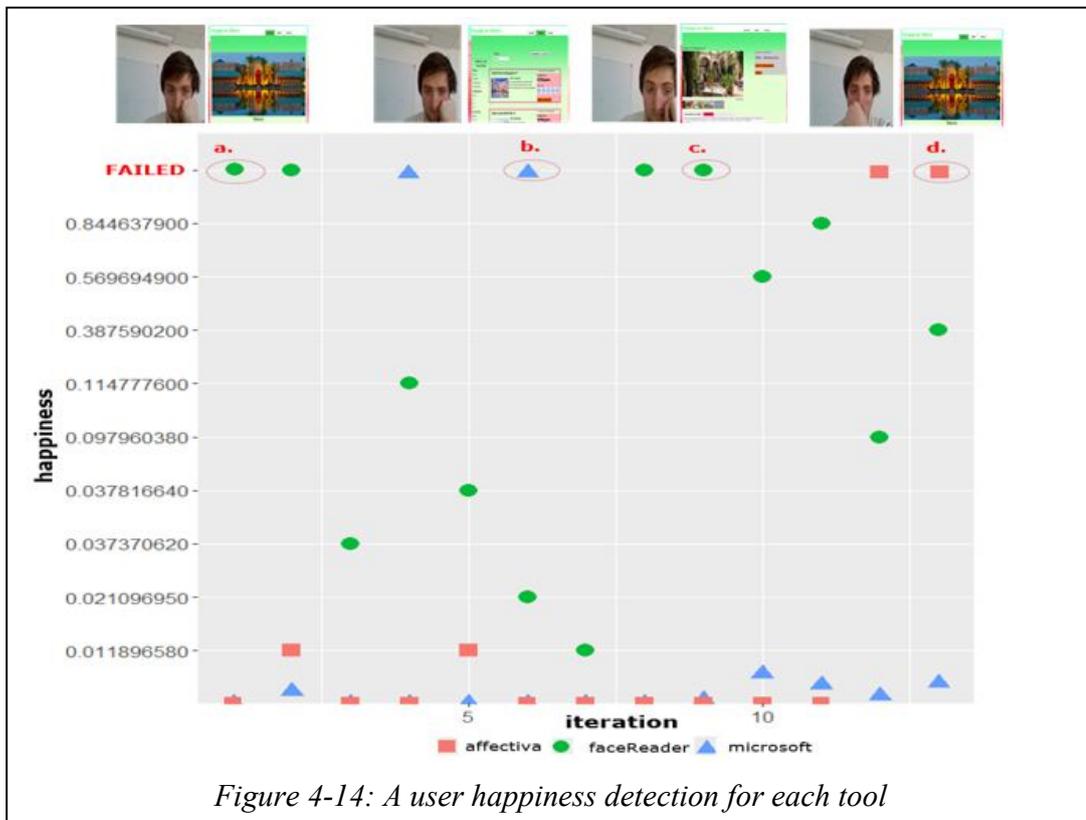


Figure 4-14: A user happiness detection for each tool

#### 4.6 Summary

This chapter presents our approach to address UI adaptation based on emotions. We proposed the *Perso2U* architecture. It includes an Inferring engine, an Adaptation engine and an Interactive System. A particular treatment was given to the inferring engine which allows the inference of emotions based on facial emotion recognition. By following these features, a prototype was implemented for *web site interaction*.

The study of the inferring engine will be based on an experiment whose protocol has been described here. The first results of the experiment show the Inferring Engine independence from the facial emotion recognition tools at detecting emotions (happiness, contempt, anger, disgust, fear, sadness, surprise and neutral).

## CHAPTER 5 UI influence on emotions depending on user characteristics and UI quality factors

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### 5.1 Introduction

*Chapter 4* mainly introduces a runtime UI adaptation approach relying on emotions at run-time (*Perso2U*). As a first step toward a system to adapt UIs based on emotions, we explore how detected emotion can be used to trigger adaptation. Considering that emotions depend on users' characteristics (Hume, 2012), we explore whether emotions in a HCI context are influenced by two main human characteristics: age and gender.

This chapter studies the effect of aesthetics and usability depending on users' main characteristics, i.e. age and gender, by analysing emotions (Galindo et al., 2019). The importance of usability and aesthetics has been recognized in UX (De Angeli et al., 2006; Tractinsky et al., 2000; Tuch et al., 2012). The aesthetical quality of elements such as shape, text and color has been shown to influence user's attitudes and determines the success and credibility of an interface (De Angeli et al., 2006; Robins & Holmes, 2008). Similarly, a low degree of usability can cause a negative UX by producing discouragement, dissatisfaction and distrust when using a UI (Flavián et al., 2006). Hence, this chapter presents the results of an experiment designed to understand how aesthetics and usability can influence UX as reflected by detected emotions with two factors: gender and age.

Similarly, this chapter describes the experiment analysis relying on the protocol shown in *section 4.4*. The following section presents the hypotheses and variables before describing every step of the data analysis process. Then, subsequent parts highlight the current findings for women and men, discussion, and summary.

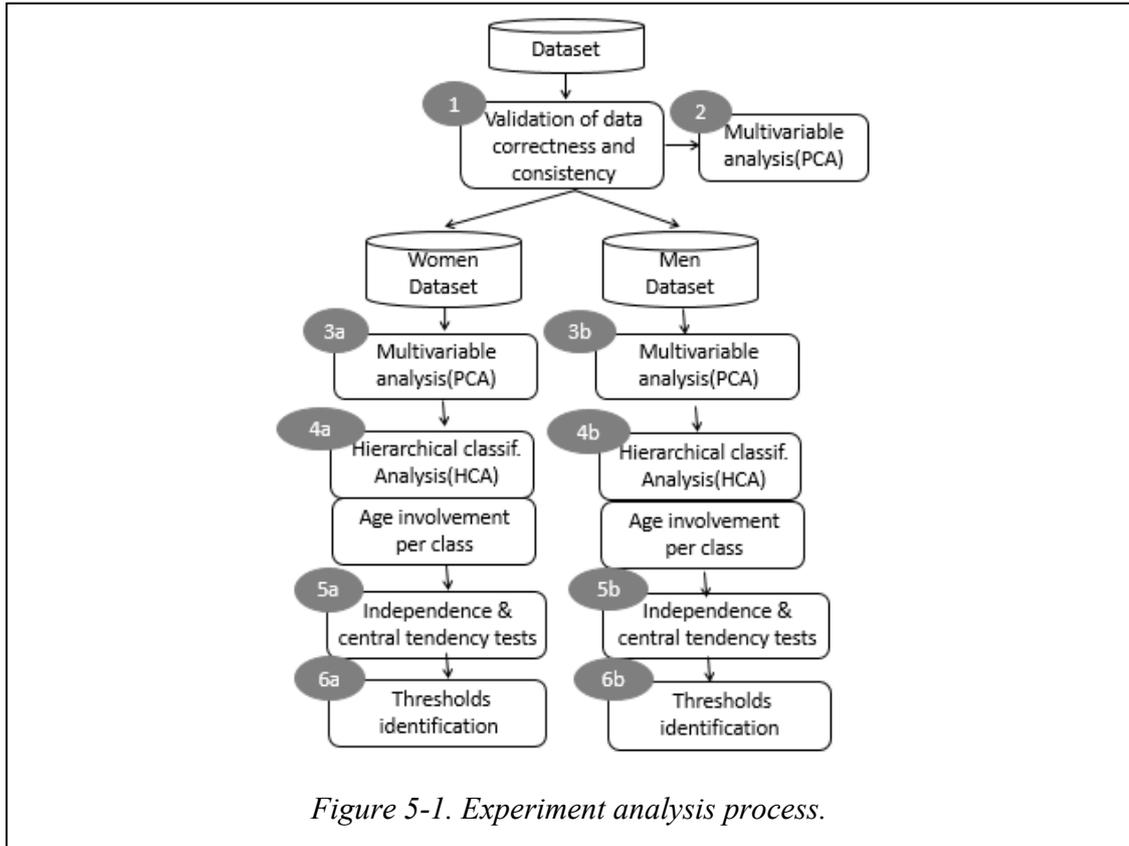
### 5.2 Hypotheses

The experiment hypotheses are:

**Hypothesis1 (H1):** the UI quality factors (aesthetics and/or usability) influence the emotions detected (sadness, contempt, neutral, fear, disgust, anger and happiness) depending on age and gender.

**Hypothesis2 (H2):** the level (low and/or high) of UI quality factors impacts emotion detected differently depending on age and gender.

To validate them, the analysis process is introduced below.



### 5.3 Analysis process

This experiment used the detected emotion values from one tool, Microsoft Emotion API, since (1) it detects Ekman emotions (Ekman & Keltner, 1970), (2) there is a high similarity at detecting such emotions among Microsoft, FaceReader and Affdex tools (*section 4.5*) and also because (3) this tool has the potential to get back emotions during web interaction through its API.

The analysis of data collected from the tool relies on a statistical analysis process which included six steps (*Figure 5-1*):

- a. “Validation of Data correctness and consistency” **1**, which aimed to clean up the collected data to guarantee its consistency,
- b. Since this research deals with many dependent and continuous variables (happiness, contempt, anger, disgust, fear, sadness, surprise plus neutral), a multivariable analysis (PCA, for Principal Component Analysis (Hotelling, 1933; Jolliffe, 2002; Pearson, 1901)) was performed first to reduce the data complexity **2**. By identifying initial differences in the emotion values distributed in two principal components, it allowed the independent exploration

of the male and female data. The data set was divided in two elements: women and men data set. The same structure was used in both cases with 7 variables (continuous emotion) with a different data quantity: women (742) and men (988).

- c. A data complexity reduction method was applied by PCA for the men and women data set ③ to facilitate the analysis and the observation processes by identifying the main influence components.
- d. To study the link with age, observations were aggregated by age classes for both population using a hierarchical statistical analysis ④ (Lebart, PIRON, Lebart, Morineau, & Piron, 2000, p. 156) with k-means to cluster data (Plonsky, 2015, chap. 11). Then, each class was analysed by measures of central tendency (mean) into the men and women datasets so that each class was characterised by a unique age interval
- e. Since each class represented the set of user emotions detected per age across all versions of the website (UIs), the influence of the UIs quality factors on each class was explored by independence tests ⑤ (Pearsons' Chi-square independence tests with Yates continuity correction) for **HI** the UI quality factors (aesthetics and/or usability) influence the emotions detected (sadness, contempt, neutral, fear, disgust, anger and happiness) depending on age and gender. Three independence tests were performed: classes vs. websites, classes vs. usability (low/high levels) and classes vs. aesthetics (low/high levels). These tests therefore investigated the influence of aesthetics and usability per class.

Furthermore, we refined the analysis to know how this influence is stronger for particular emotions by retrieving relevant emotions among the set of detected emotions per class trough calculating central tendencies. It was achieved by using z-tests with the following formulation:

$$Z_{ij} = \frac{(\bar{X} - \mu_{ij})}{\sigma_{ij}} \text{ where:}$$

$i = \{disgust, anger, fear, sadness, contempt, neutral, happiness\}$ ,

$j = \{class1, class2, class3\}$  a set of classes for each gender element,

$\sigma$  (standard deviation),

$\bar{X}$  (population mean) is known, sample size (PCA scores) > 30,

$Z_{ij}$  is the z score of emotion  $i$  in class  $j$ , and

$\mu_{ij}$  is the mean.

Moreover, the z retrieved values into the acceptance region ([-1.96,1.96]) indicated the best concentration of emotions per class (age) for women and men.

Thus, this step shows the aesthetics and usability influence per class and how this influence is stronger for particular emotions as the best concentration of emotions per class (age) for women and men, therefore validating the 1st hypothesis.

Although ⑤ validated that there exist UI influence of aesthetics and usability on emotions per class, it does not show how the level (low/high) of aesthetics and usability impacts emotion detected. Thus, we move into **H2**.

- f. **H2)** the level (low and/or high) of UI quality factors impacts emotion detected differently depending on age and gender, was explored by the identification of emotion thresholds (confidence intervals analysis) ⑥ between the level (low/high) of aesthetics and usability, and emotions values in each class retrieved. The main goal of these thresholds computation is to identify a different emotion behaviour caused by the UIs versions. These thresholds, mean different emotion values (min. and max), are associated with age classes, UI, usability and aesthetics levels (low/high) and a particular emotion. The thresholds computation is based on the study of emotion means by website versions. These means are represented by box-plots. Thus, the impact of different UI quality levels is represented by the thresholds per class, emotion and UIs allowing the validation of **H2**.

Overall, ① to ⑤ contributes to **H1** while ⑥ covers **H2** with the same process for women and men.

## 5.4 Results

This section aims at presenting the main findings following the analysis process shown in the previous one (Figure 5-1). It is divided in three parts: It will show the first exploration results from step ②, which results in the distinction between men and women emotion observations; then the results from steps ③ to ⑥ are presented for women and finally for men data sets.

### *First Multivariable Exploration*

After the validation of the data set, step ② identified two main components, i.e. 2 combinations of variables that are the most significant for understanding data variability: PC1 and PC2. Table 5-1 presents the standard deviation, the proportion of variance, and its accumulation for each component [PC1, PC7]. The extraction of PC1 and PC2 were mostly explained by data variability in 64% with  $\sigma > 1$ .

	<i>Standard deviation(<math>\sigma</math>)</i>	<i>Proportion of variance</i>	<i>Cumulative Proportion</i>
<b>PC1</b>	1,85	<b>0,49</b>	0,49
<b>PC2</b>	1,03	<b>0,15</b>	<b>0,64</b>
<b>PC3</b>	0,96	0,13	0,77
<b>PC4</b>	0,89	0,11	0,88
<b>PC5</b>	0,74	0,08	0,96
<b>PC6</b>	0,44	0,03	0,98
<b>PC7</b>	0,33	0,02	1,00

Table 5-1. Standard deviations, variance and cumulative proportion per component

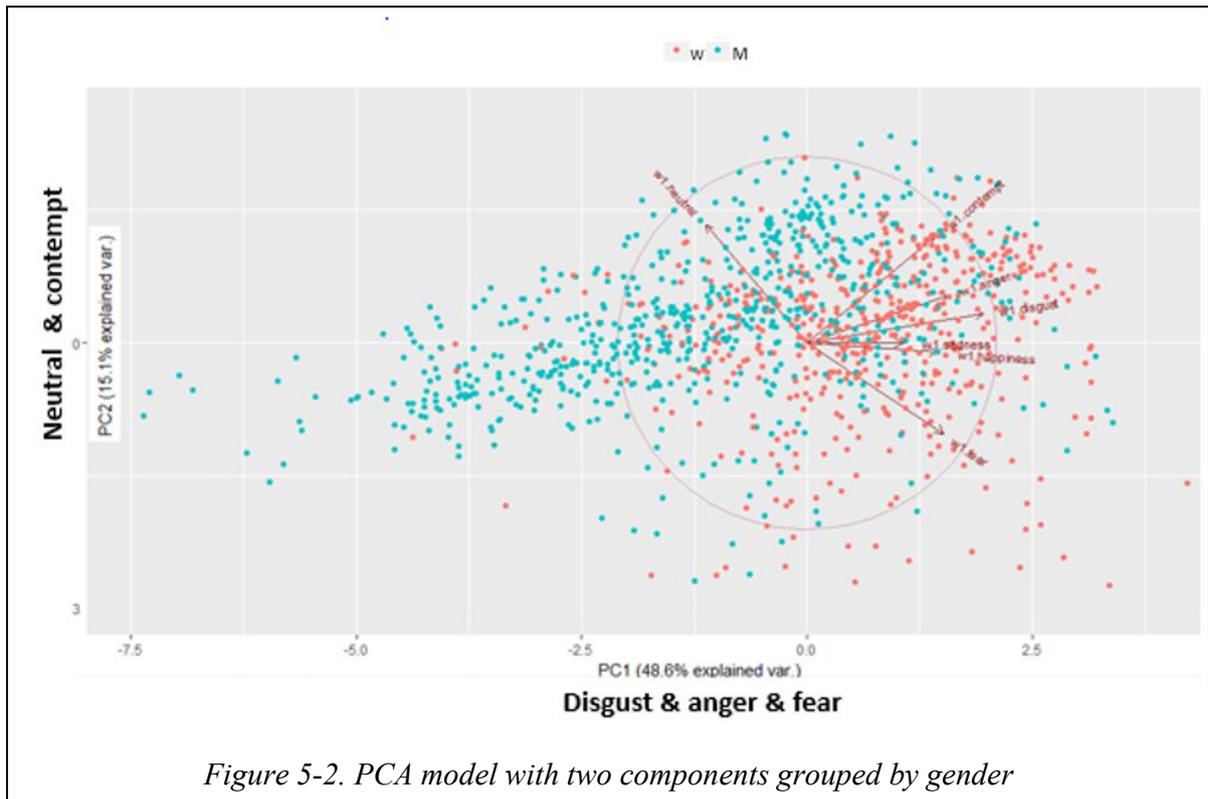
	<i>absolute</i>		<i>relative</i>	
	<i>pc1(%)</i>	<i>pc2(%)</i>	<i>pc1(%)</i>	<i>pc2(%)</i>
<i>disgust</i>	<b>0,26</b>	0,02	<b>-0,87</b>	0,03
<i>anger</i>	<b>0,16</b>	0,06	<b>-0,55</b>	0,07
<i>fear</i>	<b>0,15</b>	0,22	<b>-0,52</b>	-0,24
<i>happiness</i>	0,14	0,00	-0,48	-2E-03
<i>contempt</i>	0,13	<b>0,31</b>	-0,45	<b>0,33</b>
<i>neutral</i>	0,08	<b>0,38</b>	0,28	<b>0,40</b>
<i>sadness</i>	0,08	0,00	-0,26	-5E-08

Table 5-2. Absolute and relative contribution per variable and principal component

Table 5-2 exposes the absolute and relative contributions of PC1 and PC2. This table suggests that the combination of disgust, anger and fear were the most significant emotions detected in absolute (57%) and relative contribution (-1.94%) for building PC1 (Lebart et al., 2000). The negative relative values explain that variables are positioned on opposite sides in each component. For instance, in PC1, all variables (disgust, anger, fear, happiness, contempt and sadness) are set opposite to neutral; while fear, happiness and sadness are positioned opposite to disgust, anger, contempt and neutral in PC2. The absolute contribution represents the extent to which each emotion *contributed* to building the corresponding principal component axis; while the relative contribution explains the *quality* of such contribution on the mentioned axis (Lebart et al., 2000). Contempt and neutral were both found significant in absolute (69%) and relative contribution (73%) for PC2.

To see whether differences exist between men and women, we studied the distribution. Figure 5-2 shows the different distribution between men (left side, blue points) and women observations (right side, red points) in PC1 and PC2 (data variability in 64% with  $\sigma > 1$ ). Overall, there exists (1) initial differences on observations per gender (men-left vs. women-right emotions) spread through the axes PC1 (disgust, anger and fear) and PC2 (neutral and contempt) with (2) the

highest accumulated data variability (almost 64% of variance, PC1 with 48.6%, PC2 with 15.1%). Consequently, these initial differences on observations per gender leads to an **interpretation** by separates groups of the concentration of emotions detected. We start this analysis by women results. Thus, the data set was divided in two elements: women and men data set.



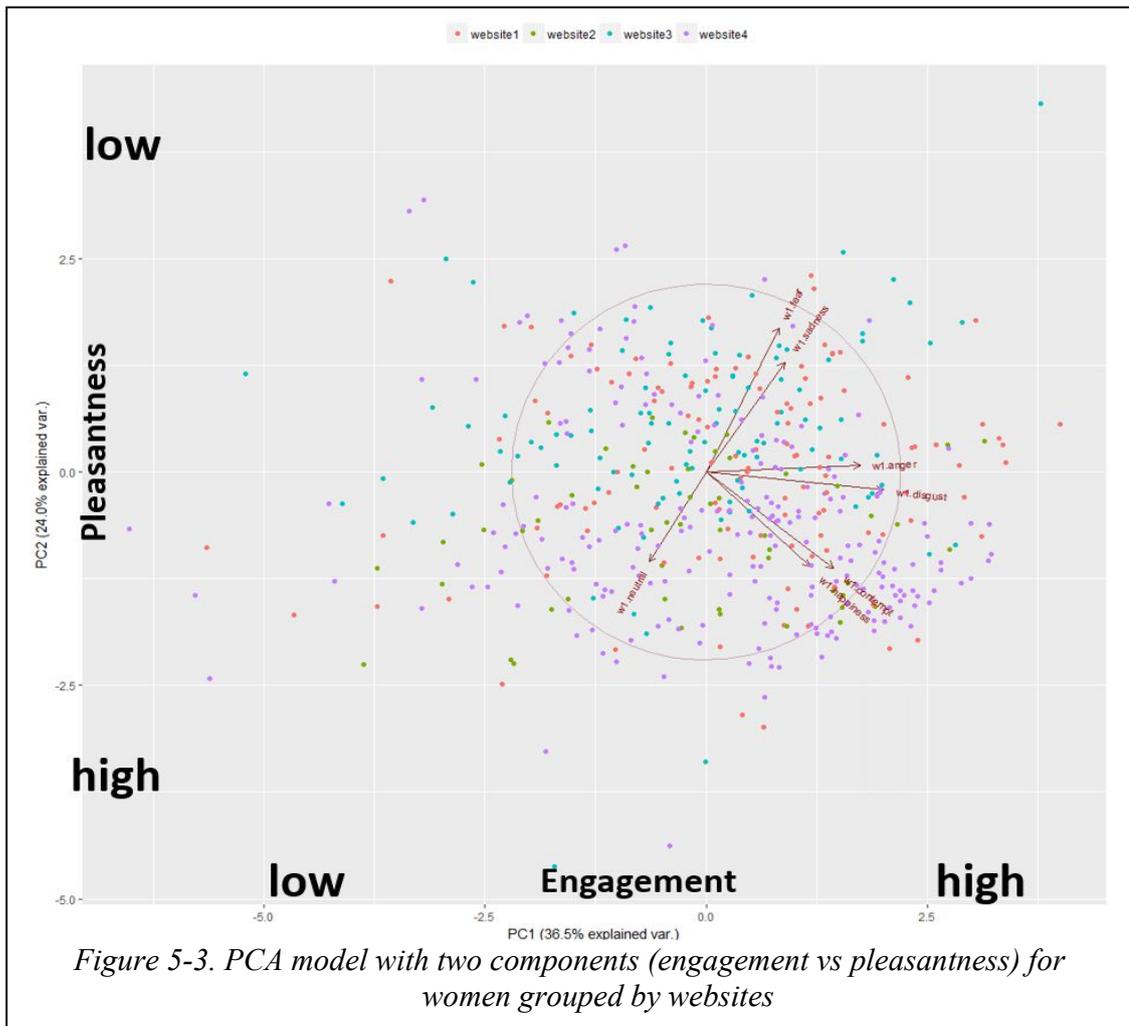
#### 5.4.1 Women Results

##### *Two independent PCA dimensions & variables contribution*

Based on women emotion observations, Step 3a reported two new women principal components which mainly extracted information about disgust-anger (**pcw1**) and fear-sadness (**pcw2**). Both components explain 61% of the detected emotions' variance.

Moreover, emotion distribution was checked by positive and negative coefficients (Lebart et al., 2000, p. 56), as illustrated by Figure 5-3. Interestingly, it showed how **pcw1** (disgust-anger) created an emotion distribution contrast; with neutral on the left side against disgust, anger, contempt, happiness, sadness and fear on the right side (*engagement*). In contrast, **pcw2** (fear-

sadness) distinguished the emotion variables in a fuzzier manner with four negative coefficients (bottom) against three positive ones (top). Despite this, happiness (-0.39) and sadness (0.45) represented an independent axis (*pleasantness*).



Interestingly, the emotion distribution can be understood by using the Positive Activation & Negative Activation (PANA) model (Watson & Tellegen, 1985). Mainly, it includes two dimensions: *engagement* (quiet against aroused emotions) and also *pleasantness* (happiness against sadness). So, we can interpret **pcw1** (disgust-anger) as a no strong feeling on the left (neutral or quiet) while all other emotions are aroused and concentrated highly on the right side. Consequently, **pcw1** (disgust-anger) is characterized by *engagement*. Similarly, **pcw2** (fear-sadness) distinguishes particularly happiness and sadness so that this component matches exactly the dimension *pleasantness*. Thus, **pcw1** and **pcw2** can be understood as user responses contrasting *engagement* vs *pleasantness*.

To summarise, step ③-a clarified the observations' distribution where (1) **pcw1** (disgust-anger) mainly contrasted neutral against all other emotions variables (*engagement*), (2) **pcw2** (fear-sadness) contrasted happiness and sadness (*pleasantness*) in particular.

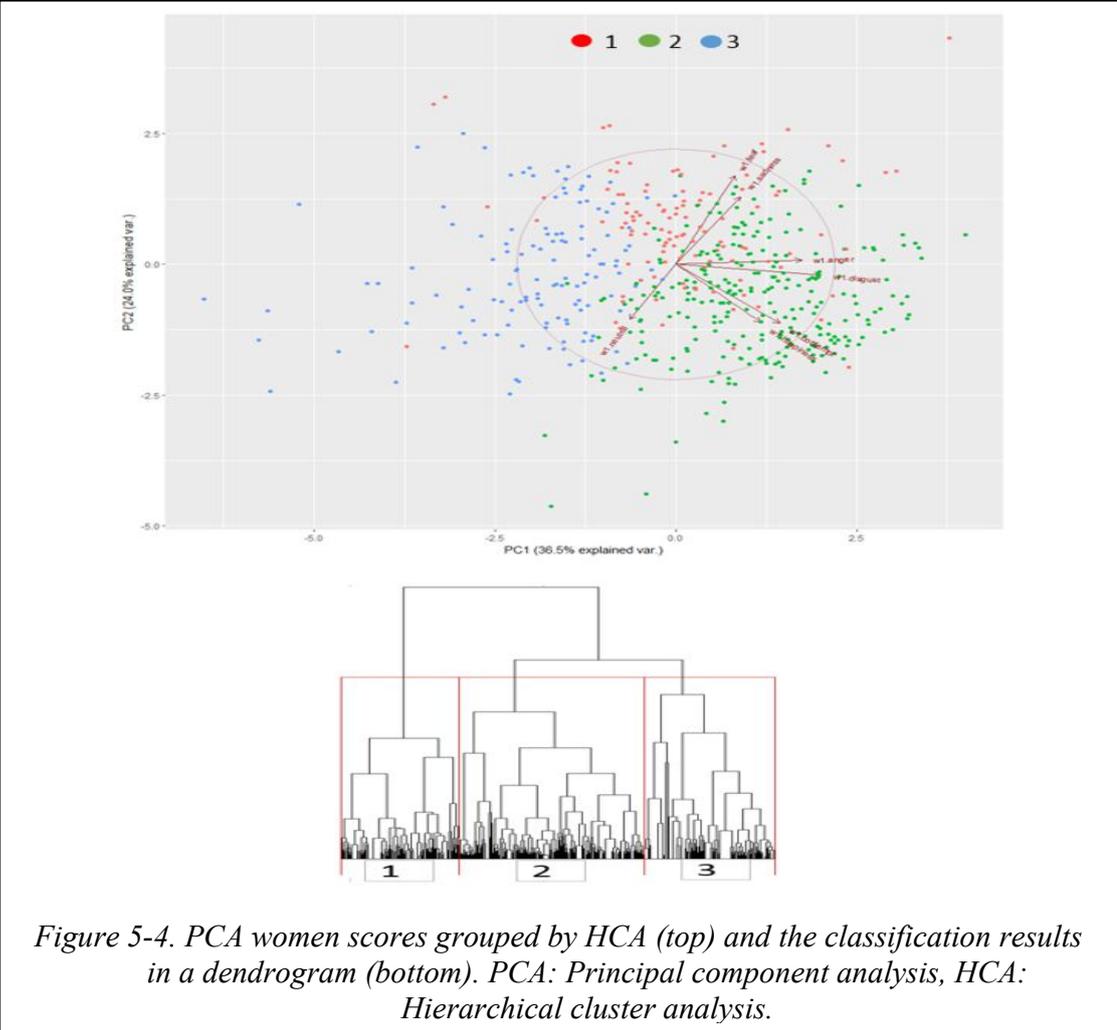
Although the emotions observation gave us some insights about their usefulness, they still need to be analysed considering age in order to study our first hypothesis (the UI quality factors influence the emotions detected depending on age and gender). Thus, a manner to group emotions based on age is underlined below.

### *Hierarchical Classification*

Hierarchical cluster analysis conducted on the women data set (④-a) identified three classes (1,2,3) which represents respectively 30%, 42% and 27% of the women dataset. With this classification, Figure 5-4 shows the PCA women scores grouped uniformly by these classes (top) represented also by a dendrogram (bottom). It opposes class3 and class2 while class1 is mostly grouped on the top. Thus, it shows that emotions were grouped successfully in three heterogeneous classes: women class1 (classW1), women class2 (classW2) and women class3 (classW3).

Thanks to this classification, the second factor, age, is investigated. Table 5-3 shows a set of age measures (e.g. the age interval ) for classW1, classW2 and classW3. Here, classW3 represents the youngest participants with an average of 28 years old ([23,28]). The middle-aged group, classW1, had a central value of 31 years of age ([29,31]). Finally, the oldest group held an average of 37 years in classW2 ([32,63]). Overall, step ④-a revealed that PCA women observations were distributed in three classes with associated age intervals: classW1 (middle age) [28,31], classW2(older adults) [32,63] and classW3(younger adults) [23,28].

Considering link between emotion and age (classes), it is feasible to test **H1**, the UI quality factors (aesthetics and/or usability) influence the emotions detected (sadness, contempt, neutral, fear, disgust, anger and happiness) as explored in the next step.



	<i>classW1</i>	<i>classW2</i>	<i>classW3</i>
<b>Min.</b>	23	23	23
<b>1st Qu.</b>	26	27	24
<b>Median</b>	27	28	25
<b>Mean</b>	31	37	28
<b>3rd Qu.</b>	29	51	28
<b>Max.</b>	63	63	51
<b>Interval Age</b>	[29 - 31] Middle-aged adult	[32 - 63] Older adult	[23 - 28] Young adult

*Table 5-3. Women age measures for class1, class2 and class3*

*Independence tests for H1*

In order to study whether the quality factors (aesthetics and usability) have an impact on the detected emotions by age, three independence tests were performed in step **5-a** on classes-websites, classes-usability (low/high levels) and classes-aesthetics (low/high levels). First, it revealed that the observations (PCA scores) differed significantly depending on the websites versions into each class ( $X^2(6, N = 742) = 35.47, p < 0.01, \phi$  (effect size) = 0.11). Second, there was an influence of usability levels (high/low) on the observations per class ( $X^2(2, N = 742) = 12.34, p < 0.002, \phi = 0.09$ ). Finally, there was influence of aesthetics levels (high/low) on the observations per class ( $X^2(2, N = 742) = 6.53, p < 0.04, \phi = 0.07$ ).

Hence, different UIs quality (aesthetics and/or usability) affect women observations based on age, which validated the first hypothesis, **H1**) the UI quality factors (aesthetics and/or usability) influence the emotions detected (sadness, contempt, neutral, fear, disgust, anger and happiness) depending on age, for the women dataset.

	classW1	classW2	classW3
<b>Website 1</b> (low aesthetics/high usability)	0,49	1,52	-2,41
<b>Website 2</b> (high aesthetics/high usability)	-3,87	1,84	1,79
<b>Website 3</b> (low aesthetics/low usability)	-0,13	-0,18	0,36
<b>Website 4</b> (high aesthetics/ low usability)	1,24	-1,76	0,89

*Table 5-4. Women positive and negative residuals for the independence tests*

As a secondary result, the independence tests computation also released which websites **influenced** some classes more than others by using the positive (blue) and negative (red) residuals (Table 5-4). A positive value signifies a positive influence (attraction) while a negative value signifies a negative influence (repulsion) between websites versions and classes. The results reported that: ClassW1 (middle age) showed positive influence with website1 (low aesthetics, high usability) & website4 (high aesthetics, low usability, classW2 (older adults) with website1 (low aesthetics, high usability) and website2 (high aesthetics, high usability) and classW3 (young adults) with every version except website1.

As a summary, the independence tests results reported **5-a**:

1. There is an **influence** of the UI usability and/or aesthetics into the women observations i.e. emotions per class (representing a unique age interval) could be observed,
2. the most important effect was produced by usability ( $\phi = 0.09$  vs.  $\phi = 0.07$  in aesthetics), and
3. specific UIs (websites) showed more association (influence) than others on the classes' observations: website1(low aesthetics, high usability) & website4 (high aesthetics, low usability) with classW1, website1& website2 (high aesthetics, high usability) with classW2 and all except website1 with classW3.

We refined the analysis by searching for relevant emotions by women classes. Comparison tests (z-normal-distribution) per emotion across classes were computed to find the most representative emotions (best data concentration) per class. Table 5-5 shows the results of z-values computation of classW1[29,31], classW2[32,63] and classW3[23,28] across all emotions (the biggest and most positive values into [-1.96,1.96] with  $\alpha=5\%$  are marked in red per emotion). **Relevant** emotions were identified per class: classW1 (middle-aged adults) (anger, fear, sadness), classW2 (older adults) (disgust, happiness, contempt) and classW3 (young adults) (neutral).

	classW1	classW2	classW3
<b>disgust</b>	-0,16	0,27	-15,16
<b>anger</b>	0,16	0,02	-13,18
<b>fear</b>	0,20	-0,08	-0,47
<b>sadness</b>	0,39	-0,08	-0,69
<b>happiness</b>	-0,33	0,25	-8,72
<b>neutral</b>	-0,46	-0,12	1,38
<b>contempt</b>	-0,76	0,23	-11,61

Table 5-5. Z-values for emotions across classes for women observations. Values in the acceptance region are marked in red

Figure 5-5 summarises the step 5-a results. It illustrates the previous computation of positive (blue) and negative (red) influences between age classes (also linked to **relevant** emotions) and websites (1 to 4).

First, relevant emotions per age classes are underlined by this figure:

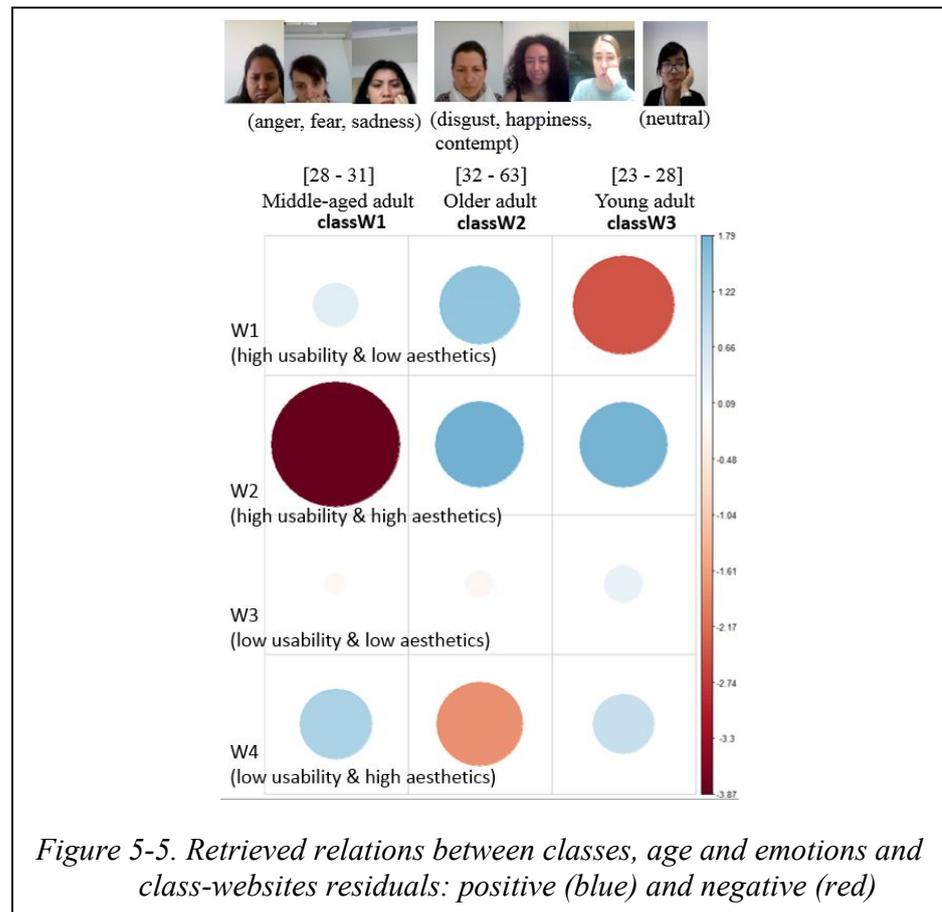
- anger, fear, sadness for classW1 (middle-aged adults) [28,31],
- disgust, happiness, contempt for classW2 (older adults) [32,63]
- and neutral for classW3 (young adults) [23,28].

Second, the positive influence on classes is more relevant in some websites than others:

- classW1(middle-aged adults) [28,31] with websites 4 (high aesthetics, low usability) & 1 (low aesthetics, high usability),
- classW2 (older adults) [32,63] with websites 2 (high aesthetics, high usability) &1 (low aesthetics, high usability), and
- classW3 (young adults) [23,28] with mainly websites 2&4.

Third, the negative influence on classes is also more significant in some websites than others:

- classW1 with websites 2 &3 (low aesthetics, low usability),
- classW2 with websites 4&3, and
- classW3 only with website1.



From these results, **H1** is validated for the women data set (① to ⑤): UI aesthetics and/or usability can influence user emotions (anger, contempt, disgust, sadness, fear, neutral and happiness) in a different manner depending on women's age. Although aesthetics or usability revealed a different impact on UX (user emotions) in real-time interaction, it does not detail how their level (low and/or high) impact each emotion. Consequently, the next section explores emotions behaviour depending on aesthetics and usability levels (low and/or high) for women in different classes of age (**H2**).

### Implications for H1

Mainly, step ⑤-a shows that the UI influences the detected women emotions (anger, fear, sadness, disgust, happiness, contempt and neutral) depending on women age. Then, this step also underlines initially in Figure 5-5 that some UIs influence more than others in each women emotions. From these results, **H1** is validated for the women data set (① to ⑤): UI aesthetics and/or usability can influence user emotions (anger, contempt, disgust, sadness, fear, neutral and happiness) in a different manner depending on women's age. Although aesthetics

or usability revealed a different impact on UX (user emotions) in real-time interaction, it does not detail how their level (low and/or high) impact each emotion. So, we are able to say that the UI impact women emotions differently based on their age but it is not clear whether high or low changes in the UI quality influence women detected emotions (**H2**). Consequently, the next section explores emotions behaviour depending on aesthetics and usability levels (low and/or high) for women in different classes of age (**H2**).

### *Emotion thresholds identification for H2*

To validate our second hypothesis, we studied emotion means by website versions i.e. by level of aesthetics and usability. These means are represented by box plots. The analysis identified 7 box-plots (95% of confidence intervals) for each class as illustrated in Figure 5-6 for the middle-aged adult class (classW1). Since confidence intervals are of 95%, results can be reproduced in 95 percent of cases. The 5% of uncertainty can be overpassed by the definition of the expected interval values to determine a women behaviour.

Thanks to each box-plot, emotions behaviours are identified per level of usability and aesthetics, per women age class. First, in classW1 (middle-aged women), the emotional impact exists in “opposite” websites i.e. the best (website2 with high aesthetics and high usability) vs. the worst one (website3 with low aesthetics and low usability). Figure 5-6 shows distinct emotions for website 2 and 3: fear has a low level [6.7E-04,6.2E-03] for website2, and a high level [5.4E-02,1.2E-01] for website 3; neutral has a high level for website2 whereas it is much lower for website3. Heterogeneous behaviour was only detected for these two emotions in websites 2 and 3 for middle aged women. Thus, some emotions (fear and neutral) are impacted when women participants interacted with an opposite UI quality: website 2 (high aesthetics, high usability) and website 3 (low aesthetics, low usability).

Following the same principle, we studied the emotions means for all classes of women when a clear distinction was visible (i.e. no overlapping between emotion means for all website versions) then we defined some thresholds. Table 5-6 shows the minimum and maximum thresholds per class associating also the websites (2&3), usability-aesthetics level (low/high), emotion, and emotion intensity (to know how the facial expression or emotion occurs and/or intensifies releasing emotion values from 0 meaning a no facial expression to 1 as facial expression fully present) (*section 2.2.2, Face*). Overall, there is a clear difference in emotion values per age class and aesthetics-usability levels: fear and neutral for middle-aged women (classW1); anger, disgust, sadness and neutral for older adults (classW2); and fear, anger, neutral and contempt for young women (classW3).

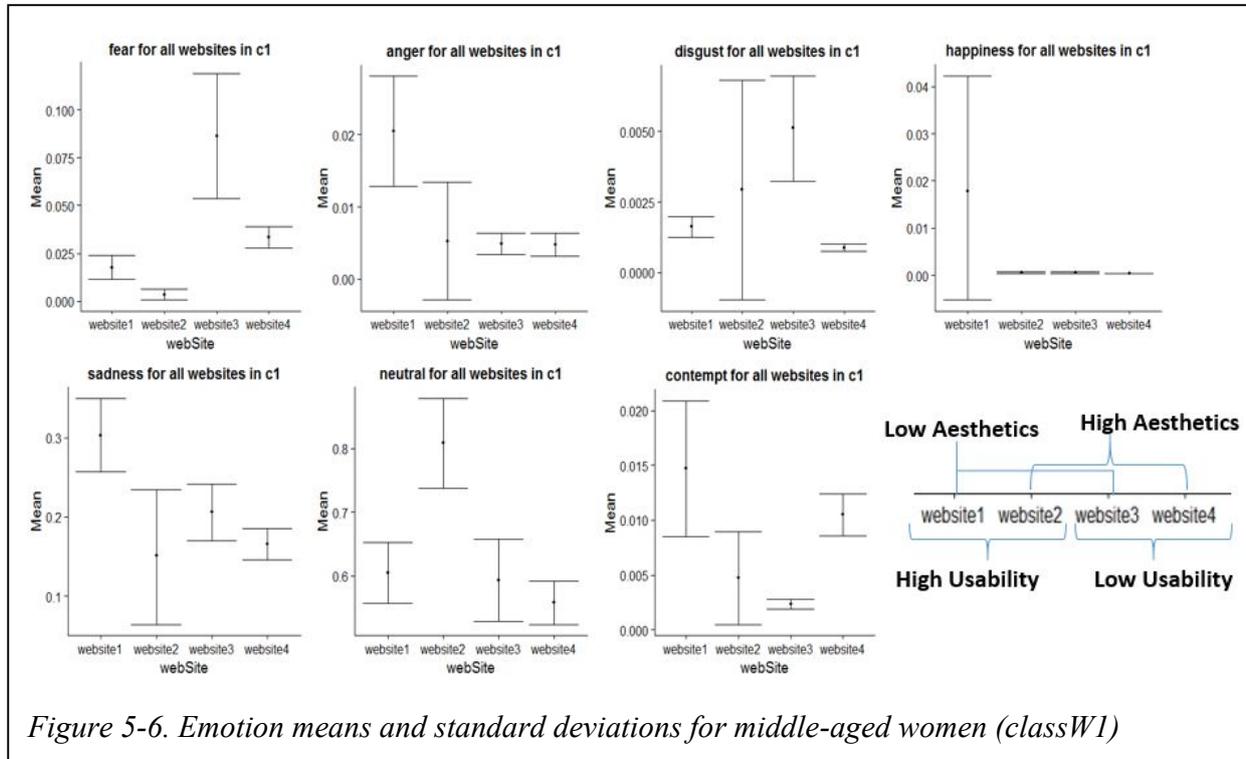


Figure 5-6. Emotion means and standard deviations for middle-aged women (classW1)

Similarly, websites with differences either in the aesthetics or in the usability level were compared: website1 (low aesthetics, high usability) & website4 (high aesthetics, low usability) (Table 5-7). In fact, for middle-aged women, the box-plots for fear, anger, disgust and sadness prove dissimilar emotion behaviour for website 1 & website4. Overall, it shows that if a UI has a different quality factor (e.g. high usability and low aesthetics for website1) then there is a contrast in the intensity of some emotions per age class: fear, anger, disgust and sadness for middle-aged women (classW1); fear, anger, disgust, sadness and contempt for older adults (classW2); and fear, disgust and sadness for young women (classW3).

### Implications for H2

The emotion thresholds result 6-b allowed us to validate H2 that concerns the study of the level (low and/or high) of UI quality (aesthetics and usability) impacts differently the emotions detected depending on age and gender. It was evidenced for the women data set by the thresholds analysis per class shown in Table 5-6 and Table 5-7 which associates the UI quality levels (high/low vs. aesthetics/usability), emotions and age (women classes). Thus, we are able to say that if the UI quality levels are always different (sometimes for usability, sometimes for aesthetics) then there is an impact on the emotions detected for women in different ages.

		UI quality	UX impact	Threshold		
User		Usability				
Class	UI	Aesthetics	Emotion	Intensity	Min.	Max.
classW1	w2	High	Fear	Low	6,7E-04	6,2E-03
	w3	Low		High	5,4E-02	1,2E-01
	w2	High	Neutral	High	7,4E-01	8,8E-01
	w3	Low		Low	5,3E-01	6,6E-01
classW2	w2	High	Anger	High	5,3E-03	1,5E-02
	w3	Low		Low	2,1E-03	2,9E-03
	w2	High	Disgust	High	5,1E-03	9,2E-03
	w3	Low		Low	1,2E-03	2,2E-03
	w2	High	Sadness	Low	2,6E-02	5,2E-02
	w3	Low		High	1,2E-01	1,5E-01
	w2	High	Neutral	High	7,6E-01	8,5E-01
	w3	Low		Low	6,3E-01	7,0E-01
classW3	w2	High	Fear	Low	8,8E-05	4,3E-04
	w3	Low		High	1,4E-03	1,6E-02

		UI quality	UX impact	Threshold			
User		Usability					
Class	UI	Aesthetics	Emotion	Intensity	Min.	Max.	
classW1	w1	High	Fear	Low	1,1E-02	2,4E-02	
	w4	Low		High	High	2,8E-02	3,9E-02
	w1	High	Anger	Low	High	1,3E-02	2,8E-02
	w4	Low		High	Low	3,1E-03	6,4E-03
classW2	w1	High	Disgust	High	1,3E-03	2,0E-03	
	w4	Low		High	Low	7,4E-04	1,0E-03
	w1	High	Sadness	High	2,6E-01	3,5E-01	
	w4	Low		High	Low	1,5E-01	1,9E-01
	w1	High	Fear	High	1,1E-02	1,8E-02	
	w4	Low		High	Low	9,2E-04	9,8E-03
	w1	High	Anger	High	6,0E-03	1,2E-02	
	w4	Low		High	Low	2,1E-03	4,1E-03
classW3	w1	High	Disgust	High	7,6E-03	1,1E-02	
	w4	Low		High	Low	2,9E-03	4,8E-03

	w2	High	Anger	Low	7,1E-05	1,4E-04
	w3	Low		High	3,1E-04	5,4E-04
	w2	High	Neutral	High	8,8E-01	9,6E-01
	w3	Low		Low	8,2E-01	8,8E-01
	w2	High	Contempt	High	2,0E-03	4,7E-03
	w3	Low		Low	9,1E-04	1,5E-03

Table 5-6. Thresholds for opposite quality level (high or low aesthetics and usability) websites in the women data set

	w1	High	Low	Sadness	High	1,5E-01	2,0E-01
	w4	Low	High		Low	8,9E-02	1,2E-01
	w1	High	Low	Contempt	Low	1,7E-02	2,9E-02
	w4	Low	High		High	7,1E-02	1,0E-01
classW3	w1	High	Low	Fear	Low	1,5E-03	5,0E-03
	w4	Low	High		High	1,1E-02	2,0E-02
	w1	High	Low	Disgust	Low	9,1E-05	1,3E-04
	w4	Low	High		High	1,8E-04	2,4E-04
	w1	High	Low	Sadness	High	7,6E-02	1,3E-01
	w4	Low	High		Low	2,5E-02	3,7E-02

Table 5-7. Thresholds for different UI quality level in the women data set

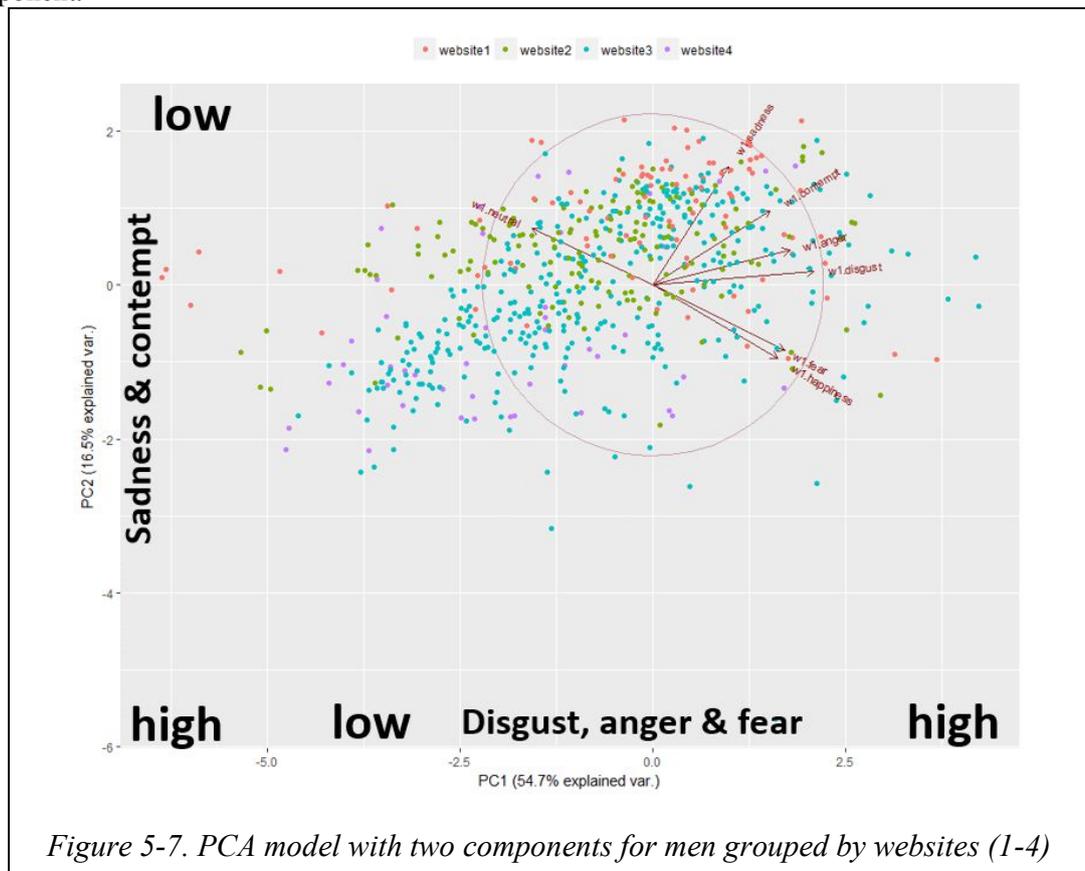
## 5.4.2 Men Results

The analyses performed for the men population followed the process and explanations previously mentioned for the women population.

### *Two independent PCA dimensions & variables contribution*

A data complexity reduction method was applied by PCA for the men data set to facilitate the analysis and the observation processes. **3-b** reported two new men principal components which mainly extracted information about disgust-anger-fear (**pcm1**) and sadness-contempt (**pcm2**). The two components accounted for 71.2% of the detected emotions' variance with the highest quality of emotions' contribution.

Like in women observations, Figure 5-7 shows that the variables distribution in **pcm1** contrasted neutral (left) against all other emotions (right) *-engagement-*. While **pcm2** distinguished fear and happiness (bottom) against others (top) *-pleasantness-* building an independent axe. Thus emotions are distributed in a different manner on each principal component.



### Hierarchical Classification

To study the link with age, observations were aggregated by age classes (HCA) (4b). This classification released three classes, which represent 55%, 30% and 15% of the men dataset. Figure 5-8 shows this classification with the PCA men scores grouped uniformly by these classes (top) and a dendrogram (bottom). It mainly contrasted two groups (class1, class2) with a small proportion in class3 (right side).

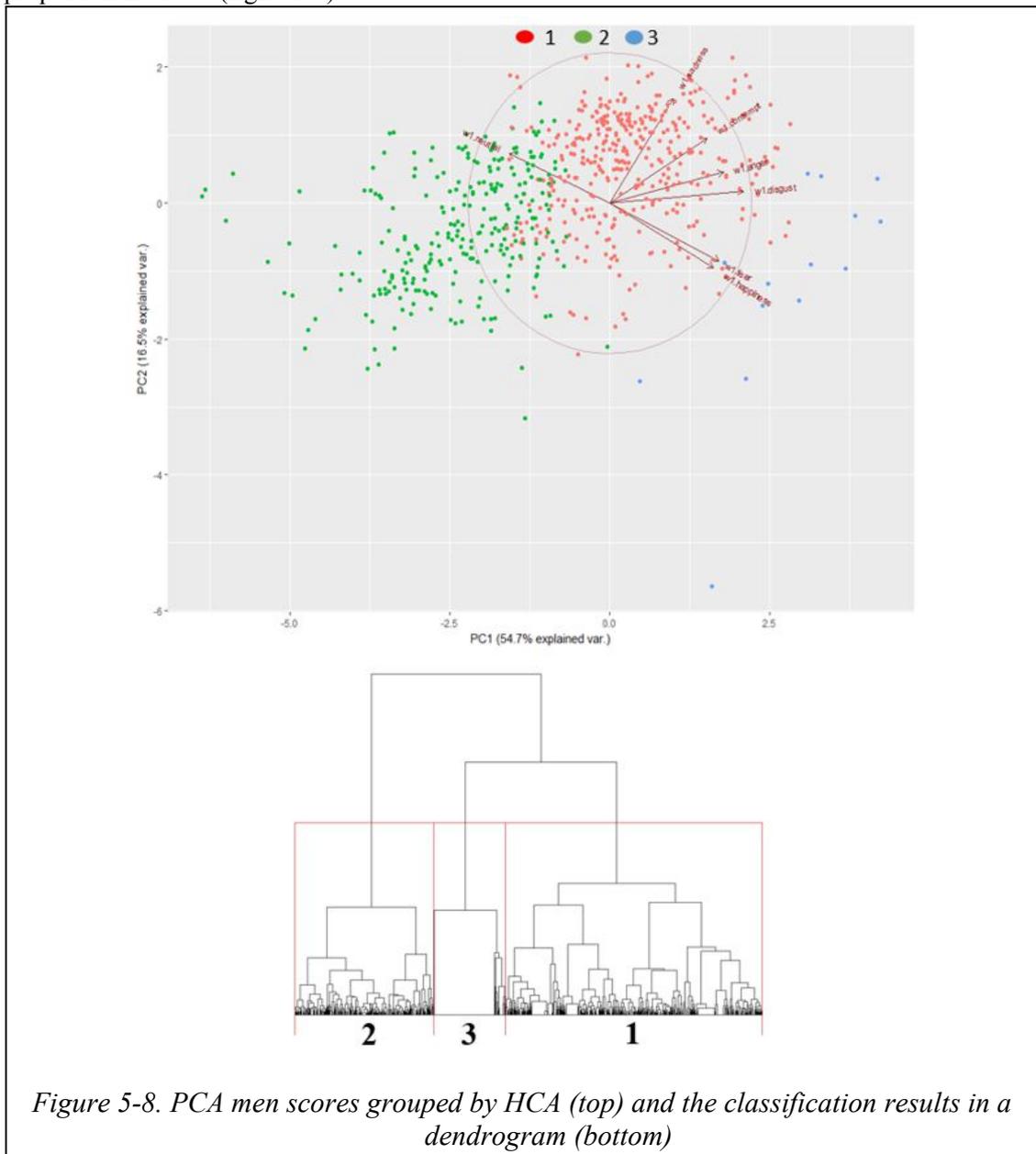


Figure 5-8. PCA men scores grouped by HCA (top) and the classification results in a dendrogram (bottom)

Following this classification, Table 5-8 reported an age distinctions with a set of centrality measures (e.g. mean) for classM1 (middle-aged adult), classM2 (young adult) and classM3 (older adult). ClassM2 represents the youngest participants with an average of 26 years old ([19,26]). The middle-aged class, classM1, holds a central value of 28 ([27,28]). Finally, the oldest class, classM3, comprises an average of almost 43 years old ([29,67]). Overall, step **4-b** revealed that PCA men observations were distributed in three classes with associated age intervals: classM1[27,28], classM2[19,26] and classM3[29,67]. Thus, we are able to explore **H1** for the men data set, the UI quality factors (aesthetics and/or usability) influence the emotions detected depending on age and gender as explained below.

	<i>classM1</i>	<i>classM2</i>	<i>classM3</i>
<i>Min.</i>	19.0	19.00	19.00
<i>1st Qu.</i>	21.0	20.00	32.00
<i>Median</i>	27.0	20.00	39.00
<i>Mean</i>	27.9	26.04	42.54
<i>3rd Qu.</i>	32.0	27.00	53.00
<i>Max.</i>	67.0	53.00	67.00
<i>Interval Age</i>	[27 - 28] Middle-aged adult	[19 - 26] Young adult	[29 - 67] Older adult

*Table 5-8. Men age measures for classM1, classM2 and classM3*

#### *Independence tests for H1*

Each retrieved class represented the set of men emotions detected per age across all versions of the website (UIs) so that the influence of the UIs quality factors on each class was tested by independence tests. Three independence tests were performed in step **5-b** on classes-websites, classes-usability and classes-aesthetics to address the aesthetics and usability influence on men detected emotions. The first test (classes-websites) revealed that the observations (PCA scores) in classes significantly differed by the website so that there was an influence of websites into each class ( $X^2((6, N = 988) = 524.55, p < 2.2e-16, (\text{effect size}) = 0.4)$ ). Second, it was also showed (classes-usability) the influence of usability (high/low) in the observations per class ( $X^2((2, N = 988) = 414.34, p < 2.2e-16, \phi = 0.5)$ ). Finally, there was an influence of aesthetics (high/low) in the observations per class as the third test (classes-aesthetics) ( $X^2((2, N = 988) = 148.19, p < 2.2e-16, \phi = 0.3)$ ). Similarly, to the results for the women population, **5-b** underlined that the different UIs regarding their quality (aesthetics and/or usability) affected men observations based on age, validating **H1** the UI quality factors (aesthetics and/or usability) influence the emotions detected (sadness, contempt, neutral, fear, disgust, anger and happiness) depending on age, for the men dataset.

As a secondary result, the independence tests computation also revealed which websites **influenced** some classes more than others, Table 5-9 exposed positive residuals: classM1

(middle-aged adult) with websites 1 (low aesthetics, high usability) & 3 (low aesthetics, low usability), classM2 (young adult) with websites 4 (high aesthetics, low usability) & 3 (low aesthetics, low usability), and classM3 (older adult) with websites 2&1.

	<i>classM1</i>	<i>classM2</i>	<i>classM3</i>
<i>w1</i>	1,10	-7,52	8,39
<i>w2</i>	-4,61	-1,96	11,47
<i>w3</i>	3,72	2,61	-10,68
<i>w4</i>	-3,87	8,41	-4,40

*Table 5-9. Positive and negative residuals for the independence tests in men*

To summarize the independence tests results for the men data set **5-b**, three key points are underlined: it reveals mainly that (1) there was an influence of UI quality factor into the observations i.e. emotions per class (representing a unique age interval) which validated **H1 for men observations**, (2) the most considerable effect size in UI quality was given by usability ( $\phi = 0.5$  vs.  $\phi = 0.3$  in aesthetics) and (3) specific UIs had more association (influence) than others on the classes' observations: Websites 1 (low aesthetics, high usability) & 3 (low aesthetics, low usability) associated with middle-age adult (classM1); websites 3 & 4 (high aesthetics, low usability) associated with young adult (classM2); and websites 1 & 2 (high aesthetics, high usability) associated with older adult (classM3).

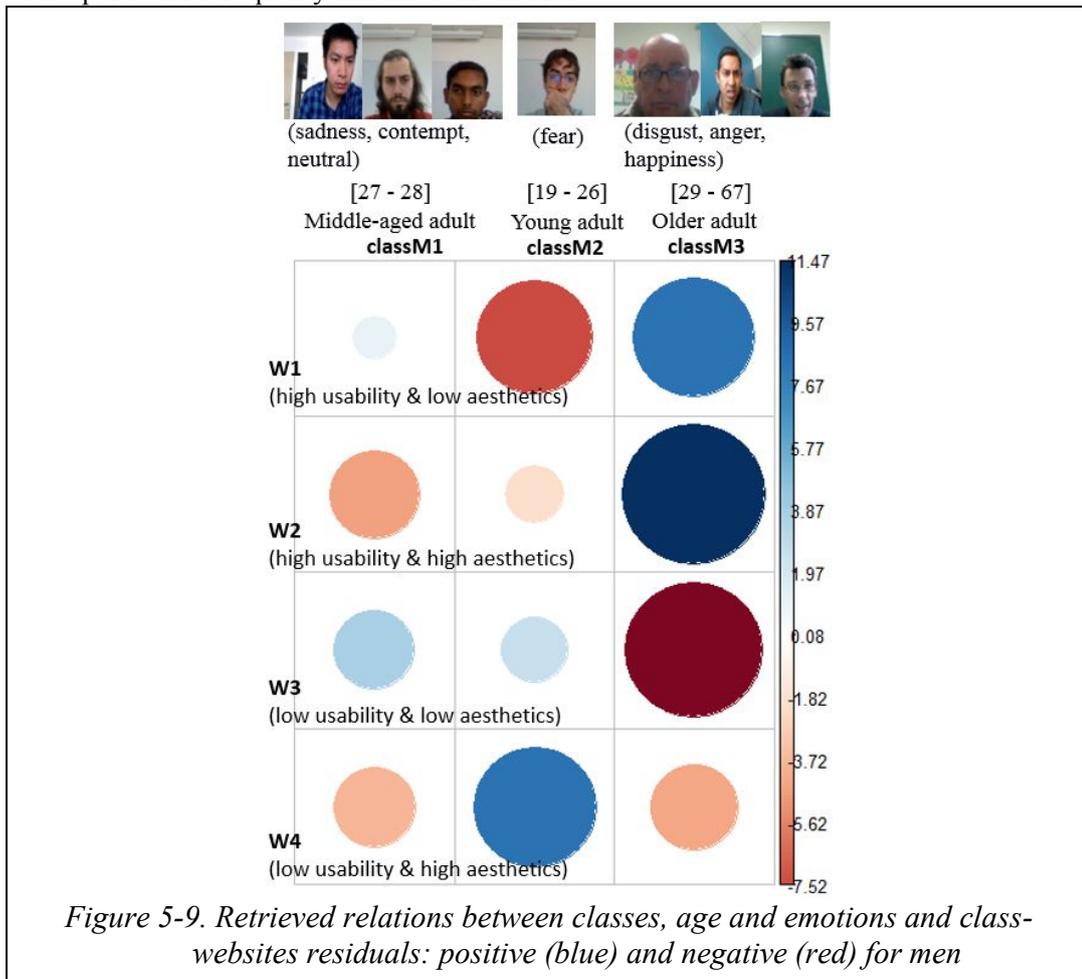
	<b>class1</b>	<b>class2</b>	<b>class3</b>
<b>disgust</b>	-0,75	-98,14	<b>0,59</b>
<b>anger</b>	-0,09	-40,38	<b>0,85</b>
<b>fear</b>	-3,00	<b>0,16</b>	2,39
<b>sadness</b>	<b>0,29</b>	-3,31	-0,48
<b>happiness</b>	-0,21	-21,77	<b>0,36</b>
<b>neutral</b>	<b>0,10</b>	2,21	-3,32
<b>contempt</b>	<b>0,15</b>	-23,22	-0,98

*Table 5-10. Z-values for emotions across classes for men observations. Values in the acceptance region are marked in red*

To find relevant emotions per men classes, we refined the analysis. Table 5-10 shows the results of z-values computation (comparison tests to find the most representative emotions concentration) of classM1, classM2 and classM3 across all emotions. Relevant emotions were identified per class (linked to age): classM1 (sadness, contempt, neutral), classM2 (fear), classM3 (disgust, anger and happiness).

Figure 5-9 summarised the results. Similar to women results, it shows the UI influence on men age classes with positive (blue) and negative (red) residuals. The positive influence on classes turned out more relevant in some websites than others: middle-aged adults with websites 3 (low aesthetics, low usability) & 1 (low aesthetics, high usability), young adults with websites 2 (high aesthetics, high usability) & 1 and older adults with websites 2&1. The negative influence on classes was also more significant in some websites: middle-aged adults with websites 2 (high

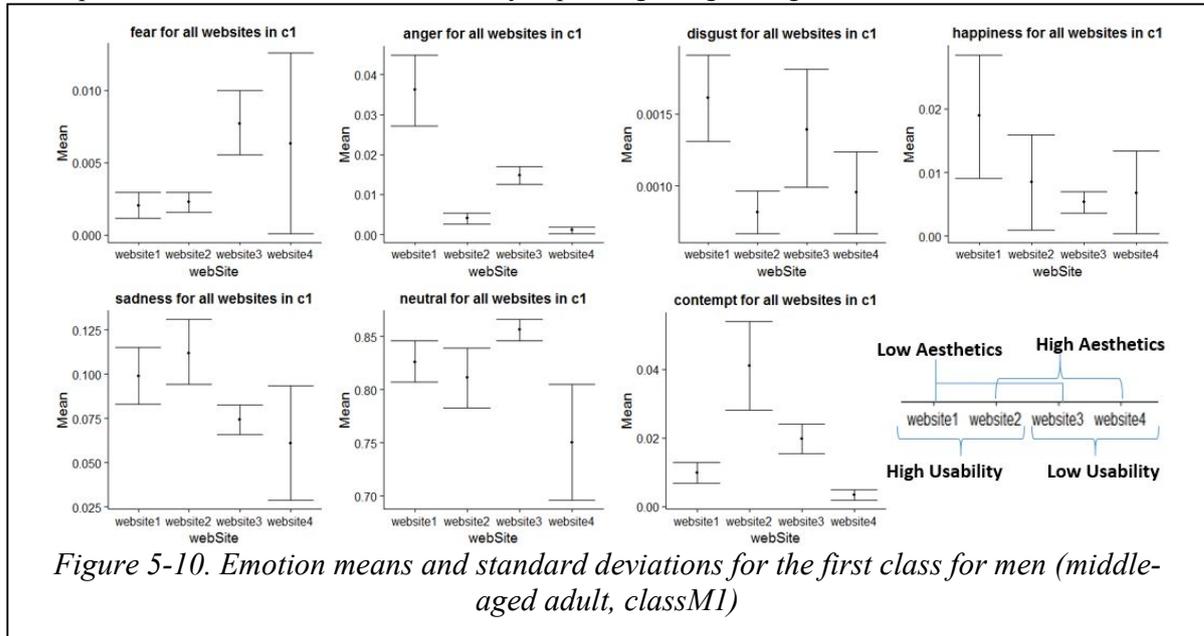
aesthetics, high usability) & 4 (high aesthetics, low usability), young adults with websites 1 (low aesthetics, high usability) & 2 (high aesthetics, high usability) and older adults with websites 3 (low aesthetics, low usability) & 4 (high aesthetics, low usability). Therefore, men emotions can be categorised according to their age and gender and to the levels of UI usability and/or aesthetics with a particular UIs quality influence on emotions.



### Implications for H1

① to ⑤ validated the first hypothesis (H1) for men: the UI quality factor level (aesthetics and usability) influenced the men's emotions (sadness, contempt, neutral, fear, disgust, anger and happiness) differently based on their age [19,67]. Second, some UIs versions influenced each men emotions more than others (⑤-b). For instance, positive residuals in websites 1 (low aesthetics, high usability) & 2 (high aesthetics, high usability) in contrast to negative ones in websites 3 (low aesthetics, low usability) & 4 (high aesthetics, low usability) for older adults. Similar to the women results, ⑤-b revealed a different UI impact on user emotions in real-time interaction; however, it did not clarify the degree of the UI quality (e.g. high aesthetics & usability) what

produce the detected emotion as matter of **H2** the level (low and/or high) of UI quality factors impacts the emotions detected differently depending on age and gender.



#### Emotion thresholds identification for H2

To address **H2**, we studied emotion means by website versions for the men data set. This step 6-b reported 7 box-plots for each class to identify emotions behaviours per level of usability and aesthetics in each class (Figure 5-10). This figure illustrates that fear has no overlapping thresholds for website2 ([1.6E-03,3.0E-03]) and website3 ([5.6E-03,1.0E-02]); where website2 implied a lower negative fear emotion than website3. Similarly, it is clearly seen that the set of emotions in middle-aged adults held independent thresholds results for fear, anger, disgust, sadness, neutral and contempt in websites 2&3. Only happiness showed overlapping thresholds in such websites.

Following this notion, Table 5-11 (next page) summarises the complete box-plots analysis for websites 2&3. It reported different emotion intensity in each men class at having the same level in usability and aesthetic (websites 2&3). Similarly, the analysis of different levels of aesthetics and usability (websites 1&4) shows that there was less differences in emotion thresholds than the same level of aesthetics and usability (Table 5-12).

Websites with differences either in the aesthetics/usability level were compared: website1 (low aesthetics, high usability) & website4 (high aesthetics, low usability). The box-plots for anger, disgust, neutral and contempt evidence dissimilar thresholds in Table 5-12. To clarify, the two different thresholds expose in anger with values of [2.7E-02;4.5E-02] and [2.8E-04;1.9E-03] for websites 1&2 accordingly. So, these two thresholds are independent showing that the UIs (websites 1&4) evoked negative emotions with different range values. Unfortunately, this is not the case for all emotions fear, happiness, sadness which have overlapped thresholds for middle-aged adults (classM1). Hence, there is a difference of the detected values for some emotions

(anger, disgust, neutral and contempt) caused by a different UI quality (websites 1&4) in classM1.

The complete results are given in Table 5-12 for middle-aged (classM1), young (classM2) and older adults (classM3). Similar to the previous table, it includes the same columns but applied for websites 1 and 4.

		UI quality	UX impact		Threshold	
User		Usability				
Class	UI	&Aesthetics	Emotion	Intensity	Min.	Max.
classM1	w2	High	Fear	Low	1,6E-03	3,0E-03
	w3	Low		High	5,6E-03	1,0E-02
	w2	High	Anger	Low	2,6E-03	5,5E-03
	w3	Low		High	1,3E-02	1,7E-02
	w2	High	Disgust	Low	6,7E-04	9,7E-04
	w3	Low		High	9,9E-04	1,8E-03
	w2	High	Sadness	High	9,5E-02	1,3E-01
	w3	Low		Low	6,6E-02	8,3E-02
	w2	High	Neutral	Low	7,8E-01	8,4E-01
	w3	Low		High	8,5E-01	8,7E-01
	w2	High	Contempt	High	2,8E-02	5,4E-02
	w3	Low		Low	1,5E-02	2,4E-02
classM2	w2	High	Fear	Low	2,1E-05	5,1E-05
	w3	Low		High	2,1E-04	7,8E-04
	w2	High	Happiness	Low	2,4E-05	6,6E-05
	w3	Low		High	1,5E-04	2,4E-04
	w2	High	Sadness	High	1,1E-02	1,8E-02
	w3	Low		Low	4,8E-03	7,2E-03
	w2	High	Contempt	High	5,5E-04	7,7E-04
	w3	Low		Low	3,0E-04	3,9E-04
classM3	w2	High	Fear	High	5,5E-01	5,7E-01
	w3	Low		Low	5,9E-03	1,8E-02
	w2	High	Anger	Low	6,6E-02	6,9E-02
	w3	Low		High	8,5E-02	2,2E-01

(continuation)						
classM3	w2	High	Fear	High	5,5E-01	5,7E-01
	w3	Low		Low	5,9E-03	1,8E-02
	w2	High	Anger	Low	6,6E-02	6,9E-02
	w3	Low		High	8,5E-02	2,2E-01
	w2	High	Disgust	Low	2,1E-02	2,2E-02
	w3	Low		High	5,0E-02	1,3E-01
	w2	High	Happiness	Low	2,3E-02	4,7E-02
	w3	Low		High	1,4E-01	4,1E-01
	w2	High	Sadness	Low	5,5E-03	6,8E-03
	w3	Low		High	2,3E-02	1,6E-01
	w2	High	Neutral	High	5,2E-01	5,2E-01
	w3	Low		Low	2,1E-01	3,0E-01
	w2	High	Contempt	Low	2,3E-03	3,3E-03
	w3	Low		High	6,3E-03	1,1E-02

*Table 5-11. Thresholds for the same UI quality level (high or low aesthetics and usability) in the men data set*

User	Class	UI quality		UX impact		Thresholds	
		Usability	Aesthetics	Emotion	Intensity	Min.	Max.
classM1	w1	High	Low	Anger	High	2,7E-2	4,5E-2
	w4	Low	High		Low	2,8E-4	1,9E-3
	w1	High	Low	Disgust	High	1,3E-3	1,9E-3
	w4	Low	High		Low	6,7E-4	1,2E-3
	w1	High	Low	Neutral	High	8,1E-1	8,5E-1
	w4	Low	High		Low	7,0E-1	8,1E-1

	w1	High	Low	Contempt	High	6,8E-3	1,3E-2
	w4	Low	High		Low	1,9E-3	5,0E-3
classM2	w1	High	Low	Disgust	Low	3,7E-6	1,4E-5
	w4	Low	High		High	2,3E-5	5,4E-5
	w1	High	Low	Happiness	Low	2,8E-5	1,0E-4
	w4	Low	High		High	3,8E-4	1,1E-3
classM3	n.a						

n.a. not available.

*Table 5-12. Thresholds for different UI quality level in the men data set*

We can notice that for men in classM3 [29,67] years old, there are observations in websites 1 (low aesthetics, high usability), 2 (high aesthetics, high usability) and 3 (low aesthetics, low usability) but not in website 4 (high aesthetics, low usability). This is why it does not allow to compare website 3&4. Overall, the emotion thresholds identification highlights that (1) if UI has a different quality (e.g. high usability and low aesthetics for website1) then there is also a clear contrast or different impact in the emotion intensity (low or high) revealed in each threshold in middle-aged and young adults and (2) this impact is evidenced in some emotions per class: anger, disgust, neutral and contempt in middle-aged adults; and disgust and happiness in young adults.

### *Implications for H2*

Overall, these results ⑥-b complement the women findings. The emotion thresholds (Figure 5-10) process allowed us to partly validate **H2** for the men dataset. It concerns the study of the level (low and/or high) of UI quality (aesthetics and usability) which impacts differently the emotions detected depending on age for men participants. It was possible to find a correlation between the intensity of some men emotions and the level of UI quality factors (Table 5-11 and Table 5-12).

The emotion intensity depends on age but there is one class for which there was insufficient data (classM3, [29,67] years old). Thus, it partly concluded that the level (high and/or low) of UI quality factors (aesthetics and usability) can impact user emotions differently depending on age (**H2**) for men. The main difference against women thresholds analysis is that more observations are needed for older adults (classM3) in order to validate whether the UI quality in websites 1 (low aesthetics, high usability) & 4 (high aesthetics, low usability) also implies a distinction in high and low emotions.

### 5.4.3 Discussion

The analysis validates **H1**) the UI quality factors (aesthetics and/or usability) influence the emotions detected (sadness, contempt, neutral, fear, disgust, anger and happiness) depending on age and gender (steps ① to ⑤), totally while **H2**) partially, the level (low and/or high) of UI quality factors seems to have different impact in emotion intensity depending on age and gender, even if the analysis did not succeed in showing it for a men class (step ⑥-b) for which the number of data was insufficient.

Another data collection is required to robust the sample size. Although (Mandran, 2017) suggests a minimum of 6 participants for profile to analyse user traces, 45 users did not imply a high resulting power ( $\phi = 0.5$  in usability vs.  $\phi = 0.3$  in aesthetics). It could be extended by including more users per class and balancing the sample size properly. Moreover, although the differences in the sample can imply a bias in the experiment, the data analysis is performed independently. It means that the two independent datasets (women & men) were analysed and interpreted separately to minimize the impact of an unbalance sample.

Regarding emotion intensity in the UX, we can wonder if emotions are strong enough to provide relevant feedback. We noticed that there is an emotion variation trough UI interaction. Some plots (Figure 5-6 & Figure 5-10) showed higher values in neutral suggesting that users were mostly without emotional changes (e.g. no variation in the emotion detected in fear); however, Figure 5-6 evidenced a fluctuation of neutral levels across websites for women. It is supported by the variation of the other studied emotions such as fear and contempt. A similar case is shown in Figure 5-10 for men mainly with anger, disgust and contempt. Thus, the user experienced a significant variation in his detected emotions at interacting with the UI.

## 5.5 Summary

In this chapter, we presented the results of the experimental analysis to understand the UI influence on emotions depending on age and gender. It shows two tendencies: (1) UI quality factors (aesthetics and/or usability) influences user emotions differently based on age and gender, (2) the level (high and/or low) of UI quality factors seem to impact emotions differently based on age and gender. Thus, we are able to say that if the level is the same for aesthetics and usability (high aesthetics, high usability) & (low aesthetics, low usability) or different (low aesthetics, high usability) & (high aesthetics, low usability) then it is likely to have a different impact on emotions detected for women and men in different ages.

Despite this, the results need to be strengthened for men for which one of the classes did not contain enough data which could consolidate the current results.

Since there is a UI influence on emotions regarding age and gender, these emotions are used to explore how to preserve or improve UX at runtime, by triggering UI adaptations. This notion will be explored in the next chapter.

## CHAPTER 6 Using emotions to trigger UI adaptation

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### 6.1 Introduction

The previous chapter underlines that (1) UI quality factors (aesthetics and/or usability) influences user emotions differently depending on age and gender, (2) the level (high and/or low) of UI quality factors seem to impact emotions differently depending on age and gender. Considering this evidence of UI influence on user emotions based on age and gender, this section goes further to explore how to use such influence to preserve or improve UX at runtime, by triggering UI adaptations (Galindo et al., 2018).

With this purpose, we complete the analysis of our experiment to identify if a problem exists in UI usability and/or aesthetics and then to choose if some adaptation must be triggered. Lastly, these results are used in the Inferring Engine to trigger adaptations in the *Perso2U* prototype proposed in *section 4.3*.

### 6.2 Hypotheses

The analysis aims at identifying usability and/or aesthetics problems based on users' age and gender at runtime to trigger UI adaptation. To achieve this goal, it is necessary to detect fine grain emotions at runtime. Thus, it reuses two elements: (1) the protocol from *section 4.4*, and (2) the data analysis process along with the detected emotion values from one tool, Microsoft Emotion API shown in previous analysis (*section 5.3*).

Our hypotheses are thus:

**Hypothesis1 (H1):** it is possible to categorize emotions depending on users' age and gender and on UI aesthetics and usability levels;

**Hypothesis2 (H2):** there exist emotions thresholds for detecting usability and aesthetics problems from users' age and gender.

### 6.3 Experimental analysis method

As learned in *section 5.3*, it is possible to follow a logic set of steps to analyze detected emotions for retrieving emotions intervals from which it is possible to detect a UI problem. This process is improved in this analysis thanks to a two new steps: (1) a better treatment of age to balance more properly the sample size (central tendency for age) and (2) UI problem identification based on thresholds computation (UI problem identification). To permit an implementation, we aimed at keeping the same number of persons in each age category in order to have enough individuals in each category to conduce the data analysis process. Thus, before analyzing data, each data sample (women and men) was divided by using a measure of central tendency applied in the age variable: *median* as the middle score in a data set (Lazar, Feng, & Hochheiser, 2009, p. 75). The data analysis process (*section 5.3*) finishes with emotion intervals which determine emotions thresholds. Further, these thresholds are recomputed (based on the new data sample classification) and interpreted to deduce a UI problem to trigger UI adaptation in aesthetics/usability for women or men independently.

Specifically, the data analysis process to study the two hypotheses is illustrated by Figure 6-1. It reuses these steps from *section 5.3*: “Validation of Data correctness and consistency” ①, multivariable analysis ②, hierarchical classification analysis ④, and thresholds identification ⑤. Beyond this, the main process difference is introduced by adding the two new steps previously mentioned: central tendency for age ③ and UI problem identification ⑥.

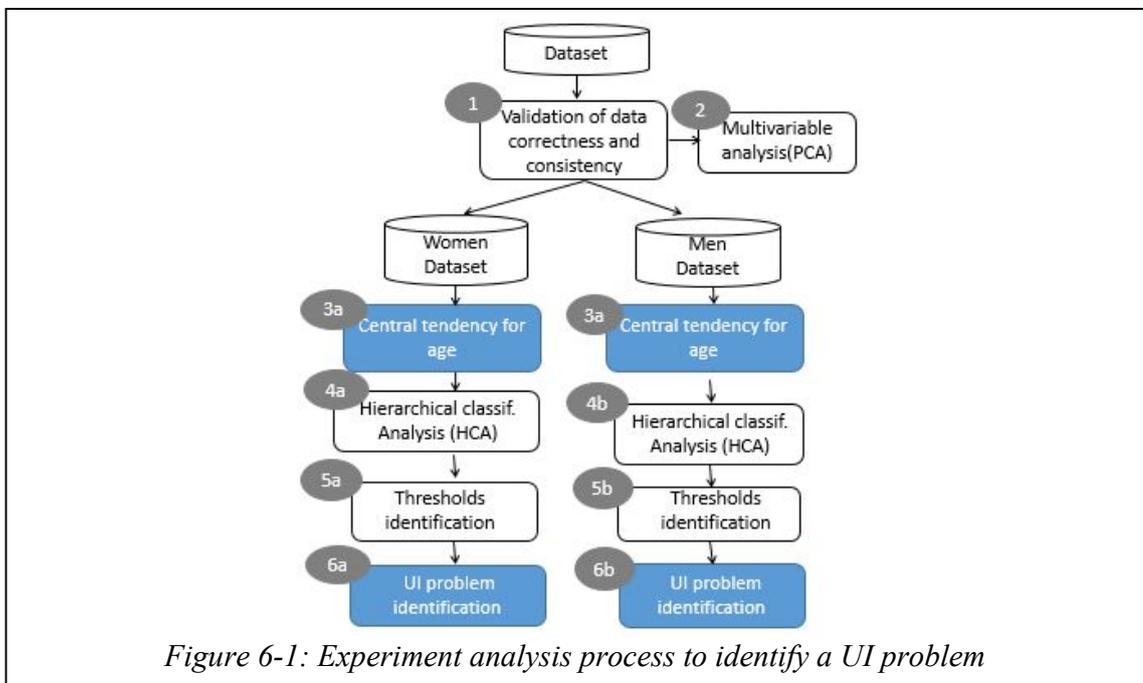
We recall the reused steps and introduce the new ones as follows:

- g. The first step applied a clean up to the collected data to ensure its consistency ①,
- h. The complexity of the data was reduced thanks to a multivariable analysis (PCA, Principal Component Analysis (Hotelling, 1933; Jolliffe, 2002; Pearson, 1901)) ②. Since this step used the same data (detected emotions) and the same technique (PCA) as previous experiment (*section 5.4*), it lead us to identify initial women and men differences in the emotion distributed in two principal components. Hence, the independent examination of women and men data set was performed in this step. The same structure was used in both cases with 7 variables (sadness, contempt, neutral, fear, disgust, anger and happiness) with a different data quantity: women (742) and men (988).
- i. Once steps ① & ② are computed, each data set (women and men) was divided by using a central tendency measure (median) applied in age ③. This technique helps us to figure out how the data is located into two equal parts. This task divided the sample into 4 categories depending on gender and age. For age, the median was computed as the middle score in a data set (e.g. 50% data in each women category) (Lazar et al., 2009, p. 75). It serves as an age threshold to obtain 2 categories by gender inside each data set: women under/equal to and over the age threshold, men under/equal to and over the age threshold.
- j. Although emotion observations are spread into categories, they are not aggregated uniformly, therefore we applied a hierarchical statistical analysis to each category ④. This distributed the detected emotions (women and men) into uniform classes per age category.
- k. Despite emotions values are aggregated by gender and age, they were not linked with UI quality levels. Thus, it was not possible yet to categorize emotions depending on gender, age and also usability and aesthetics levels (low/high). To

go deeper, we extended the emotion categorization by using emotions thresholds **5**. These thresholds signify different emotion values (min. and max) associated with age classes, UI, usability and aesthetics levels (low/high) and a particular emotion. It allowed us to extend step **4** by understanding how emotions are categorized by UI quality levels. Since emotions are categorized based on gender, age and UI quality levels, it allowed us to validate **H1**) it is possible to categorize emotions depending on users' age and gender and on UI aesthetics and usability levels.

1. To explore **H2**), there exist emotions thresholds for detecting usability and aesthetics problems from users' age and gender, we explored deeper previous results (emotion thresholds) to find how emotions can reveal a UI problem **6**. We identified emotions behaviours (in relation to one emotion or a combination of emotions) that can permit to identify a website version. It allowed the identification of aesthetics/usability problems in some classes so that some emotions based on gender and age can be used to discover a UI problem. Consequently, a UI problem is attached to class (age and gender), website version (aesthetics and usability levels), some emotions with their associated thresholds (min. & max) validating **H2**.

Overall, **1** to **5** contributes to **H1** while **6** covers **H2** with the same process for women and men.



## 6.4 Results

This section aims at presenting the main findings following the analysis process shown in Figure 6-1. It will show the first exploration results from step ②, which results in the distinction between men and women emotion observations; then the results from steps ③ to ⑥ are presented sequentially for both women and men data sets.

### *First Multivariable Exploration*

To see whether differences exist between men and women, principal component analysis (PCA) was applied in the same manner as section 5.4. It released the same findings: initial differences on observations per gender. Consequently, the data set was divided in two elements: women and men data set.

### *Central tendency for age*

Next, each data set (women and men) was divided by using a central tendency measure applied in age ③ to keep the same number of persons in each category. Each data set was divided into 2 categories depending on age to analyze women and men independently. To achieve it, we computed the median as the middle score in a data set (Lazar et al., 2009, p. 75). It released 27 as the age threshold for both gender. Hence, these categories were retrieved: (1) women less than or equal to 27, (2) women more than 27, (3) men less than or equal to 27, (4) and men more than 27.

### *Hierarchical Classification*

To aggregate detected emotions in a uniform manner, a hierarchical statistical analysis was applied to each category ④ found in the previous step. The goal of this technique is to create some classes sufficiently distinct from each other but with an intrinsic homogeneity. Hierarchical Cluster Analysis produced significant partitions with 3 classes for each case (women<=27, women>27, men<=27, men>27, see Table 6-1). Each class represents a more balanced percentage of the data in each category. For instance, 27.7 (class1), 33.2 (class2), 39.0 (class3) per cent for women <=27. This table shows how the PCA scores are distributed between classes and women and men categories. The PCA scores are the transformed variable values corresponding to each particular data point or emotion value. Overall, this analysis distributed the women detected emotions into uniform classes per age category.

	Class 1	Class 2	Class 3
<b>Women &lt;= 27</b>	216	259	314
<b>Women &gt; 27</b>	274	508	28
<b>Men &lt;= 27</b>	337	558	310
<b>Men &gt; 27</b>	422	259	97

*Table 6-1: Number of scores between classes and women age categories in the Hierarchical Cluster Analysis*

By analyzing these classes per category, 4 of them appeared to have not enough discriminating behaviors (see Table 6-1, Women > 27 in class 1 and 3 and Men > 27 in classes 2 and 3, which are the strikethrough numbers). More than 83% of women's scores who are more than 27 years old are in the second class, making the two other ones not enough representative. Thus, we retrieved four women classes corresponding to: women  $\leq 27$  for class1, class2 and class3; and women >27 for class2. In the group of men over 27 years, one website version is not represented in the data of class 2 (website 4) and class 3 (website 1). Thus, we acquired five classes: men  $\leq 27$  for class1, class2 and class3; men >27 for class1. Therefore, we did not use these 4 classes (class1 and class3 in women >27, class2 and class3 in men >27) into women and men categories from our results analysis in order to keep relevant results.

#### *Emotion thresholds identification*

Although emotions values are grouped by gender and age, they are not linked with UI quality levels (e.g. which emotions belongs to high usability and low aesthetics). To validate **H1**, it is necessary to categorize emotions depending on users' age and gender and on **UI aesthetics and usability levels**, then we extended the emotion categorization by studying the relationship between emotions detected and the website version used (low/high usability/aesthetics) per class (uniform partition into each category) and category (women less than or equal to 27, women more than 27, men less than or equal to 27 and men more than 27). We compute emotion thresholds (confidence intervals analysis). It aims to identify a different emotion behaviour caused by the UIs versions. These thresholds signify different emotion values (min. and max) per category linked to classes, UI, usability and aesthetics levels (low/high) and a particular emotion. The thresholds computation relies on the study of emotion means by website versions represented by box-plots. We obtained 7 box-plot for each class into each category (Figure 6-2) **5**.

Since our goal is to link emotion values with UI quality levels then we can see in Table 6-2 and Table 6-3 (next page) that each threshold is linked to the women/men category, class (1, 2 or 3), website (high/low level of aesthetics/usability), emotion and emotion threshold (min. and max). These tables show all thresholds corresponding to women and men  $\leq 27$  for class1. Hence, the reader is referred to *appendix A and B* to observe the remaining quantity of computed women & men thresholds for class1, class2 and class3 excluding the four mentioned classes.

User category	class	website	UI quality			Threshold	
			Usability	Aesthetics	emotion	Min.	Max.
Women <=27	1	website1	high	low	anger	1.84e-04	3.84e-04
	1	website2	high	high	anger	3.23e-05	6.98e-05
	1	website3	low	low	anger	1.48e-04	2.69e-04
	1	website4	low	high	anger	2.39e-04	3.74e-04
	1	website1	high	low	contempt	2.47e-03	3.89e-03
	1	website2	high	high	contempt	2.39e-03	5.15e-03
	1	website3	low	low	contempt	8.10e-04	1.50e-03
	1	website4	low	high	contempt	1.69e-03	2.62e-03
	1	website1	high	low	disgust	1.04e-04	2.16e-04
	1	website2	high	high	disgust	9.43e-05	2.01e-04
	1	website3	low	low	disgust	4.11e-04	5.42e-04
	1	website4	low	high	disgust	2.50e-04	3.28e-04
	1	website1	high	low	fear	8.28e-05	3.80e-04
	1	website2	high	high	fear	2.33e-05	4.80e-04
	1	website3	low	low	fear	8.79e-04	1.93e-03
	1	website4	low	high	fear	3.72e-04	5.62e-04
	1	website1	high	low	happiness	9.75e-05	2.64e-04
	1	website2	high	high	happiness	-1.37e-03	1.76e-02
	1	website3	low	low	happiness	4.70e-04	1.69e-03
	1	website4	low	high	happiness	2.04e-03	6.80e-03
	1	website1	high	low	neutral	9.30e-01	9.61e-01
	1	website2	high	high	neutral	8.83e-01	9.61e-01
	1	website3	low	low	neutral	9.03e-01	9.43e-01
	1	website4	low	high	neutral	9.34e-01	9.61e-01
	1	website1	high	low	sadness	3.45e-02	6.44e-02
	1	website2	high	high	sadness	2.69e-02	1.02e-01
	1	website3	low	low	sadness	4.22e-02	8.52e-02
	1	website4	low	high	sadness	1.82e-02	4.51e-02

Table 6-2: Women emotion thresholds under or equal to 27 for class 1

User category	class	website	UI quality			Threshold	
			Usability	Aesthetics	emotion	Min.	Max.
Men <=27	1	website1	high	low	anger	3.97e-02	6.46e-02
	1	website2	high	high	anger	1.43e-02	2.65e-02
	1	website3	low	low	anger	1.93e-02	2.86e-02
	1	website4	low	high	anger	-4.45e-04	6.17e-03
	1	website1	high	low	contempt	8.08e-03	1.69e-02
	1	website2	high	high	contempt	-1.66e-03	9.26e-03
	1	website3	low	low	contempt	8.42e-03	1.96e-02
	1	website4	low	high	contempt	1.48e-03	9.18e-03
	1	website1	high	low	disgust	1.46e-03	2.03e-03
	1	website2	high	high	disgust	3.88e-04	7.99e-04
	1	website3	low	low	disgust	6.80e-04	1.04e-03
	1	website4	low	high	disgust	2.01e-04	1.25e-03
	1	website1	high	low	fear	3.47e-05	7.16e-05
	1	website2	high	high	fear	1.69e-03	5.54e-03
	1	website3	low	low	fear	1.04e-04	5.36e-04
	1	website4	low	high	fear	-1.41e-04	9.20e-03
	1	website1	high	low	happiness	6.32e-04	2.41e-03
	1	website2	high	high	happiness	1.13e-05	1.88e-04
	1	website3	low	low	happiness	2.68e-04	4.97e-04
	1	website4	low	high	happiness	1.81e-05	2.66e-05
	1	website1	high	low	neutral	8.50e-01	8.86e-01
	1	website2	high	high	neutral	8.75e-01	9.02e-01
	1	website3	low	low	neutral	9.05e-01	9.24e-01
	1	website4	low	high	neutral	8.15e-01	8.67e-01
	1	website1	high	low	sadness	5.09e-02	7.68e-02
	1	website2	high	high	sadness	5.28e-02	7.81e-02
	1	website3	low	low	sadness	3.52e-02	5.27e-02
	1	website4	low	high	sadness	1.20e-01	1.55e-01

Table 6-3: Men emotion thresholds under or equal to 27 for class 1

### *Implications for H1*

Our first research question is related to the possibility to categorize emotions depending on users' age and gender and on UI aesthetics and usability levels. This first hypothesis is partly validated by our experimental results (steps ① to ⑤). Indeed, the identification of classes by gender and age tends to show that it is possible to categorize emotions to obtain emotions behavior depending on usability and aesthetics levels. However, 4 of our classes (class1 and class3 in women >27, class2 and class3 in men >27) are not relevant currently ⑤. More data would be required to show the relevance of all classes. In spite of this, the current relevant classes are significant and can be used for hypothesis 2) there exist emotions thresholds for detecting usability and aesthetics problems from users' age and gender.

### *UI problem identification*

The second hypothesis concerns the analysis of emotions thresholds for detecting usability and aesthetics problems from users' age and gender for each category (women<=27, women>27, men<=27, men>27).

First of all, we need to identify emotions behaviors (in terms of one emotion or a combination of emotions) that can permit to identify a website version and so a usability and/or an aesthetics problem for a class into each category.

For instance, we can see on Figure 6-2 that the means for fear, disgust and contempt for website 3 (low usability and low aesthetics version, women under 27 years) are very different from the values obtained on the other websites for these same emotions. So, a low usability and a low aesthetics problem can be identified thanks to the detection of a certain unique level of fear, disgust or contempt for young women of class1.

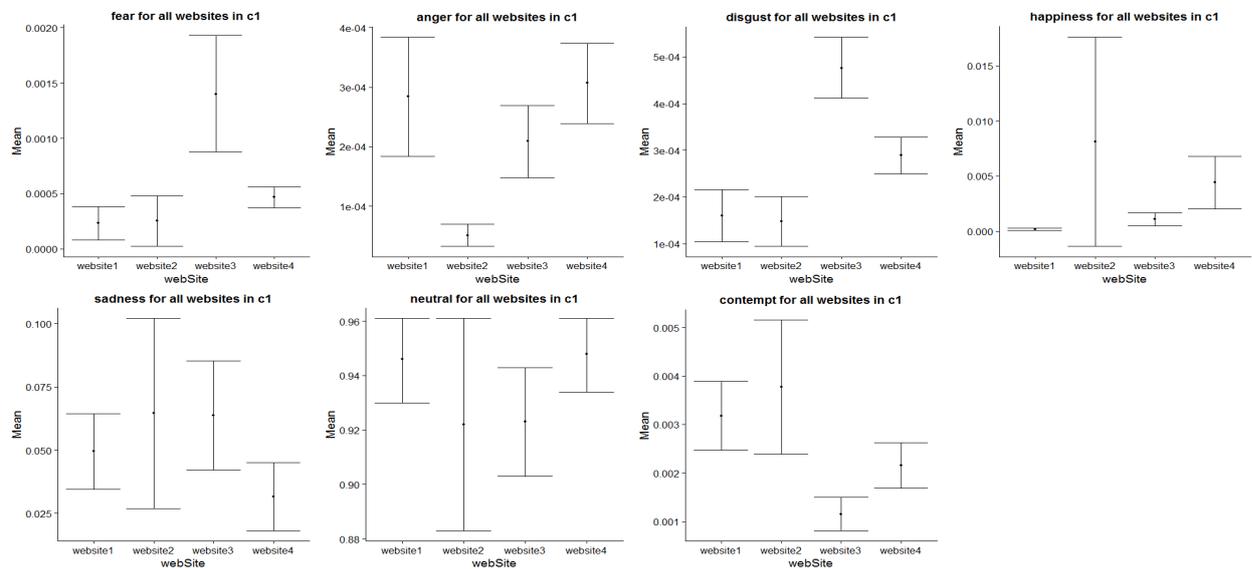


Figure 6-2: Emotion means and standard deviations for class 1 for women under or equal to 27 years

Following this notion, the analysis of all box-plots in the remaining classes reported means differences summarized in Table 6-4 and Table 6-5. The previous analyzed case for women under/equal to 27 years is shown at the top: contempt, disgust and fear for the low usability and low aesthetics version (website3). Mainly, this table shows that we can identify emotion behavior (mean differences) in women and men categories in some classes, usability/aesthetics levels (websites) and emotions.

Since there are differences in central emotion values (mean) associated with gender, age, class and usability/aesthetics levels shown in Table 6-4 and Table 6-5, we can extend the analysis to consider the minimum and maximum emotion values, it is the potential existence of thresholds needed for **H2**, to show that it is possible to detect usability and aesthetics problems from users' age and gender.

Second, we can see from Figure 6-2 that each mean is given with a confidence interval. Here confidence intervals are of 95%, results can be reproduced in 95 percent of cases. This 5% of uncertainty can be used to determine the interval of values expected to determine a behavior. For instance, the emotion behavior studied previously is based on fear, disgust or contempt. The confidence interval for fear is between  $8.79 \cdot 10^{-4}$  and  $1.93 \cdot 10^{-3}$  (even if these numbers are close to 0, the difference is significant at 5% thresholds). These intervals provide us the emotions thresholds for identifying an UI problem. In our example, for women under 27 years, if fear is between  $8.79 \cdot 10^{-4}$  and  $1.93 \cdot 10^{-3}$ , or disgust between  $4.11 \cdot 10^{-4}$  and  $5.42 \cdot 10^{-4}$  or contempt between  $8.10 \cdot 10^{-4}$  and  $1.5 \cdot 10^{-3}$ , the corresponding website version can only be website 3. So, there are problems of aesthetics and usability.

user category	class	webSite	UI quality		
			Usability	Aesthetics	emotion
women <=27	1	website3	low	low	contempt
		website3	low	low	disgust
		website3	low	low	fear
	2	website2	high	high	happiness
		website3	low	low	contempt
		website3	low	low	neutral
		website4	low	high	happiness
	3	website1	high	low	sadness
		website2	high	high	anger
		website2	high	high	fear
		website2	high	high	sadness
		website3	low	low	disgust
women >27	2	website2	high	high	sadness
		website3	low	low	anger
		website4	low	high	fear
		website4	low	high	happiness

*Table 6-4: Emotions with mean differences per website and class for women*

user category	class	webSite	UI quality		
			Usability	Aesthetics	emotion
men <=27	1	website1	high	low	anger
		website1	high	low	disgust
		website1	high	low	happiness
		website3	low	low	happiness
		website3	low	low	neutral
		website4	low	high	anger
		website4	low	high	sadness
		website4	low	high	contempt
	2	website1	high	low	anger
		website1	high	low	contempt
		website1	high	low	disgust
		website1	high	low	fear
		website1	high	low	neutral
		website2	high	high	contempt
		website2	high	high	neutral
		website3	low	low	fear
	3	website3	low	low	neutral
		website4	low	high	happiness
		website4	low	high	neutral
		website4	low	high	sadness
		website4	low	high	anger
		website4	low	high	contempt
		website4	low	high	happiness
		website4	low	high	neutral
Men >27	1	website3	low	low	anger
		website4	low	high	contempt

*Table 6-5: Emotions with mean differences per website and class for men*

To know if there is only a problem of usability (resp. aesthetics), we must study the behavior of website 4, i.e., high aesthetics/low usability version, (resp. website 1, i.e., low aesthetics/high usability version). By analyzing Figure 6-2, we can provide conclusions for women under 27 years of age of class 1:

- Website 1 (low aesthetics version) is characterized by the level of anger (between  $2.84 \cdot 10^{-4}$  and  $3.84 \cdot 10^{-4}$ ) AND the level of disgust (between  $1.04 \cdot 10^{-4}$  and  $2.16 \cdot 10^{-4}$ ). A problem with aesthetics can thus be identified if both emotions are detected between these levels.
- Website 4 (low usability version) can be identified by the level of disgust (between  $2.5 \cdot 10^{-4}$  and  $3.28 \cdot 10^{-4}$ ). So, a usability problem can be detected for young women, if emotions are inside these thresholds.

- Even if this does not help in identifying UI problem, we can notice that the version with high aesthetics and high usability (website 2) can be identified by the low level of anger (between  $3.23 \cdot 10^{-5}$  and  $6.88 \cdot 10^{-5}$ ).

We studied the 8 classes in a similar manner. Table 6-6 for women and Table 6-7 for men summarize the results of this analysis (next page). If it is the combination of several emotions values that discriminates, all emotions listed are required. This information is given by an “&” between emotions in the tables. Otherwise any of the listed emotions can be used to determine a problem.

We can notice that for men, there are some cases where no emotion data can discriminate an emotional behavior. For men under or equal to 27 years old, for only one class, there is one behavior that we cannot identify: class2 and website3 (low aesthetics, low usability). For men older than 27 years, only one emotional behavior is significant: this is the one related to problem in aesthetics and usability.

User category	Class	Website version	Emotions	Thresholds (min and max)	Problem
Women <= 27	c1	website1	anger	1.84*10 <sup>-4</sup> and 3.84*10 <sup>-4</sup>	aesthetics
			& disgust	1.04*10 <sup>-4</sup> and 2.16*10 <sup>-4</sup>	
		website3	fear	8.79*10 <sup>-4</sup> and 1.93*10 <sup>-3</sup>	aesthetics and usability
			disgust	4.11*10 <sup>-4</sup> and 5.42*10 <sup>-4</sup>	
			contempt	8.10*10 <sup>-4</sup> and 1.5*10 <sup>-3</sup>	
		website4	disgust	2.5*10 <sup>-4</sup> and 3.28*10 <sup>-4</sup>	usability
	c2	website1	anger	4.08*10 <sup>-4</sup> and 1.02*10 <sup>-3</sup>	aesthetics
			& fear	4.78*10 <sup>-4</sup> and 1.11*10 <sup>-3</sup>	
		website3	neutral	9.11*10 <sup>-1</sup> and 9.26*10 <sup>-1</sup>	aesthetics and usability
			contempt	2.33*10 <sup>-3</sup> and 2.4*10 <sup>-3</sup>	
		website4	anger	2.49*10 <sup>-3</sup> and 4.47*10 <sup>-3</sup>	usability
			happiness	5.12*10 <sup>-2</sup> and 8.22*10 <sup>-2</sup>	
	c3	website1	sadness	3.05*10 <sup>-1</sup> and 3.61*10 <sup>-1</sup>	aesthetics
			neutral	6.02*10 <sup>-1</sup> and 6.64*10 <sup>-1</sup>	
		website3	disgust	1.72*10 <sup>-3</sup> and 2.22*10 <sup>-3</sup>	aesthetics and usability
			sadness	8.89*10 <sup>-2</sup> and 1.09*10 <sup>-1</sup>	
			contempt	1.63*10 <sup>-3</sup> and 1.99*10 <sup>-3</sup>	
		website4	neutral	8.26*10 <sup>-1</sup> and 8.67*10 <sup>-1</sup>	usability
fear			4.07*10 <sup>-2</sup> and 5.20*10 <sup>-2</sup>		
anger			2.96*10 <sup>-4</sup> and 3.76*10 <sup>-4</sup>		
sadness			1.14*10 <sup>-1</sup> and 1.5*10 <sup>-1</sup>		
c2	website1	contempt	5.09*10 <sup>-3</sup> and 8.6*10 <sup>-3</sup>	aesthetics	
		happiness	1.82*10 <sup>-2</sup> and 5.12*10 <sup>-2</sup>		
	website3	anger	3.25*10 <sup>-3</sup> and 4.82*10 <sup>-3</sup>		aesthetics and usability
website4	fear	2.46*10 <sup>-4</sup> and 5.78*10 <sup>-4</sup>	usability		
	& happiness	1.70*10 <sup>-4</sup> and 7.04*10 <sup>-4</sup>			

Table 6-6: Thresholds and UI problems detected for women

User category	Class	Website version	emotions	Thresholds (min and max)	Problem
Men <= 27	c1	website1	anger	3.97*10 <sup>-2</sup> and 6.46*10 <sup>-2</sup>	aesthetics
			disgust	1.46*10 <sup>-3</sup> and 2.03*10 <sup>-3</sup>	
			happiness	6.32*10 <sup>-4</sup> and 2.41*10 <sup>-3</sup>	
		website3	happiness	2.68*10 <sup>-4</sup> and 4.97*10 <sup>-3</sup>	aesthetics and usability
			& neutral	9.05*10 <sup>-1</sup> and 9.24*10 <sup>-1</sup>	
		website4	anger	4.45*10 <sup>-4</sup> and 6.17*10 <sup>-3</sup>	usability
	sadness		1.20*10 <sup>-1</sup> and 1.55*10 <sup>-1</sup>		
	c2	website1	anger	1.01*10 <sup>-3</sup> and 3.57*10 <sup>-3</sup>	aesthetics
		website3		no discriminant values	
		website4	contempt	1.31*10 <sup>-4</sup> and 4.18*10 <sup>-3</sup>	usability
	c3	website1	fear	1.46*10 <sup>-1</sup> and 2.66*10 <sup>-1</sup>	aesthetics
			anger	1.83*10 <sup>-2</sup> and 3.27*10 <sup>-2</sup>	
			disgust	6.45*10 <sup>-3</sup> and 1.09*10 <sup>-2</sup>	
		website3	neutral	5.82*10 <sup>-1</sup> and 6.38*10 <sup>-1</sup>	aesthetics and usability
			contempt	3.30*10 <sup>-3</sup> and 6.54*10 <sup>-3</sup>	
			fear	1.7*10 <sup>-2</sup> and 3.09*10 <sup>-2</sup>	
	website4	happiness	1.01*10 <sup>-2</sup> and 4.07*10 <sup>-2</sup>	usability	
		neutral	6.98*10 <sup>-1</sup> and 7.48*10 <sup>-1</sup>		
c2	website1		no discriminant values		
	website3	anger	1.85*10 <sup>-1</sup> and 3.55*10 <sup>-1</sup>	aesthetics and usability	
	website4		no discriminant values		
	website4		no discriminant values		

Table 6-7: Thresholds and UI problems detected for men

### *Implications for H2*

Our second research question is related to the existence of thresholds for detecting usability and aesthetics problems from users' age and gender. It is validated for some classes by the identification of emotions behaviors through our experimental results (step ⑥). In fact, 27 women and 19 men thresholds were retrieved (Table 6-6 and Table 6-7) where each one is associated with: women/men category, relevant classes found in ⑤, usability/aesthetics levels (websites), emotions, emotion thresholds and UI problems (usability/aesthetic). Four of the found classes in ⑤ (class1 and class3 in women >27, class2 and class3 in men >27) are not included in the threshold analysis since more data would be required to show the relevance of all classes.

#### **6.4.1 Discussion**

The analysis allows us to partly validate our hypotheses: it shows that **H1**) it seems possible to categorize emotions depending on users' age and gender and on UI aesthetics and usability levels and **H2**) some emotions thresholds can be used for detecting usability and aesthetics problems from users' age and gender. As we choose confidence intervals of 95%, results can be reproduced in 95 percent of cases. Of course, an uncertainty of 5 percent remains. This is thus a first answer the lack identified in the related work: identifying potential issues to keep or improve the UI (**H2**) requires to establish links between UI quality factor (aesthetics and usability), emotions and user features (age and gender).

The main limit of this work is that it does not allow us to fully cluster emotional behavior. Some classes are not relevant and others do not discriminate enough emotions. Even if this is a limit, it does not challenge our approach. It simply implies that more data would be necessary to fully validate our hypotheses. However, results are currently good enough to be used in the *Perso2U* prototype presented in chapter 4.

### **6.5 Extension of the Perso2U inferring engine**

*Perso2U* is an approach for adapting dynamically UIs to user's emotions (*see section 4.2*). The *Perso2U* architecture was designed containing three main components: (1) Inferring Engine, (2) Adaptation Engine and (3) Interactive System. Mainly. The first two components work together to inferred contextual information and to define changes in the UI. The inferring engine recognizes the user's situation and in particular him/her emotions (happiness, anger, disgust, sadness, surprise, fear, contempt, neutral). While the adaptation engine selects the best suitable UI structure and computes UI parameters (e.g. Font-size) based on such the context of use sent by the inferring engine.

The analysis in section 6.4 shows that it can be possible to detect a negative emotion behavior depending on user's gender and age. The Inferring Engine is in charge on computing this behavior. The calculation relies on the user's emotions – detected at runtime by emotion detection tool and used as dynamic variables – and his/her age and gender – which can be declared by the user or deduced from pictures by the emotion detection tool and are used as static variables. Then the Inferring Engine sends the context of use with the user's emotions to the Adaptation Engine for adapting UI appropriately.

But to propose a relevant personalization to emotions, the Adaptation Engine must also know if the problem is related to UI aesthetics or usability. So, the Inferring Engine must also send the identified problem source to the Adaptation Engine. This means that our prototype must be modified to add a parameter, the problem source that we name UI-problem, from the Inferring Engine to the Adaptation Engine.

From the experimental results, we can propose some inference rules about UI quality, that provide the eventual UI problem (aesthetics or usability) based on emotions. Let's take as example: the case of women under 27 years of age for which the experimental results show that if fear is between  $8.79 \cdot 10^{-4}$  and  $1.93 \cdot 10^{-3}$ , or disgust between  $4.11 \cdot 10^{-4}$  and  $5.42 \cdot 10^{-4}$  or contempt between  $8.10 \cdot 10^{-4}$  and  $1.5 \cdot 10^{-3}$ , there are problems of aesthetics and usability. As any of the emotions detected in these intervals can discriminate the aesthetics and usability problem, the conditions about emotions thresholds are thus linked by an "or". When discrimination requires the combination of several emotions, conditions are linked by an "and". This is the case for the level of anger (between  $2.84 \cdot 10^{-4}$  and  $3.84 \cdot 10^{-4}$ ) and the level of disgust (between  $1.04 \cdot 10^{-4}$  and  $2.16 \cdot 10^{-4}$ ) that are both needed for discriminating a problem of aesthetics for women younger than 27 years old.

```
1 //Emotion Treshold for women <= 27
2 //c1
3 //w1
4 //anger
5 var globalWc1w1Amin = 1.84e-4;
6 var globalWc1w1Amax = 3.84e-4;
7 //disgust
8 var globalWc1w1Dmin = 1.04e-4;
9 var globalWc1w1Dmax = 2.16e-4;
10
11 //w3
12 //fear
13 var globalWc1w3Fmin = 8.79e-4;
14 var globalWc1w3Fmax = 1.93e-3;
15 //disgust
16 var globalWc1w3Dmin = 4.11e-4;
17 var globalWc1w3Dmax = 5.42e-4;
18 //contempt
19 var globalWc1w3Cmin = 8.1e-4;
20 var globalWc1w3Cmax = 1.5e-3;
21 //w4
22 //disgust
23 var globalWc1w4Dmin = 2.5e-4;
24 var globalWc1w4Dmax = 3.28e-4;
```

*Figure 6-3: Emotion thresholds definitions in the Inferring Engine for women under or equal to 27 years old.*

The implementation of this case in the **Perso2U** prototype is realized in two steps. First, Figure 6-3 shows the thresholds definitions inside the inferring engine for women under or equal to 27 years (class1). This section serves to include all needed thresholds variables previously defined in Table 6-6 and Table 6-7 without making distinction between clusters.

Secondly, a new function *checkUIquality* was coded to identify UI quality problem from users' current detected emotions as illustrated in Figure 6-4. Here, the Inferring Engine reads the static (gender, age) and dynamic (emotions) variables to make a comparison between the predefined thresholds and the current emotions. The conditions follow the criteria defined in Table 6-6 for class 1.

```

1 function checkUIQuality() {
2   if (contextUse.user.gender == 'w') {
3     //////////////// W <= 27 ////////////////
4     if (contextUse.user.age <= 27) {
5       //////////////// c1 ////////////////
6       //c1w1
7       if ((globalAngerValue >= globalWc1w1Amin &&
8         globalAngerValue <= globalWc1w1Amax &&
9         globalDisgustValue >= globalWc1w1Dmin &&
10        globalDisgustValue <= globalWc1w1Dmax) && web == "w1") {
11        contextUse.user.emotion = '-'; //negative
12        globalUIproblem = 'A'; //aesthetics
13        globalUserTestClusterIdentified = "c1,w1";
14      } else {
15        //c1w3
16        if (((globalFearValue >= globalWc1w3Fmin &&
17          globalFearValue <= globalWc1w3Fmax) ||
18          (globalDisgustValue >= globalWc1w3Dmin &&
19          globalDisgustValue <= globalWc1w3Dmax) ||
20          (globalContemptValue >= globalWc1w3Cmin &&
21          globalContemptValue <= globalWc1w3Cmax)) && web == "w3") {
22          contextUse.user.emotion = '-'; //negative
23          globalUIproblem = 'AU'; //aesthetics & usability
24          globalUserTestClusterIdentified = "c1,w3";
25        } else {
26          //c1w4
27          if ((globalDisgustValue >= globalWc1w4Dmin &&
28            globalDisgustValue <= globalWc1w4Dmax) && web == "w4") {
29            contextUse.user.emotion = '-'; //negative
30            globalUIproblem = 'U'; //usability
31            globalUserTestClusterIdentified = "c1,w4";
32          }
33        }
34      }
35    }
36  }
37 }
38

```

Figure 6-4: Inferring Engine Rule to find a UI quality issue.

Of course, other conditions are required for the other behaviors of Table 6-6 and Table 6-7. Every condition results from the deduction of two variables: the user emotion with negative (“-”) or positive (“+”); and the UI quality problem with aesthetics (“A”), usability (“U”) or aesthetics & usability (“AU”). Following this learning (class1 for women under/equal to 27, Figure 6-3, Figure 6-4), all the thresholds defined in Table 6-6 and Table 6-7 and their associated inferring engine rules were implemented in the inferring engine :

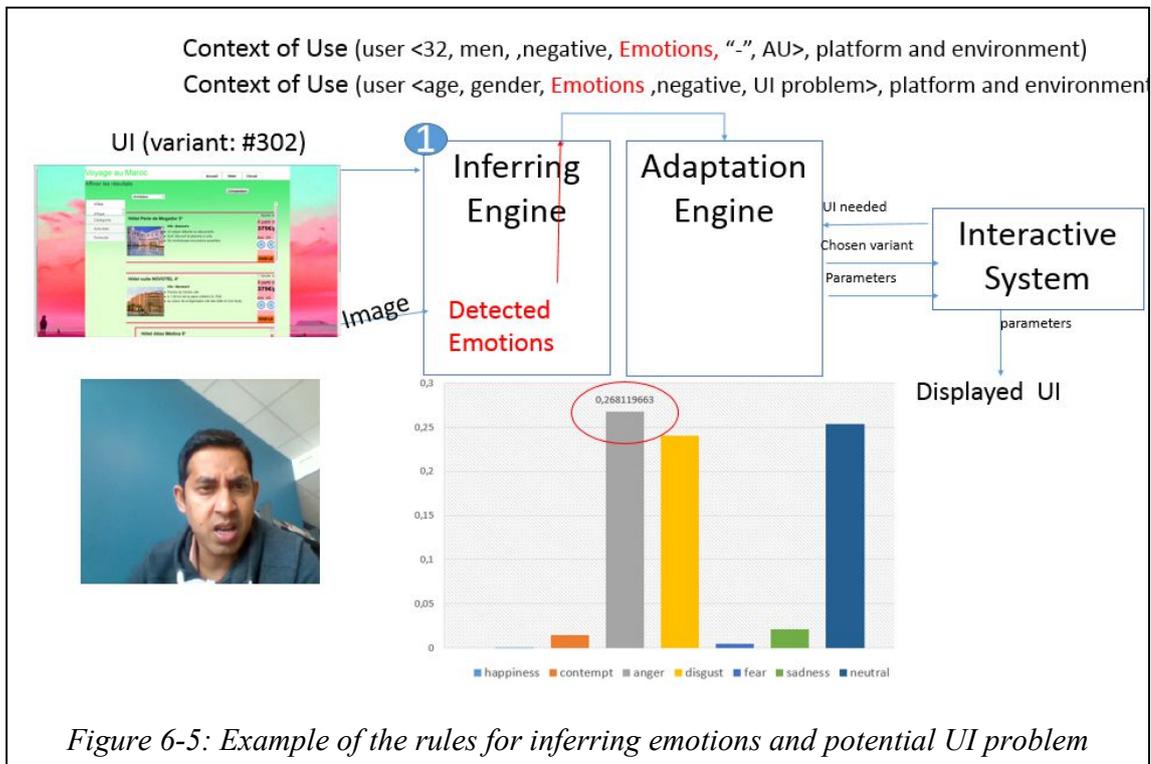
- emotion thresholds definitions in the Inferring Engine for women under/equal to and older than 27 (class1, class2, class3) shown in appendix A,
- emotion thresholds definitions in the Inferring Engine for men under/equal to and older than 27 (class1, class2, class3) shown in appendix B,
- Inferring Engine Rules to find a UI quality issue for women under/equal to and older than 27 (class1, class2, class3) shown in appendix C, and
- Inferring Engine Rules to find a UI quality issue for men under/equal to and older than 27 (class1, class2, class3) shown in appendix D.

- Finally, user emotion and UI-problem are stored in the context of use (user model). Thus, the context of use is formed in this manner: Context of use (user <age, gender, seven emotions, negative, UI problem>, platform, environment).

Currently, detected emotions behavior is used to identify some UI problems and for sending negative emotions to the Adaptation Engine. All emotions data that are not in the identified thresholds are considered as positive (“+”). A more precise algorithm could use the discriminant values for the website with high aesthetics and high usability to detect positive emotions and keep the neutral values for all data that do not permit discrimination. For instance, in Figure 6-2 (emotions levels per website), we have identified that the website with high aesthetics and high usability can be discriminated by a low level of anger (the lowest emotion level) for a class of women under 27 years of age. So, this lack of anger could be interpreted as positive. Currently positive emotions (e.g. happiness) are not used by the adaptation engine and no distinction is made between positive and neutral emotions.

To illustrate the execution of the proposed implementation into Perso2U architecture, we present its resulting process below.

Figure 6-5 shows a man participant (32 years old) interacting with website3 (low aesthetics, low usability) at the hotel web page (UI variant 302) . First, user’s gender (men) and age (32) are stored in the context of use in the user model. Then, while the user interacts with the UI (website3, low aesthetics, low usability), the emotion wrapper ❸ retrieves the detected emotions: happiness (0.004321849), contempt (0.01437737), sadness (0,0207980052), anger (0.268119663), disgust (0,2404475), fear (0,00432184944), neutral (0,254058033) from the emotion recognition tool (Microsoft Emotion API). From detected emotions, the Inferring Engine ❶ calls the function checkUIquality to look for predefined negative behaviors. This quality function validates if anger is between 0.185 and 0.355 (see appendix C from line 111 to 114). Since the detected anger validates this condition as true (0.268119663 is into [0.185,0.355]) then the quality function releases contextUse.user.emotion = '-' and globalUIproblem = 'AU' (aesthetics and usability). Thus, as a negative behavior is detected (i.e. emotions values followed the conditions exposed in Table 6-7), user emotions and UI-problem parameters are modified and sent with other contextual elements to the Adaptation Engine: context of use (user <32, men, seven emotions,-, AU>, platform, environment). The Adaptation Engine ❷ reads the upgraded Context of use (including the potential UI-problem) and can trigger an appropriate UI adaptation.



## 6.6 Testing of the new inference rules in Perso2u

The implementation of the rules for inferring emotions contains a lot of conditions which correspond to the verification of the thresholds defined by the statistical analysis. However, the implementation removes the classes of the analysis, as the Inferring Engine cannot know in advance which class a person belongs to. So, we need to test carefully if the results of the Inferring Engine are correct.

The test aims at verifying if a correct emotion and UI issue is provided to the Adaptation Engine by using the inference rules. We tested the inference rules for women less than or equal to 27 years (105 images) and then with the correction of errors, all the remaining age categories (women>27, men <=27, men >27) were implemented along with additional tests: 106 images for women >27 (class2), 48 images for men<=27 (class1, class2, class3) and 15 images for men >27 (class2).

First, the inference rule for women less than or equal to 27 years old was tested with 105 images of three users. The test was done by comparing the expected and observed values (inferred and sent to the Adaptation Engine). These values include the inferred emotion (negative, positive) and the UI issue: aesthetics (A), usability (U) or aesthetics & usability (AU) or not available (n.a.) when a negative emotion is not found. To illustrate the results of the test of the inferring rule algorithm, Table 6-8 shows ten results for one user. The “Test results” column shows if the

observed value matches the expected one (OK) or not (not OK). For instance, for image #1 in Table 6-8, has expected values {negative, A} (emotion is negative, there is an aesthetics problem), while its observed values are {negative, A}, that correspond exactly to the expectations.

User					UI	Detection time			Detected Emotions							Expected		Observed			
# Image	UserId	Age	Gender	image	Web	minute	second	neutral	fear	anger	sadness	disgust	contempt	happiness	Emotion	UI issue	Emotion	UI issue	cluster	Test results	
1	1	26	W	18/95/1.jpg	w1	45	13	0,612451136	0,004084732	0,0003121	0,3783435	0,0001941	0,0020064	0,0006083	negative	A	negative	A	c3	OK	
2	1	26	W	18/95/2.jpg	w1	45	22	0,7462314	0,000322715	0,0001651	0,0268834	0,0001811	0,1816033	0,0432199	positive	n.a.	positive	n.a.	n.a.	OK	
3	1	26	W	18/95/3.jpg	w1	45	32	0,7428729	0,000623453	0,0005082	0,0414263	0,0005109	0,1683542	0,0433454	negative	A	negative	A	c2	OK	
4	1	26	W	18/95/4.jpg	w1	45	42	0,721467733	0,000603723	0,0005851	0,0605682	0,0007054	0,192517	0,0218351	negative	A	negative	A	c2	OK	
5	1	26	W	18/95/5.jpg	w1	45	52	0,729369342	0,000708876	0,0007718	0,0372388	0,0008136	0,1889769	0,039334	negative	A	negative	A	c2	OK	
6	1	26	W	18/95/6.jpg	w1	46	2	0,8091888	0,001393284	0,0007798	0,0555846	0,0005829	0,110695	0,0194708	positive	n.a.	positive	n.a.	n.a.	OK	
7	1	26	W	18/95/7.jpg	w1	46	12	0,536161959	0,003813865	0,0013723	0,4536556	0,0005061	0,0026888	0,0002076	positive	n.a.	positive	n.a.	n.a.	OK	
8	1	26	W	18/95/8.jpg	w1	46	22	0,4728568	0,005632889	0,0010341	0,5144534	0,0005723	0,0039513	0,0003561	positive	n.a.	positive	n.a.	n.a.	OK	
9	1	26	W	18/95/9.jpg	w1	46	32	0,6986122	0,003568676	0,0014565	0,293213	0,0004421	0,00125	0,0003219	positive	n.a.	positive	n.a.	n.a.	OK	
10	1	26	W	8/95/10.jpg	w1	46	42	0,75827986	0,007298846	0,0006054	0,2297023	0,0002139	0,0019421	0,0003944	positive	n.a.	positive	n.a.	n.a.	OK	

Table 6-8: Ten first results of inferring rules tests for a woman under or equal to 27 years old.

The tests allowed us to identify 4 errors corresponding to thresholds badly reported in Table 6-6 and Table 6-7. The code of the inferring rules was corrected accordingly.

Since this learning, all three additional tests were performed to verify the expected values (emotion, UI issue):

- 106 images for women >27 (class2) shown in appendix F,
- 48 images for men ≤27 (class1, class2, class3) shown in appendix G and
- 15 images for men >27 (class2) shown in appendix H.

Overall, successful test results were reported (appendix E to H). Since the first test help us to correct some errors then this learning allowed us to implement the remaining inferring engine tests with assurances. No additional errors were reported in these tests. Now the code is robust and the Inferring Engine could deduce a UI problem according to Table 6-6 and Table 6-7.

## 6.7 Summary

Beyond the UI influence on emotions regarding age and gender (*chapter6*), this chapter use these emotions to detect usability or aesthetics problems at runtime to trigger UI adaptations. To achieve this, We completed our experimental analysis so that it shows 1) it can be possible to categorize emotions depending on users' age and gender and on UI aesthetics and usability levels and that 2) some emotions thresholds can be defined for detecting usability and aesthetics problems from users' age and gender. Consequently, these findings allowed the improvement of our *Perso2U* implementation. The inferring Engine is able to compute a negative emotion behavior thanks to inferring rules based on emotion thresholds. Then, this engine sends the context of use, including a UI problem (aesthetics and/or usability), to the adaptation engine for conducting an appropriate UI adaptation.

## CHAPTER 7 Conclusions and Perspectives

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#### 7.1 Summary of contributions

In order to answer the initial research question: “*How to drive UI adaptation with a model of the user based on emotions and user characteristics (age & gender) to check or improve UX if necessary?*”, we propose 4 main contributions.

Our *first contribution* is a global approach which proposes the adaptation of user interfaces at run-time thanks to user emotions and user characteristics such as age and gender (Galindo, Dupuy-Chessa, et al., 2017). In this approach, facial emotions are recognized and used as user responses to interaction. Then, this information is used as user feedback of the interaction aiming to detect UI problem and then to trigger UI adaptation. Our approach relies on an architecture called **Perso2U** which stands for “**Personalize to you**”. It was designed to model the user and adapt the UI regarding with detected emotions and user characteristics (age and gender).

Our *second contribution* is the exploration of the UI influence on emotions depending on age and gender by a second experimental analysis. It was achieved because User Experience relies on user interaction quality factors like aesthetics and usability, and on individual user characteristics such as age and gender (*section 3.3*). The results tend to show that: (1) UI quality factors (aesthetics and/or usability) influence user emotions differently based on age and gender, (2) the level (high and/or low) of UI quality factors seem to impact emotions differently based on age and gender. These key findings need to be strengthened for men for which one of the classes did not contain enough data.

Our *third contribution* is the use of detected emotions to in the Perso2U architecture. Based on the extension of the previous experimental analysis (3<sup>rd</sup> contribution), it consists of an inferring engine that deduces negative emotions and UI problems based on users’ emotions, age and gender.

In order to better understand the scope of our contributions, our approach is analyzed and compared to related work presented in chapter 3 (Table 1) using the analysis criteria presented in *section 3.2.1*: Emotion, Emotion measure, Emotion detection method, Adaptation technique, UI adaptation (content/aesthetics/usability), user characteristics (Gender, Age), Adaptation type (design/run-time) and UI type.

As we can notice in Table 1, our approach supports the emotion detection of Ekman emotions plus neutral by facial emotion recognition at run-time. The adaptation technique is mainly based on the inference of the contextual information of the user (age, gender, emotions, negative emotion, aesthetics/usability problem). The UI adaptation is conceived to support

usability/aesthetics changes in the UI by three components: Inferring Engine, Adaptation Engine and Interactive System. There is a clear use of the association between gender and age (women and men into [23,63] and [19,67] years respectively).

Furthermore, our work position in UI adaptation can be highlighted by the ISATINE framework (López-Jaquero, Vanderdonck, Montero, & González, 2007). This framework consists of a loop with seven stages for each adaptation cycle based on Norman's mental model. These stages are goals for adaptation, initiative, specification, application, transition, interpretation, and evaluation. A closer insight into each one revealed that the second state “initiative for adaptation” includes the detection of the adaptation need. This one can be associated with the identification of a problem sent by the inferring engine (context of use) to the adaptation engine. Since this, a UI adaptation may start when there exists a potential UI problem inferred by the inferring engine. Conversely, the remaining steps are not cover in our work. For instance, the specification (definition of changes) of the adaptation could be matter of the adaptation engine (define the best UI changes into UI parameters); while the application stage (execution of changes) could be aligned with the interactive system (executes the changes based on UI parameters).

In terms of adaptation questions (Knutov et al., 2009), our work contributes to these questions:

- “what can we adapt to?”: to the Context of use: user characteristics (emotions, age, gender) and
- “when can we apply adaptation?”: when a UI problem is detected with an unknown delay. We don't know exactly the delay to drive the UI adaptation.

## 7.2 Limitations

The current prototype implementation suffers from several limits. Even if we focus on the inferring engine, it could be improved. First other input data such as the use of Physiological signals could be used to strengthened the detection. Secondly, the inferring engine uses a simple technique based on if-then statemens without considering more sophisticated ones like machine learning (Vanderdonck, 2016). More than the inferring engine, the current prototype is limited in terms of adaptations. Thus, we do not provide a full solution in UI adaptation. Only simplistic rules are implemented and the two other elements of the context of use (platform, environment) are not studied in detail.

Considering the experimental part of our work, another data collection would be required to robust the sample size (*chapter 5*). It could be extended by including more users per class and balancing the sample size properly (same size for women and men participants). Although, it can imply a bias in the experiment, the data analysis is performed independently. The two independent datasets (women & men) were analysed and interpreted independently to decrease the unbalance sample impact. Moreover, we build our results on only one website, four predefined versions, with very simple usability or aesthetics elements. Other experiments are necessary to generalize the results.

Our analyses of emotions are based on means of emotions. But Our examination of the inference of emotions to trigger UI adaptation evoked a spotlight in Emotions. Although Ekman ones make sure that the majority of users evoke them culturally independent, a deeper analysis based on this basic set of emotions could release more relevant emotions in web interaction.



<i>Reference</i>	<i>Emotion</i>	<i>Emotion measure</i>	<i>Emotion detection Method</i>	<i>Adaptation Technique</i>	<i>Content</i>	<i>Aesthetics</i>	<i>Usability</i>	<i>Gender</i>	<i>Age</i>	<i>Adaptation type</i>	<i>UI Type</i>
(Hudlicka & Mcneese, 2002)	Affective state	Physiological signals	Objective (sensors) & Subjective (diagnostic tasks)	Compensatory strategy	+	+				Runtime	GUI
<b>Prototype implementation</b>	Anxiety	Heart rate	Heart rate sensor & anxiety self-reports	What-if rules	UI messages	Format-based				Runtime	Pilot driving system
(Nasoz, 2004)	Experimented emotions	-Physiological signals - Facial expressions -Motor movements	Objective (sensors) & Subjective (linguistic terms)	Machine learning	+			-	-	Runtime	GUI
<b>Prototype implementation</b>	Anger, panic, sleepiness, frustration	Physiological signals	Armband sensor & polar chest strap	Bayesian belief Network	UI messages			No specific associations between them		Runtime	Car driving system
(Meudt et al., 2016) Potential implementations section 4	Experimented emotion	-Speech - Facial expressions -Gestures	Objective (sensors) & Subjective (dialogs with the user)	Adaptation rating strategy	+	-				Runtime	GUI
<b>Prototype implementation</b>	Dislike	Facial expressions	Camera		Volume control and UI messages					Runtime	Car driving system
(Märtn et al., 2017)	Experimented emotion	-Eye movements -Facial expressions -body temperature	Objective (sensors)	HCI patterns & designer analysis	+	+	+		-	Runtime	Website
<b>Prototype implementation</b>	Anger	-Eye movements -Facial expressions	Camera and Eye tracking sensor	Panel pattern & designer analysis		Panel colors			No details	Runtime	Booking system
(Galindo, Dupuy-Chessa, et al., 2017)	Experimented emotion	-Facial expressions	Objective (sensors)	UI variant selection and computation of UI parameters based on emotion thresholds and inferring engine rules.	-	+	+	+	+	Runtime	Website
<b>Prototype implementation</b>	happiness, anger, disgust, sadness, surprise, fear, contempt, neutral	-Facial expressions	Camera	What-if rules		Image and text size, and background colors			Women [23,63] and Men [19,67] years	Runtime	Hotel system

*Table 7-1: Comparison with the state of the art*

### 7.3 Perspectives

#### *Strengthening the current results*

We could extend the validation of emotional behavior through more data collection. The examination of UI influence on emotions (*chapter 6*) does not lead us to cluster emotional behavior completely. In fact, some classes were not relevant and others do not discriminate enough emotions. Consequently, it implies that more data would be necessary to a full validation. Despite this, results were worthy to study how to use such influence on emotions to trigger the UI adaptation.

It would also be interesting to strengthen the statistical analysis to obtain a statistical model, which would allow us to obtain a more precise determination of UI problems. Indeed, a logistic regression can estimate the probability being in front of a type of website (e.g. low usability or low aesthetics) depending on the gender, the age and the detected emotions. This model is interesting because it makes it possible to obtain the level of confidence of the prediction, while in our rules the thresholds are at 5% level. The statistical model is more precise than the rules model.

A correlation of implicit and explicit feedback could strengthen the emotion results. Regarding emotion intensity in UX, we question if emotions are strong enough to provide relevant feedback (*chapter 5*). Mainly, individuals can be inconsistent in their rational and emotional thinking (*chapter 1*). We noticed that there is an emotion variation (women & men) through UI interaction not only in neutral but also in other emotions such as fear, contempt, anger and disgust. Hence, it should be interesting to correlate this implicit feedback with an explicit manner to detect emotion intensity as the Self-Assessment Manikin (*section 2.1.2*). With this, we could strengthen the current emotion results through another experiment to collect implicit and explicit data to find their correlation.

#### *Improvement of the inferring engine*

The two other elements of the context of use (platform, *environment*) needs to be examined which should be inferred, analyzed and sent to the Adaptation Engine. For instance, environment changes such as noisy and light variations. Particularly, emotions are “**reactions** to situational events in an individual’s *environment* that are appraised to be relevant to his/her needs, goals, or concerns” (Zhang, 2013, p. 11) (*chapter 2*). Thus, we could reuse the existing work with platform and environment to combine/correlate them with emotions so that we could have a more integrated contextual information.

It would also be interesting to reinforce the current prototype by introducing relevant work in psychology related to user emotions and their variables affecting intensity. In fact, the logic structure of emotions explains that each emotion is associated with intensity variables (Steunebrink, 2010). For instance, liking intensity of an appealing object is intensified by two

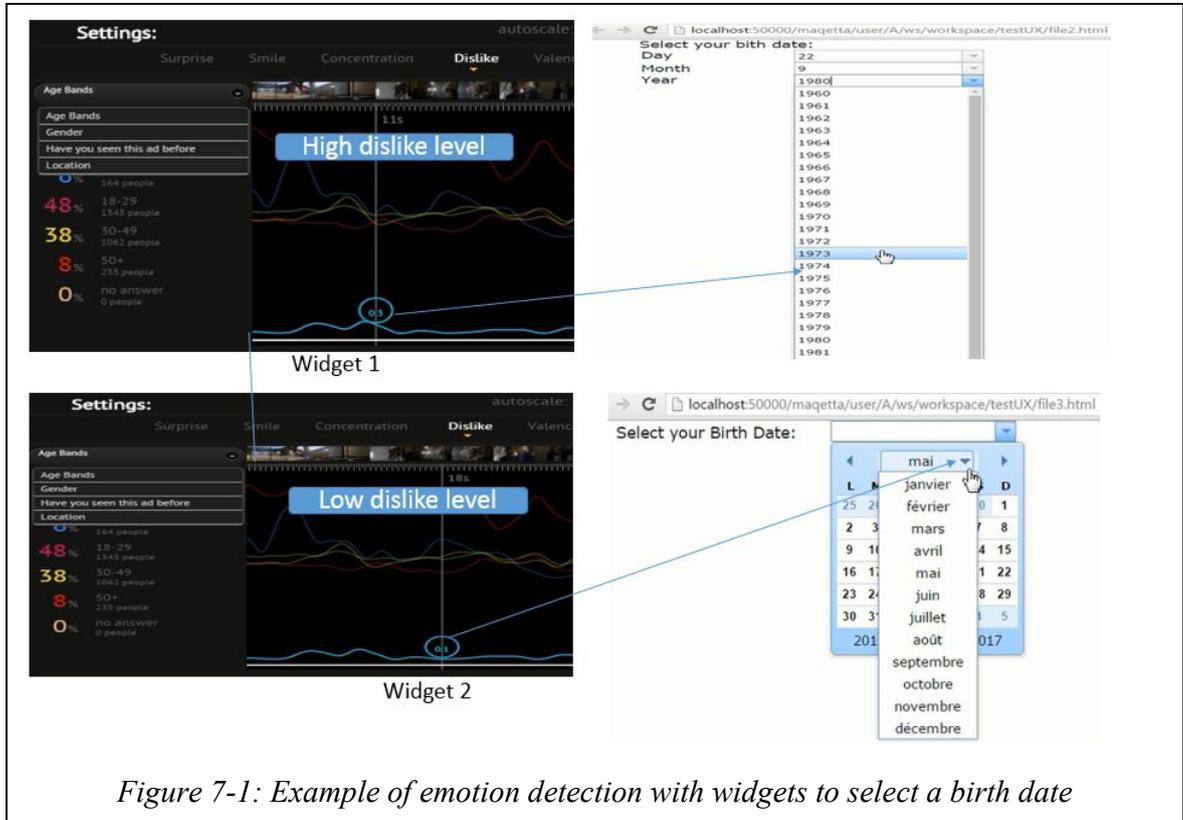
variables: (1) appealingness, the degree to which the object is appealing, and (2) familiarity, the degree of the user familiarity with the object. Thus, these variables could be attached to the detected emotions to find a potential correlation which can explain why a user prefer some UI element than other.

Moreover, our experimental results can be overlapped with other existing technologies to uncover emotions during interaction such as galvanic skin response, heart rate, voice and eye recognition. Coupling this biometric knowledge into the adaptation engine would expand the interpretation of emotional states in real-time. With this, we could have a higher precision in emotion detection to provide a more relevant inferring engine.

### *Personalization based on emotions*

We could propose a personalization system based on emotions with adaptation rules specific to each user. Emotions thresholds may reveal that there are specific emotions behavior pertain to each combination of UI quality factors per website versions. The design pattern approach aims to solve recurring problems in design (Eelke, 2015). Similarly, we could try to find ***design-emotion patterns*** to solve recurring problems in UI adaptation per user. If we know that one user is having a recurrent negative emotion at using some UI element (e.g. widget) with task1, then we can find into the widget-like pattern which widget the user prefers at doing task1 so that the system can propose this new widget to the user. Then while user is interacting, the system will confirm which elements needs to be modified or changed at releasing new emotions related with each UI element. This vision can be characterized by the acronym: “**WYLIWYG**” standing for “What you love is what you get”. With this, the adaptation may propose UI elements based on known solutions to regular problems. For instance, button-like, menu-like or search-like pattern which explains which kind of button/menu/search the user prefers. The user may have a sense of uniformity while he is interacting with websites. If the user likes the search button on the top-right of the interface so that the system can propose this pattern for each website.

Currently, our prototype proposes simple adaptations (image and text size, and background colors) to emotions. Thus, the implementation of other adaptations could extend the adaptation engine with some personalized rules. In fact, the inferring engine could detect in a more precise manner which widget evokes the highest negative emotions per user in a time period so that the UI can propose new widgets to the user based on new inference rules. For instance, Figure 7-1 shows a user test to detect dislike while the user was interacting with two widgets (select list vs. pick calendar date) during 32 seconds to perform the same task: the selection of his birth date. We can see for this simple test that there is a lowest dislike level with a pick calendar rather than a select list. It could thus create an adaptation rule to change widget1 for widget2. A regular monitoring of the user feedback of this new change would be needed to define the threshold and ensure that the user is conformable with the adaptation.



### Usability evaluation

Our experimental results can also be used in UI evaluation as they allow a system to detect some usability or aesthetics problems. It would be possible as the thresholds section underlines how UI quality levels implies a positive or negative user response. It means that when the user has a negative response (e.g. high level of anger) at using some UI then there is a potential issue in aesthetics or usability. This opens a large spectrum of possibilities for UI evaluation based on emotions. For instance, designers can evaluate usability issues before launching the product to the market. In this manner, the evaluation results (negative emotions and usability issues) detected in an implicit manner could be used to improve the product cyclically reducing user interruptions.

Even if lots of questions remain opened, this work is a first step toward providing better UX thanks to emotions so that we can “*build products that bring joy and excitement, pleasure and fun, and, yes, beauty to people’s lives.*” – Don Norman (Norman, 2004a)”.



## Appendices

## Appendix A

This appendix shows the emotion thresholds implementation for women.

1	//Emotion Treshold for women <= 27	45	//happiness
2	//c1	46	var globalWc2w4Hmin = 5.12e-2;
3	//w1	47	var globalWc2w4Hmax = 8.22e-2;
4	//anger	48	//c2
5	var globalWc1w1Amin = 1.84e-4;	49	//c3
6	var globalWc1w1Amax = 3.84e-4;	50	//w1
7	//disgust	51	//sadness
8	var globalWc1w1Dmin = 1.04e-4;	52	var globalWc3w1Smin = 3.05e-1;
9	var globalWc1w1Dmax = 2.16e-4;	53	var globalWc3w1Smax = 3.61e-1;
10		54	
11	//w3	55	//neutral
12	//fear	56	var globalWc3w1Nmin = 6.02e-1;
13	var globalWc1w3Fmin = 8.79e-4;	57	var globalWc3w1Nmax = 6.64e-1;
14	var globalWc1w3Fmax = 1.93e-3;	58	//w3
15	//disgust	59	//disgust
16	var globalWc1w3Dmin = 4.11e-4;	60	var globalWc3w3Dmin = 1.72e-3;
17	var globalWc1w3Dmax = 5.42e-4;	61	var globalWc3w3Dmax = 2.22e-3;
18	//contempt	62	//sadness
19	var globalWc1w3Cmin = 8.1e-4;	63	var globalWc3w3Smin = 8.89e-2;
20	var globalWc1w3Cmax = 1.5e-3;	64	var globalWc3w3Smax = 1.09e-1;
21	//w4	65	//contempt
22	//disgust	66	var globalWc3w3Cmin = 1.63e-3;
23	var globalWc1w4Dmin = 2.5e-4;	67	var globalWc3w3Cmax = 1.99e-3;
24	var globalWc1w4Dmax = 3.28e-4;	68	//neutral
25	//c1	69	
26	//c2	70	var globalWc3w3Nmin = 8.26e-1;
27	//w1	71	var globalWc3w3Nmax = 8.67e-1;
28	//anger	72	//w3
29	var globalWc2w1Amin = 4.08e-4;	73	//w4
30	var globalWc2w1Amax = 1.02e-3;	74	//fear
31	//fear	75	var globalWc3w4Fmin = 4.07e-2;
32	var globalWc2w1Fmin = 4.78e-4;	76	var globalWc3w4Fmax = 5.20e-2;
33	var globalWc2w1Fmax = 1.11e-3;	77	//anger
34	//w3	78	var globalWc3w4Amin = 2.96e-4;
35	//neutral	79	var globalWc3w4Amax = 3.76e-4;
36	var globalWc2w3Nmin = 9.11e-1;	80	//sadness
37	var globalWc2w3Nmax = 9.26e-1;	81	var globalWc3w4Smin = 1.14e-1;
38	//contempt	82	var globalWc3w4Smax = 1.5e-1;
39	var globalWc2w3Cmin = 2.33e-3;	83	//contempt
40	var globalWc2w3Cmax = 2.4e-3;	84	var globalWc3w4Cmin = 5.09e-3;
41	//w4	85	var globalWc3w4Cmax = 8.6e-3;
42	//anger	86	//w4
43	var globalWc2w4Amin = 2.49e-3;	87	//c3
44	var globalWc2w4Amax = 4.47e-3;	88	//Emotion Treshold for women <= 27

```
89 //Emotion Treshold for women > 27 (W2)
90 //c2
91 //w1
92 //happiness
93 //contempt
94 var globalW2c2w1Hmin = 1.82e-2;
95 var globalW2c2w1Hmax = 5.12e-2;
96 //w1
97 var globalW2c2w1Cmin = 8.14e-3;
98 var globalW2c2w1Cmax = 1.42e-2;
99 //w3
100 //w3
101 //anger
102 var globalW2c2w3Amin = 3.25e-3;
103 var globalW2c2w3Amax = 4.82e-3;
104 //w3
105 //w4
106 //fear
107 var globalW2c2w4Fmin = 2.46e-4;
108 var globalW2c2w4Fmax = 5.78e-4;
109 //happiness
110 var globalW2c2w4Hmin = 1.70e-4;
111 var globalW2c2w4Hmax = 7.04e-4;
112 //w4
113 //Emotion Treshold for women > 27
```

## Appendix B

This appendix shows the emotion thresholds implementation for men.

<pre>1 //Men &lt;= 27 2 //c1 3 //website1 4 //anger 5 //3.97e-2 and 6.46e-2 6 var globalMc1w1Amin = 3.97e-2; 7 var globalMc1w1Amax = 6.46e-2; 8 9 //aesthetics 10 //disgust 11 //1.46e-3 and 2.03e-3 12 var globalMc1w1Dmin = 1.46e-3; 13 var globalMc1w1Dmax = 2.03e-3; 14 //happiness 15 //6.32e-4 and 2.41e-3 16 var globalMc1w1Hmin = 6.32e-4; 17 var globalMc1w1Hmax = 2.41e-3; 18 //website3 19 //happiness 20 //2.68e-4 and 4.97e-3 21 var globalMc1w3Hmin = 2.68e-4; 22 var globalMc1w3Hmax = 4.97e-3; 23 //aesthetics and usability 24 //&amp; neutral 25 //9.05e-1 and 9.24e-1 26 var globalMc1w3Nmin = 9.05e-1; 27 var globalMc1w3Nmax = 9.24e-1; 28 //website4 29 //anger 30 //4.45e-4 and 6.17e-3 31 var globalMc1w4Amin = 4.45e-4; 32 var globalMc1w4Amax = 6.17e-3; 33 //usability 34 //sadness 35 //1.20e-1 and 1.55e-1 36 var globalMc1w4Smin = 1.20e-1; 37 var globalMc1w4Smax = 1.55e-1; 38 //c2 39 //website1 40 //anger 41 //1.01e-3 and 3.57e-3 42 var globalMc2w1Amin = 1.01e-3; 43 var globalMc2w1Amax = 3.57e-3; 44 //aesthetics</pre>	<pre>45 //website3 46 //no discriminant values 47 //website4 48 //contempt 49 //1.31e-4 and 4.18e-3 50 var globalMc2w4Cmin = 1.31e-4; 51 var globalMc2w4Cmax = 4.18e-3; 52 //usability 53 //c3 54 //website1 55 //fear 56 //1.46e-1 and 2.66e-1 57 var globalMc3w1Fmin = 1.46e-1; 58 var globalMc3w1Fmax = 2.66e-1; 59 //aesthetics 60 //anger 61 //1.83e-2 and 3.27e-2 62 var globalMc3w1Amin = 1.83e-2; 63 var globalMc3w1Amax = 3.27e-2; 64 //disgust 65 //6.45e-3 and 1.09e-2 66 var globalMc3w1Dmin = 6.45e-3; 67 var globalMc3w1Dmax = 1.09e-2; 68 //neutral 69 //5.82e-1 and 6.38e-1 70 var globalMc3w1Nmin = 5.82e-1; 71 var globalMc3w1Nmax = 6.38e-1; 72 //contempt 73 //3.30e-3 and 6.54e-3 74 var globalMc3w1Cmin = 3.30e-3; 75 var globalMc3w1Cmax = 6.54e-3; 76 //website3 77 //fear 78 //1.7e-2 and 3.09e-2 79 var globalMc3w3Fmin = 1.7e-2; 80 var globalMc3w3Fmax = 3.09e-2; 81 //aesthetics and usability 82 //happiness 83 //1.01e-2 and 4.07e-2 84 var globalMc3w3Hmin = 1.01e-2; 85 var globalMc3w3Hmax = 4.07e-2; 86 //neutral 87 //6.98e-1 and 7.48e-1 88 var globalMc3w3Nmin = 6.98e-1;</pre>
---	---

```
89  var globalMc3w3Nmax = 7.48e-1;
90  //website4
91  //sadness
92  //4.06e-1 and 4.06e-1
93  var globalMc3w4Smin = 4.06e-1;
94  var globalMc3w4Smax = 4.06e-1;
95  //usability
96  //men <=27 //////////////////////////////////////
```

## Appendix C

This appendix shows the implementation for the inferring engine rules for women under/equal to and over 27.

```
1 if (contextUse.user.gender == 'w') {
2     /////////////// W <= 27 ///////////////
3     if (contextUse.user.age <= 27) {
4         /////////////// c1 ///////////////
5         //c1w1
6
7         if ((globalAngerValue >= globalWc1w1Amin &&
8             globalAngerValue <= globalWc1w1Amax &&
9             globalDisgustValue >= globalWc1w1Dmin &&
10            globalDisgustValue <= globalWc1w1Dmax) && web == "w1") {
11            contextUse.user.emotion = '-'; //negative
12            globalUIproblem = 'A'; //aesthetics
13            globalUserTestClusterIdentified = "c1,w1";
14
15        } else {
16
17            //c1w3
18            if (((globalFearValue >= globalWc1w3Fmin &&
19                globalFearValue <= globalWc1w3Fmax) ||
20                (globalDisgustValue >= globalWc1w3Dmin &&
21                globalDisgustValue <= globalWc1w3Dmax) ||
22                (globalContemptValue >= globalWc1w3Cmin &&
23                globalContemptValue <= globalWc1w3Cmax)) && web == "w3") {
24                contextUse.user.emotion = '-'; //negative
25                globalUIproblem = 'AU'; //aesthetics & usability
26                globalUserTestClusterIdentified = "c1,w3";
27            } else {
28
29                //c1w4
30                if ((globalDisgustValue >= globalWc1w4Dmin &&
31                    globalDisgustValue <= globalWc1w4Dmax) && web == "w4") {
32                    contextUse.user.emotion = '-'; //negative
33                    globalUIproblem = 'U'; //usability
34                    globalUserTestClusterIdentified = "c1,w4";
35                }
36
37            }
38        }
39        /////////////// c1 ///////////////
40        /////////////// c2 ///////////////
41        //c2
42        //c2w1
43        if (((globalAngerValue >= globalWc2w1Amin && globalAngerValue <= globalWc2w1Amax) &&
44            (globalFearValue >= globalWc2w1Fmin && globalFearValue <= globalWc2w1Fmax))
45            && web == "w1") {
46            contextUse.user.emotion = '-'; //negative
47            globalUIproblem = 'A'; //aesthetics
48            globalUserTestClusterIdentified = "c2,w1";
49        } else {
50            //c2w3
51            if (((globalNeutralValue >= globalWc2w3Nmin && globalNeutralValue <= globalWc2w3Nmax) ||
52                (globalContemptValue >= globalWc2w3Cmin && globalContemptValue <= globalWc2w3Cmax))
53                && web == "w3") {
54                contextUse.user.emotion = '-'; //negative
55                globalUIproblem = 'AU'; //aesthetics & usability
56                globalUserTestClusterIdentified = "c2,w3";
57            } else {
58                //c2w4
59                if (((globalAngerValue >= globalWc2w4Amin && globalAngerValue <= globalWc2w4Amax) ||
60                    (globalHappinessValue >= globalWc2w4Hmin && globalHappinessValue <= globalWc2w4Hmax))
61                    && web == "w4") {
62                    contextUse.user.emotion = '-'; //negative
63                    globalUIproblem = 'U'; //usability
64                    globalUserTestClusterIdentified = "c2,w4";
65                }
66            }
67        }
68        /////////////// c2 ///////////////
69        /////////////// c3 ///////////////
70        //c3w1
71        if (((globalSadnessValue >= globalWc3w1Smin && globalSadnessValue <= globalWc3w1Smax) ||
72            (globalNeutralValue >= globalWc3w1Nmin && globalNeutralValue <= globalWc3w1Nmax))
73            && web == "w1") {
74            contextUse.user.emotion = '-'; //negative
75            globalUIproblem = 'A'; //aesthetics
76            globalUserTestClusterIdentified = "c3,w1";
77        } else {
78
79            //c3w3
80            if (((globalDisgustValue >= globalWc3w3Dmin && globalDisgustValue <= globalWc3w3Dmax) ||
81                (globalSadnessValue >= globalWc3w3Smin && globalSadnessValue <= globalWc3w3Smax) ||
82                (globalContemptValue >= globalWc3w3Cmin && globalContemptValue <= globalWc3w3Cmax))
83                && web == "w3") {
84                contextUse.user.emotion = '-'; //negative
85                globalUIproblem = 'AU'; //aesthetics & usability
86            }
87        }
88    }
89}
```

```

87     globalUserTestClusterIdentified = "c3,w3";
88 } else {
89     //c3w4
90     if (((globalFearValue >= globalWc3w4Fmin && globalFearValue <= globalWc3w4Fmax) ||
91         (globalAngerValue >= globalWc3w4Amin && globalAngerValue <= globalWc3w4Amax) ||
92         (globalSadnessValue >= globalWc3w4Smin && globalSadnessValue <= globalWc3w4Smax) ||
93         (globalContemptValue >= globalWc3w4Cmin && globalContemptValue <= globalWc3w4Cmax))
94         && web == 'w4') {
95         contextUse.user.emotion = '-'; //negative
96         globalUiproblem = 'U'; //usability
97         globalUserTestClusterIdentified = "c3,w4";
98     }
99 } //////////////// c3 ////////////////
100 } //////////////// w <= 27 ////////////////
101 } else {
102     //////////////// w > 27 //////////////// //Emotion Threshold for women > 27
103     //c2w1
104     if (((globalHappinessValue >= globalW2c2w1Hmin && globalHappinessValue <= globalW2c2w1Hmax) ||
105         (globalContemptValue >= globalW2c2w1Cmin && globalContemptValue <= globalW2c2w1Cmax))
106         && contextUse.user.web_preference == 'w1') {
107         contextUse.user.emotion = '-'; //negative
108         globalUiproblem = 'A'; //aesthetics
109         globalUserTestClusterIdentified = "c2,w1 women>=27";
110     } else {
111         //c2w3
112         if ((globalAngerValue >= globalW2c2w3Amin && globalAngerValue <= globalW2c2w3Amax) &&
113             contextUse.user.web_preference == 'w3') { //globalWc1w1Wmax
114             contextUse.user.emotion = '-'; //negative
115             globalUiproblem = 'AU'; //aesthetics & usability
116             globalUserTestClusterIdentified = "c2,w3 women>=27";
117         } else {
118             //c2w4
119             if (((globalFearValue >= globalW2c2w4Fmin && globalFearValue <= globalW2c2w4Fmax) &&
120                 (globalHappinessValue >= globalW2c2w4Hmin && globalHappinessValue <= globalW2c2w4Hmax)) &&
121                 contextUse.user.web_preference == 'w4') {
122                 contextUse.user.emotion = '-'; //negative
123                 globalUiproblem = 'U'; //usability
124                 globalUserTestClusterIdentified = "c2,w4 women>=27";
125             }
126         }
127     }
128     //////////////// w >= 27 ////////////////
129 }

```

## Appendix D

This appendix shows the implementation for the inferring engine rules for men under/equal to and over 27.

```

1  /////////////////////////////////// men ///////////////////////////////////
2  if (contextUse.user.gender == 'm') {
3  /////////////////////////////////// M <= 27 ///////////////////////////////////
4  if (contextUse.user.age <= 27) {
5
6      //c1
7      //w1
8      //var globalMc1w1Hmin=6.32e-4;
9      //var globalMc1w1Hmax= 2.41e-3;
10
11      if ((globalAngerValue >= globalMc1w1Amin && globalAngerValue <= globalMc1w1Amax) ||
12          (globalDisgustValue >= globalMc1w1Dmin && globalDisgustValue <= globalMc1w1Dmax) &&
13          web == "w1") {
14          contextUse.user.emotion = '-'; //negative
15          globalUIproblem = 'A'; //aesthetics
16          globalUserTestClusterIdentified = "c1,w1";
17      } else {
18
19          if ((globalHappinessValue >= globalMc1w1Hmin && globalHappinessValue <= globalMc1w1Hmin) &&
20              web == "w1") {
21              contextUse.user.emotion = '+'; //positive
22              globalUIproblem = 'A'; //aesthetics
23              globalUserTestClusterIdentified = "c1,w1";
24          } else {
25              //w3
26
27              if ((globalHappinessValue >= globalMc1w3Hmin && globalHappinessValue <= globalMc1w3Hmax) &&
28                  (globalNeutralValue >= globalMc1w3Nmin && globalNeutralValue <= globalMc1w3Nmax) &&
29                  web == "w3") {
30                  contextUse.user.emotion = '-'; //negative
31                  globalUIproblem = 'AU'; //aesthetics & usability
32                  globalUserTestClusterIdentified = "c1,w1";
33              } else {
34                  //w4
35
36                  if ((globalAngerValue >= globalMc1w4Amin && globalAngerValue <= globalMc1w4Amax) ||
37                      (globalSadnessValue >= globalMc1w4Smin && globalSadnessValue <= globalMc1w4Smax) &&
38                      web == "w4") {
39                      contextUse.user.emotion = '-'; //negative
40                      globalUIproblem = 'U'; //usability
41                      globalUserTestClusterIdentified = "c1,w4";
42                  } else {
43                      //c1
44
45
46          //w1
47          if ((globalAngerValue >= globalMc2w1Amin && globalAngerValue <= globalMc2w1Amax) &&
48              web == "w1") {
49              contextUse.user.emotion = '-'; //negative
50              globalUIproblem = 'A'; //aesthetics
51              globalUserTestClusterIdentified = "c2,w1";
52          } else {
53              //w4
54
55              if ((globalContemptValue >= globalMc2w4Cmin && globalContemptValue <= globalMc2w4Cmax) &&
56                  web == "w4") {
57                  contextUse.user.emotion = '-'; //negative
58                  globalUIproblem = 'U'; //usability
59                  globalUserTestClusterIdentified = "c2,w4";
60              } else {
61                  //c3
62                  //w1
63
64                  if ((globalFearValue >= globalMc3w1Fmin && globalFearValue <= globalMc3w1Fmax) ||
65                      (globalAngerValue >= globalMc3w1Amin && globalAngerValue <= globalMc3w1Amax) ||
66                      (globalDisgustValue >= globalMc3w1Dmin && globalDisgustValue <= globalMc3w1Dmax) ||
67                      (globalNeutralValue >= globalMc3w1Nmin && globalNeutralValue <= globalMc3w1Nmax) ||
68                      (globalContemptValue >= globalMc3w1Cmin && globalContemptValue <= globalMc3w1Cmax) &&
69                      web == "w1") {
70                      contextUse.user.emotion = '-'; //negative
71                      globalUIproblem = 'A'; //aesthetics
72                      globalUserTestClusterIdentified = "c3,w1";
73                  } else {
74
75                      //w3
76                      if ((globalFearValue >= globalMc3w3Fmin && globalFearValue <= globalMc3w3Fmax) ||
77                          (globalHappinessValue >= globalMc3w3Hmin && globalHappinessValue <= globalMc3w3Hmax) ||
78                          (globalNeutralValue >= globalMc3w3Nmin && globalNeutralValue <= globalMc3w3Nmax) &&
79                          web == "w3") {
80                          contextUse.user.emotion = '-'; //negative
81                          globalUIproblem = 'AU'; //aesthetics & usability
82                          globalUserTestClusterIdentified = "c3,w3";
83                      } else {
84
85                          //w4

```

```
86         if ((globalSadnessValue >= globalMc3w4Smin && globalSadnessValue <= globalMc3w4Smax) &&
87             web == "w4") {
88             contextUse.user.emotion = '-'; //negative
89             globalUproblem = 'U'; //usability
90             globalUserTestClusterIdentified = "c3,w4";
91             //c3
92         }
93     }
94 }
95 }
96 }
97 }
98 }
99 }
100 }
101 }
102 }
103 }
104 }
105 }
106 } else {
107     ///men >27 //////////
108     if (contextUse.user.age > 27) {
109         //c2
110         //w3
111         if ((globalAngerValue >= globalMic2w3Amin && globalAngerValue <= globalMic2w3Amax) &&
112             web == "w3") {
113             contextUse.user.emotion = '-'; //negative
114             globalUproblem = 'AU'; //aesthetics & usability
115             globalUserTestClusterIdentified = "c2,w3";
116         }
117     }
118     ///men >27 //////////
119 }
120 }
121 }
```

## Appendix E

This appendix shows the test results of the inferring engine rules for women under/equal to 27.

User					UI	Detection time	Detected Emotions							Expected		Observed			test results
# image	userid	age	gender	image			web	time	neutral	fear	anger	sadness	disgust	contempt	happiness	emotion	UI issue	emotion	
1	1	26	W	1/1.jpg	w1	09:49:25	0,612451136	0,004084732	0,000312111	0,3783435	0,0001941	0,0020064	0,0006083	negative	A	negative	A	class3	OK
2	1	26	W	1/2.jpg	w1	09:49:35	0,7462314	0,000322715	0,000165114	0,0268834	0,0001811	0,1816033	0,0432199	positive	n.a.	positive	n.a.	n.a.	OK
3	1	26	W	1/3.jpg	w1	09:49:45	0,7428729	0,000623453	0,000508233	0,0414263	0,0005109	0,1683542	0,0433454	negative	A	negative	A	class2	OK
4	1	26	W	1/4.jpg	w1	09:49:55	0,721467733	0,000603723	0,000585128	0,0605682	0,0007054	0,192517	0,0218351	negative	A	negative	A	class2	OK
5	1	26	W	1/5.jpg	w1	09:50:05	0,729369342	0,000708876	0,00077182	0,0372388	0,0008136	0,1889769	0,039334	negative	A	negative	A	class2	OK
6	1	26	W	1/6.jpg	w1	09:50:15	0,8091888	0,001393284	0,000779822	0,0555846	0,0005829	0,110695	0,0194708	positive	n.a.	positive	n.a.	n.a.	OK
7	1	26	W	1/7.jpg	w1	09:50:25	0,536161959	0,003813865	0,001372326	0,4536556	0,0005061	0,0026888	0,0002076	positive	n.a.	positive	n.a.	n.a.	OK
8	1	26	W	1/8.jpg	w1	09:50:35	0,4728568	0,005632889	0,001034101	0,5144534	0,0005723	0,0039513	0,0003561	positive	n.a.	positive	n.a.	n.a.	OK
9	1	26	W	1/9.jpg	w1	09:50:45	0,6986122	0,003568676	0,001456532	0,293213	0,0004421	0,00125	0,0003219	positive	n.a.	positive	n.a.	n.a.	OK
10	1	26	W	1/10.jpg	w1	09:50:55	0,75827986	0,007298846	0,000605367	0,2297023	0,0002139	0,0019421	0,0003944	positive	n.a.	positive	n.a.	n.a.	OK
11	1	26	W	1/11.jpg	w1	09:51:05	0,665655255	0,01102632	0,000626389	0,3160751	0,0002609	0,0025942	0,0006944	negative	A	negative	A	class3	OK
12	1	26	W	1/12.jpg	w1	09:51:15	0,7144275	0,005173102	0,000284071	0,2777571	7,338E-05	0,0012274	0,0001763	positive	n.a.	positive	n.a.	n.a.	OK
13	1	26	W	1/13.jpg	w1	09:51:25	0,747321963	0,00798626	0,000521092	0,2413884	0,0001143	0,0008807	0,0004344	positive	n.a.	positive	n.a.	n.a.	OK
14	1	26	W	1/14.jpg	w1	09:51:35	0,355733365	0,00717769	0,000401901	0,6256195	0,0008358	0,0071612	0,0003644	positive	n.a.	positive	n.a.	n.a.	OK
15	1	26	W	1/15.jpg	w1	09:51:45	0,9450457	3,63865E-05	0,000222841	0,0526318	8,056E-05	0,0014701	0,0003126	positive	n.a.	positive	n.a.	n.a.	OK
16	1	26	W	1/16.jpg	w1	09:51:55	0,96255964	0,00012359	0,001125659	0,0265999	0,0005464	0,0045637	0,0010346	positive	n.a.	positive	n.a.	n.a.	OK
17	1	26	W	1/17.jpg	w1	09:52:05	0,984053433	3,16519E-05	0,00063849	0,0101117	8,284E-05	0,0041892	0,0001272	positive	n.a.	positive	n.a.	n.a.	OK
18	1	26	W	1/18.jpg	w1	09:52:15	0,9364171	0,000248778	0,000585821	0,0585779	0,0002494	0,0016573	0,000296	positive	n.a.	positive	n.a.	n.a.	OK
19	1	26	W	1/19.jpg	w1	09:52:25	0,966565251	9,0911E-05	0,000689731	0,0276302	0,0001801	0,0025022	0,0001994	positive	n.a.	positive	n.a.	n.a.	OK
20	1	26	W	1/20.jpg	w1	09:52:35	0,6422167	0,032961156	0,0002941	0,3112991	0,0001655	0,000956	0,0032309	negative	A	negative	A	class3	OK
21	1	26	W	1/21.jpg	w1	09:52:45	0,6745917	0,006586865	0,000381579	0,3149773	6,674E-05	0,0003937	0,0003014	negative	A	negative	A	class3	OK
22	1	26	W	1/22.jpg	w1	09:52:55	0,7130923	0,006509271	0,000239534	0,2776704	2,724E-05	0,0001925	0,0001669	positive	n.a.	positive	n.a.	n.a.	OK
23	1	26	W	1/23.jpg	w1	09:53:05	0,700221658	0,009300958	0,000122127	0,2864357	5,143E-05	0,0005022	0,0005631	positive	n.a.	positive	n.a.	n.a.	OK
24	1	26	W	1/24.jpg	w1	09:53:15	0,7520928	0,004892668	0,000373896	0,2390498	9,653E-05	0,0008865	0,0003915	positive	n.a.	positive	n.a.	n.a.	OK
25	1	26	W	1/25.jpg	w1	09:53:25	0,496082664	0,000759713	0,000273924	0,4124382	0,0003869	0,0891758	0,0006133	positive	n.a.	positive	n.a.	n.a.	OK
26	1	26	W	1/26.jpg	w1	09:53:35	0,5544742	0,001254383	0,000487786	0,298688	0,0007591	0,1425639	0,0010356	positive	n.a.	positive	n.a.	n.a.	OK
27	1	26	W	1/27.jpg	w1	09:53:45	0,8481202	0,000960517	0,001087414	0,1092701	0,0097308	0,0142643	0,0044802	positive	n.a.	positive	n.a.	n.a.	OK
28	1	26	W	1/28.jpg	w1	09:53:55	0,642065763	0,012921873	0,000711294	0,2663839	0,0029025	0,0027465	0,0005562	negative	A	negative	A	class3	OK
29	1	26	W	1/29.jpg	w1	09:54:05	0,757083833	0,002732057	0,000468709	0,2267832	0,0009363	0,0016441	0,0004766	positive	n.a.	positive	n.a.	n.a.	OK
30	1	26	W	1/30.jpg	w1	09:54:15	0,746529	0,002099724	0,000443003	0,2394651	0,0004919	0,002128	0,0001041	positive	n.a.	positive	n.a.	n.a.	OK
31	1	26	W	1/31.jpg	w1	09:54:25	0,7737758	0,00219571	0,000680354	0,2108767	0,0012567	0,001902	0,0002964	positive	n.a.	positive	n.a.	n.a.	OK
32	1	26	W	1/32.jpg	w1	09:54:35	0,8431692	0,005430868	0,001470309	0,1177428	0,0020705	0,0049813	0,0006785	positive	n.a.	positive	n.a.	n.a.	OK
33	1	26	W	2/33.jpg	w1	09:54:45	0,422194421	0,007565917	0,000295691	0,5533375	0,0002547	0,0138976	0,0003666	positive	n.a.	positive	n.a.	n.a.	OK
34	2	25	W	2/34.jpg	w4	09:54:55	0,665869057	0,003444709	0,000112993	0,3139098	0,0039044	0,0019513	0,0002223	positive	n.a.	positive	n.a.	n.a.	OK
35	2	25	W	2/35.jpg	w4	09:55:05	0,718509436	0,001594424	7,86497E-05	0,2753035	0,0005342	0,0013517	0,0001864	positive	n.a.	positive	n.a.	n.a.	OK
36	2	25	W	2/36.jpg	w4	09:55:15	0,6426463	0,001976414	3,02661E-05	0,352172	0,0001325	0,0010693	5,834E-05	positive	n.a.	positive	n.a.	n.a.	OK
37	2	25	W	2/37.jpg	w4	09:55:25	0,387067348	0,012900055	4,56221E-05	0,5876915	0,0002019	0,0057846	6,029E-05	negative	U	negative	U	class3	OK
38	2	25	W	2/38.jpg	w4	09:55:35	0,611920655	0,000265875	1,41007E-05	0,3867685	6,077E-05	0,0005673	4,087E-05	positive	n.a.	positive	n.a.	n.a.	OK
39	2	25	W	2/39.jpg	w4	09:55:45	0,654493868	0,002270547	5,41825E-05	0,3319557	0,0009207	0,0019781	0,0003451	positive	n.a.	positive	n.a.	n.a.	OK
40	2	25	W	2/40.jpg	w4	09:55:55	0,920496762	0,004621196	0,001240382	0,0449463	0,0024634	0,0047735	0,009359	positive	n.a.	positive	n.a.	n.a.	OK
41	2	25	W	2/41.jpg	w4	09:56:05	0,7898902	0,007692383	0,000213827	0,1842865	0,0014821	0,0006118	5,515E-05	positive	n.a.	positive	n.a.	n.a.	OK
42	2	25	W	2/42.jpg	w4	09:56:15	0,9875879	5,56757E-06	5,32622E-05	0,011974	1,319E-05	0,0001626	6,965E-06	positive	n.a.	positive	n.a.	n.a.	OK
43	2	25	W	2/43.jpg	w4	09:56:25	0,8053107	0,003345143	0,000445725	0,1528101	0,001859	0,0041925	0,0229372	positive	n.a.	positive	n.a.	n.a.	OK
44	2	25	W	2/44.jpg	w4	09:56:35	0,7311749	0,017943261	0,065859444	0,1393	0,0182505	0,0082989	0,0032472	negative	U	negative	U	class3	OK
45	2	25	W	2/45.jpg	w4	09:56:45	0,9158025	0,001792562	0,003055737	0,0611895	0,0014426	0,0016718	0,0121127	positive	n.a.	positive	n.a.	n.a.	OK
46	2	25	W	2/46.jpg	w4	09:56:55	0,6474456	0,003518552	0,001265906	0,0864904	0,0014255	0,0021176	0,2560011	positive	n.a.	positive	n.a.	n.a.	OK
47	2	25	W	2/47.jpg	w4	09:57:05	0,9007879	0,009511893	0,002924341	0,0701603	0,0012197	0,0020784	0,0051058	positive	n.a.	positive	n.a.	n.a.	OK
48	2	25	W	2/48.jpg	w4	09:57:15	0,958819747	0,001564374	0,001284621	0,0279954	0,0006051	0,0007814	0,0073716	positive	n.a.	positive	n.a.	n.a.	OK
49	2	25	W	2/49.jpg	w4	09:57:25	0,354489833	0,052238904	0,000718683	0,5794904	0,0014798	0,0028267	0,001655	positive	n.a.	positive	n.a.	n.a.	OK
50	2	25	W	2/50.jpg	w4	09:57:35	0,9263956	0,004584687	0,004441547	0,0430053	0,0015042	0,0024806	0,0129305	positive	n.a.	positive	n.a.	n.a.	OK
51	2	25	W	2/51.jpg	w4	09:57:45	0,8741763	0,00249504	0,001296953	0,0615194	0,0011643	0,0039794	0,0522573	negative	U	negative	U	class2	OK
52	2	25	W	2/52.jpg	w4	09:57:55	0,537991762	0,005023279	0,000566027	0,3841731	0,0009654	0,0692576	0,0007078	positive	n.a.	positive	n.a.	n.a.	OK
53	2	25	W	2/53.jpg	w4	09:58:05	0,6421939	0,000203928	0,000327786	0,0097318	0,0007418	0,0022626	0,3439354	negative	U	negative	U	class3	OK
54	2	25	W	2/54.jpg	w4	09:58:15	0,8825404	0,001293873	0,001376593	0,0193567	0,0007039	0,075883	0,0020785	positive	n.a.	positive	n.a.	n.a.	OK

55	2	25	W	2/55.jpg	w4	09:58:25	0,884914	0,043137692	3,21656E-05	0,016763	4,485E-06	0,0002428	0,0003887	negative	U	negative	U	class3	OK
56	2	25	W	2/56.jpg	w4	09:58:35	0,868990839	0,009377482	0,000245841	0,0278553	5,059E-05	0,0017279	0,0003225	positive	n.a.	positive	n.a.	n.a.	OK
57	2	26	W	2/57.jpg	w3	09:58:45	0,8646402	0,000986434	0,00047231	0,1242582	0,0015671	0,0010738	6,919E-05	negative	AU	negative	AU	class3	OK
58	2	26	W	2/58.jpg	w3	09:58:55	0,7199251	0,03771379	0,000521951	0,1510554	0,0022618	0,0028793	0,0002263	positive	n.a.	positive	n.a.	n.a.	OK
59	2	26	W	2/59.jpg	w3	09:59:05	0,7933763	0,018579956	0,00044151	0,1073997	0,001752	0,0016134	7,472E-05	negative	AU	negative	AU	class3	OK
60	2	26	W	2/60.jpg	w3	09:59:15	0,8337605	0,009305377	0,00126418	0,0939709	0,0036071	0,0018194	0,0002044	negative	AU	negative	AU	class3	OK
61	2	26	W	2/61.jpg	w3	09:59:25	0,8632411	0,00066949	0,000114315	0,1308143	0,0005883	0,0010006	8,929E-05	negative	AU	negative	AU	class3	OK
62	2	26	W	2/62.jpg	w3	09:59:35	0,800421059	0,027721427	0,000414115	0,1047524	0,0017468	0,0019897	0,0002722	negative	AU	negative	AU	class3	OK
63	2	26	W	2/63.jpg	w3	09:59:45	0,8888485	0,007705037	0,001354637	0,0572798	0,0030237	0,0014601	0,0001802	negative	AU	negative	AU	class1	OK
64	2	26	W	2/64.jpg	w3	09:59:55	0,7926828	0,00461162	0,000119542	0,19095	0,0004892	0,0018244	0,0004505	negative	AU	negative	AU	class3	OK
65	2	26	W	2/65.jpg	w3	10:00:05	0,8759568	0,002802496	0,000376701	0,1081955	0,0013896	0,0021527	0,0006895	negative	AU	negative	AU	class3	OK
66	2	26	W	2/66.jpg	w3	10:00:15	0,9367238	0,000970269	0,000284499	0,0505036	0,0011323	0,0022459	0,0009933	positive	n.a.	positive	n.a.	n.a.	OK
67	2	26	W	2/67.jpg	w3	10:00:25	0,9585866	0,002349292	0,000409004	0,0210948	0,0004729	0,0004549	0,0003955	negative	AU	negative	AU	class1	OK
68	2	26	W	2/68.jpg	w3	10:00:35	0,896444559	0,001989104	0,001061514	0,0858203	0,0028128	0,0013134	0,0002306	negative	AU	negative	AU	class1	OK
69	2	26	W	2/69.jpg	w3	10:00:45	0,9125676	0,002744515	0,001085249	0,0494934	0,001292	0,0024033	0,0058256	negative	AU	negative	AU	class2	OK
70	2	26	W	2/70.jpg	w3	10:00:55	0,9040651	0,008288109	0,001415468	0,0442271	0,0011356	0,0022624	0,0055787	positive	n.a.	positive	n.a.	n.a.	OK
71	2	26	W	2/71.jpg	w3	10:01:05	0,96792084	0,000774657	0,000506995	0,0121204	0,0007573	0,0013082	0,0023365	negative	AU	negative	AU	class1	OK
72	2	26	W	2/72.jpg	w3	10:01:15	0,9347807	0,001338803	0,000709134	0,0301823	0,0058988	0,0024137	0,0013324	positive	n.a.	positive	n.a.	n.a.	OK
73	2	26	W	2/73.jpg	w3	10:01:25	0,9185036	0,002291346	0,000613609	0,0574028	0,0017119	0,0022878	0,0004648	negative	AU	negative	AU	class2	OK
74	2	26	W	2/74.jpg	w3	10:01:35	0,886312366	0,000272001	0,00012671	0,110347	0,0004144	0,0005241	5,961E-05	negative	AU	negative	AU	class1	OK
75	2	26	W	2/75.jpg	w3	10:01:45	0,952439845	0,002948754	8,51643E-05	0,0220995	0,0002018	0,0005556	0,0002398	positive	n.a.	positive	n.a.	n.a.	OK
76	2	26	W	2/76.jpg	w3	10:01:55	0,9632676	5,54901E-05	5,21589E-05	0,0265619	0,0004192	0,0004521	0,0051332	negative	AU	negative	AU	class1	OK
77	2	26	W	2/77.jpg	w3	10:02:05	0,9712104	0,000209299	0,000447471	0,0238911	0,000608	0,0013889	0,0005916	negative	AU	negative	AU	class1	OK
78	2	26	W	2/78.jpg	w3	10:02:15	0,956956744	0,001787025	0,00043735	0,0260391	0,0007435	0,0014127	0,0022017	negative	AU	negative	AU	class1	OK
79	2	26	W	2/79.jpg	w3	10:02:25	0,9690499	0,000845621	0,000257853	0,0237064	0,0005074	0,0007489	0,0005193	negative	AU	negative	AU	class1	OK
80	2	26	W	3/80.jpg	w3	10:02:35	0,9649588	0,000268183	0,000277145	0,0292154	0,0005158	0,0005761	3,9E-05	negative	AU	negative	AU	class1	OK
81	3	26	W	3/81.jpg	w4	10:02:45	0,721669	4,52264E-05	1,78231E-05	0,1899171	0,0001001	0,0080054	0,0801333	negative	U	negative	U	class3	OK
82	3	26	W	3/82.jpg	w4	10:02:55	0,8527124	1,91612E-05	2,93223E-05	0,0335663	0,0002538	0,0075715	0,1055888	negative	U	negative	U	class3	OK
83	3	26	W	3/83.jpg	w4	10:03:05	0,850267768	5,5623E-05	7,80603E-05	0,0836841	0,0003161	0,0135162	0,0517876	negative	U	negative	U	class2	OK
84	3	26	W	3/84.jpg	w4	10:03:15	0,864538252	2,78679E-05	3,71658E-05	0,0662825	0,000195	0,0144621	0,0542895	negative	U	negative	U	class2	OK
85	3	26	W	3/85.jpg	w4	10:03:25	0,8706543	1,64308E-05	1,94516E-05	0,0555387	0,0001677	0,0118256	0,0616263	negative	U	negative	U	class2	OK
86	3	26	W	3/86.jpg	w4	10:03:35	0,7752431	0,00014584	0,000125909	0,1575241	0,0006659	0,0330914	0,032853	positive	n.a.	positive	n.a.	n.a.	OK
87	3	26	W	3/87.jpg	w4	10:03:45	0,4794448	0,000204847	0,000219076	0,2193736	0,0007925	0,2551407	0,0446975	positive	n.a.	positive	n.a.	n.a.	OK
88	3	26	W	3/88.jpg	w4	10:03:55	0,577791	0,000365786	0,000666402	0,2320996	0,0011894	0,1487604	0,0389213	positive	n.a.	positive	n.a.	n.a.	OK
89	3	26	W	3/89.jpg	w4	10:04:05	0,7532556	7,48249E-05	0,00013901	0,084604	0,0010215	0,0727633	0,0877945	positive	n.a.	positive	n.a.	n.a.	OK
90	3	26	W	3/90.jpg	w4	10:04:15	0,6658597	0,000645378	0,001135357	0,3105988	0,0007145	0,0132417	0,0072287	positive	n.a.	positive	n.a.	class2	OK
91	3	26	W	3/91.jpg	w4	10:04:25	0,7782987	0,000453314	0,001889504	0,2011787	0,0011351	0,008609	0,0079077	positive	n.a.	positive	n.a.	n.a.	OK
92	3	26	W	3/92.jpg	w4	10:04:35	0,6642331	0,001168208	0,002940795	0,3077098	0,0018488	0,0143839	0,0065915	positive	n.a.	positive	n.a.	n.a.	OK
93	3	26	W	3/93.jpg	w4	10:04:45	0,7030564	0,000568576	0,004149409	0,2398173	0,0026658	0,0307344	0,0184618	positive	n.a.	positive	n.a.	n.a.	OK
94	3	26	W	3/94.jpg	w4	10:04:55	0,690376043	0,000866429	0,004009377	0,2758089	0,0024002	0,0167368	0,0089285	positive	n.a.	positive	n.a.	n.a.	OK
95	3	26	W	3/95.jpg	w4	10:05:05	0,7851234	0,000275158	0,000995335	0,1939556	0,0004865	0,0117362	0,0071301	positive	n.a.	positive	n.a.	class2	OK
96	3	26	W	3/96.jpg	w4	10:05:15	0,532439053	0,00093551	0,002285427	0,4142801	0,0016456	0,0419609	0,0058988	positive	n.a.	positive	n.a.	n.a.	OK
97	3	26	W	3/97.jpg	w4	10:05:25	0,7380958	0,000966545	0,001164042	0,2486482	0,0006038	0,0057029	0,0041831	negative	U	negative	U	class3	OK
98	3	26	W	3/98.jpg	w4	10:05:35	0,5861665	0,0008626	0,002067658	0,3841392	0,0010918	0,0209491	0,0042027	positive	n.a.	positive	n.a.	n.a.	OK
99	3	26	W	3/99.jpg	w4	10:05:45	0,695500433	0,000429668	0,001342239	0,2877585	0,000482	0,0090421	0,0051868	positive	n.a.	positive	n.a.	n.a.	OK
100	3	26	W	3/100.jpg	w4	10:05:55	0,5236903	0,000911015	0,001211703	0,449267	0,0006453	0,0210823	0,0027545	positive	n.a.	positive	n.a.	n.a.	OK
101	3	26	W	3/101.jpg	w4	10:06:05	0,642718732	0,003396305	0,005509441	0,307966	0,0032165	0,0218373	0,0129387	positive	n.a.	positive	n.a.	n.a.	OK
102	3	26	W	3/102.jpg	w4	10:06:15	0,762226164	0,001034884	0,002148119	0,2117993	0,0013422	0,0130424	0,0076285	positive	n.a.	positive	n.a.	n.a.	OK
103	3	26	W	3/103.jpg	w4	10:06:25	0,710804	0,000898012	0,004402942	0,2577784	0,0025804	0,0201133	0,0024274	positive	n.a.	positive	n.a.	n.a.	OK
104	3	26	W	3/104.jpg	w4	10:06:35	0,026922735	0,000135796	4,61938E-05	0,0275004	0,0001624	0,0002328	0,9445246	positive	n.a.	positive	n.a.	n.a.	OK
105	3	26	W	3/105.jpg	w4	10:06:45	0,7597237	0,001269052	0,000927191	0,1918091	0,0008866	0,0108018	0,0231619	positive	n.a.	positive	n.a.	class2	OK

## Appendix F

This appendix shows the test results of the inferring engine rules for women over 27 years old.

User					UI	Detection time		Detected Emotions							Expected		Observed			test
# image	userid	age	gender	image	web	time	neutral	fear	anger	sadness	disgust	contempt	happiness	emotion	UI issue	emotion	UI issue	class	results	
1	93	29	W	93/1.jpg	3	16:23:25	0,658686459	3,26237E-05	6,47361E-05	0,3406759	1,1808E-05	0,000227302	6,17499E-05	positive	n.a.	positive	n.a.	class2	OK	
2	93	29	W	93/2.jpg	3	16:23:35	0,9769656	0,000291459	0,000121311	0,00361223	7,6274E-06	0,000326615	0,000450957	positive	n.a.	positive	n.a.	class2	OK	
3	93	29	W	93/3.jpg	3	16:23:45	0,974542856	9,24048E-06	4,73556E-05	0,024740221	5,3697E-06	0,000197295	4,59826E-05	positive	n.a.	positive	n.a.	class2	OK	
4	93	29	W	93/4.jpg	3	16:23:55	0,830160439	0,000176754	0,001365049	0,166623428	0,000054031	0,000342426	0,000327065	positive	n.a.	positive	n.a.	class2	OK	
5	93	29	W	93/5.jpg	3	16:24:05	0,966280043	0,001487478	0,000283241	0,02271658	1,78115E-05	0,000122807	0,000273057	positive	n.a.	positive	n.a.	class2	OK	
6	93	29	W	93/6.jpg	3	16:24:15	0,8486435	0,001271938	0,03098069	0,11254543	0,001003338	0,001735897	0,000307795	positive	n.a.	positive	n.a.	class2	OK	
7	93	29	W	93/7.jpg	3	16:24:25	0,368576348	0,007927632	9,2158E-05	0,6179796	0,000133494	0,001021791	0,000394191	positive	n.a.	positive	n.a.	class2	OK	
8	93	29	W	93/8.jpg	3	16:24:35	0,68119967	0,030394774	0,0005404	0,2623115	0,000262029	0,004456451	4,89065E-05	positive	n.a.	positive	n.a.	class2	OK	
9	93	29	W	93/9.jpg	3	16:24:45	0,32452938	0,005480981	0,00025159	0,6663198	0,000168283	0,001877064	8,62083E-05	positive	n.a.	positive	n.a.	class2	OK	
10	93	29	W	93/10.jpg	3	16:24:55	0,399959534	0,002638179	0,002016221	5,8884729	0,000560799	0,005425585	8,56069E-05	positive	n.a.	positive	n.a.	class2	OK	
11	93	29	W	93/11.jpg	3	16:25:05	0,4394308	0,007734664	0,004001345	0,535768151	0,001166856	0,009075785	6,79918E-05	negative	AU	negative	AU	class2	OK	
12	93	29	W	93/12.jpg	3	16:25:15	0,3404341	0,003792627	0,006477176	0,6361657	0,002108136	0,009922217	0,000146249	positive	n.a.	positive	n.a.	class2	OK	
13	93	29	W	93/13.jpg	3	16:25:25	0,41929093	0,000582342	0,00022529	5,76335967	0,000204818	0,002402894	0,000266741	positive	n.a.	positive	n.a.	class2	OK	
14	93	29	W	93/14.jpg	3	16:25:35	0,9337601	7,8011E-05	1,02457E-05	0,06332865	2,50051E-06	3,52316E-06	8,21837E-05	positive	n.a.	positive	n.a.	class2	OK	
15	93	29	W	93/15.jpg	3	16:25:45	0,9560874	0,000428342	0,017819494	0,02192178	0,000390787	0,000850502	0,000348604	positive	n.a.	positive	n.a.	class2	OK	
16	93	29	W	93/16.jpg	3	16:25:55	0,8762744	2,8253E-05	0,002446608	0,120756634	6,171E-05	0,000151508	5,75466E-05	positive	n.a.	positive	n.a.	class2	OK	
17	93	29	W	93/17.jpg	3	16:26:05	0,9263412	0,002226626	0,004263366	0,056337033	0,000263573	0,001460796	0,001095082	negative	AU	negative	AU	class2	OK	
18	93	29	W	93/18.jpg	3	16:26:15	0,9239778	2,13896E-05	4,598E-05	0,0749927	5,94487E-06	0,000163603	0,000232817	positive	n.a.	positive	n.a.	class2	OK	
19	93	29	W	93/19.jpg	3	16:26:25	0,9912049	8,69655E-05	0,000632229	0,006221718	1,691E-05	0,000424711	7,15772E-05	positive	n.a.	positive	n.a.	class2	OK	
20	93	29	W	93/20.jpg	3	16:26:35	0,172657475	1,11737E-07	6,42791E-05	1,45806E-05	0,000360986	0,003317017	0,8234946	positive	n.a.	positive	n.a.	class2	OK	
21	111	63	W	111/21.jpg	3	16:26:45	0,8130524	0,001210616	0,006553352	0,171634808	0,000754133	0,000884785	0,003841309	positive	n.a.	positive	n.a.	class2	OK	
22	111	63	W	111/22.jpg	3	16:26:55	0,681405	0,000805322	0,007411635	0,308052331	0,000526658	0,000599775	0,000739487	positive	n.a.	positive	n.a.	class2	OK	
23	111	63	W	111/23.jpg	3	16:27:05	0,8507479	0,001435386	0,003028709	0,124394841	0,000632131	0,001211871	0,017098787	positive	n.a.	positive	n.a.	class2	OK	
24	111	63	W	111/24.jpg	3	16:27:15	0,259497851	0,090760544	0,008087169	0,5593395	0,030678738	0,012603648	0,000684943	positive	n.a.	positive	n.a.	class2	OK	
25	111	63	W	111/25.jpg	3	16:27:25	0,7184485	0,006824446	0,007043038	0,2485448	0,002412066	0,003510834	0,002232163	positive	n.a.	positive	n.a.	class2	OK	
26	111	63	W	111/26.jpg	3	16:27:35	0,594979167	0,002674199	0,002376989	0,372949481	0,001471618	0,005744012	0,002932621	positive	n.a.	positive	n.a.	class2	OK	
27	111	63	W	111/27.jpg	3	16:27:45	0,35425207	0,062062305	0,000688078	0,3487792	0,00162204	0,001726091	0,000181785	positive	n.a.	positive	n.a.	class2	OK	
28	111	63	W	111/28.jpg	3	16:27:55	0,4424266	0,116412736	0,008077016	0,2901005	0,004373155	0,001752206	0,002101473	positive	n.a.	positive	n.a.	class2	OK	
29	111	63	W	111/29.jpg	3	16:28:05	0,159031734	0,198959514	0,009865331	0,07790843	0,012776444	0,001474231	0,002519214	positive	n.a.	positive	n.a.	class2	OK	
30	111	63	W	111/30.jpg	3	16:28:15	0,47711885	0,176135764	0,001624256	0,07275488	0,000393099	0,000262159	0,003454459	positive	n.a.	positive	n.a.	class2	OK	
31	111	63	W	111/31.jpg	3	16:28:25	0,4923132	0,061523687	0,011348689	0,021758096	0,000717462	0,000539151	0,017165419	positive	n.a.	positive	n.a.	class2	OK	
32	111	63	W	111/32.jpg	3	16:28:35	0,4171399	0,028208438	0,007240769	0,014276785	0,003955724	0,00654652	0,048607934	positive	n.a.	positive	n.a.	class2	OK	
33	111	63	W	111/33.jpg	3	16:28:45	0,470243961	0,027639484	0,005571571	0,039418653	0,008882931	0,008589089	0,005521974	positive	n.a.	positive	n.a.	class2	OK	
34	111	63	W	111/34.jpg	3	16:28:55	0,119643576	0,07514795	0,004388337	0,1713431	0,006268289	0,000736156	0,364036053	negative	AU	negative	AU	class2	OK	
35	111	63	W	111/35.jpg	3	16:29:05	0,34958446	0,0764822	0,005842137	0,3974235	0,002217856	0,002135978	0,0070264	positive	n.a.	positive	n.a.	class2	OK	
36	111	63	W	111/36.jpg	3	16:29:15	0,234963611	0,1802705	0,004768675	0,3647231	0,010746415	0,006203808	0,000176755	negative	AU	negative	AU	class2	OK	
37	111	63	W	111/37.jpg	3	16:29:25	0,477662146	0,006313082	0,000792918	0,5078794	0,000552442	0,002345813	0,000271038	positive	n.a.	positive	n.a.	class2	OK	
38	111	63	W	111/38.jpg	3	16:29:35	0,522993863	0,001891127	0,002006941	0,292647272	0,002121394	0,007364181	0,1668756	positive	n.a.	positive	n.a.	class2	OK	
39	111	63	W	111/39.jpg	3	16:29:45	0,01066948	0,5657209	0,014689604	0,344090849	0,032804035	0,0016653	0,001317847	positive	n.a.	positive	n.a.	class2	OK	
40	111	63	W	111/40.jpg	3	16:29:55	0,7712258	0,011271065	0,004486776	0,09054669	0,00563366	0,009361747	0,02011994	negative	AU	negative	AU	class2	OK	
41	111	63	W	111/41.jpg	3	16:30:05	0,745490849	0,011310207	0,007224869	0,121297136	0,006245375	0,005268711	0,03279578	positive	n.a.	positive	n.a.	class2	OK	
42	111	63	W	111/42.jpg	3	16:30:15	0,5302368	0,037995037	0,001508376	0,139700845	0,002268773	0,001579275	0,002142992	positive	n.a.	positive	n.a.	class2	OK	
43	111	63	W	111/43.jpg	3	16:30:25	0,7543432	0,010657202	0,00517337	0,16280517	0,003087431	0,006334587	0,006452968	positive	n.a.	positive	n.a.	class2	OK	
44	111	63	W	111/44.jpg	3	16:30:35	0,8962843	0,001368682	0,002504518	0,07579962	0,001005224	0,001731761	0,016434958	positive	n.a.	positive	n.a.	class2	OK	
45	111	63	W	111/45.jpg	3	16:30:45	0,7975699	0,006608795	0,000331346	0,173934922	0,000280148	0,003738905	0,000657555	positive	n.a.	positive	n.a.	class2	OK	
46	111	63	W	111/46.jpg	3	16:30:55	0,314138353	0,06794962	0,000283791	0,0342443	0,000304266	0,000426297	0,003975586	positive	n.a.	positive	n.a.	class2	OK	
47	111	63	W	111/47.jpg	3	16:31:05	0,737970948	0,019171817	0,001162072	0,098299705	0,000880368	0,005578008	0,002720262	positive	n.a.	positive	n.a.	class2	OK	
48	111	63	W	111/48.jpg	3	16:31:15	0,235795334	0,07420004	0,000379067	0,05964945	0,000504258	0,000722904	0,001416301	positive	n.a.	positive	n.a.	class2	OK	
49	111	63	W	111/49.jpg	3	16:31:25	0,163690433	0,239978716	0,004856828	0,189576179	0,002839679	0,001504746	0,00042772	positive	n.a.	positive	n.a.	class2	OK	
50	111	63	W	111/50.jpg	3	16:31:35	0,6038829	0,07674091	0,00249249	0,185789272	0,000879111	0,00467055	0,003696521	positive	n.a.	positive	n.a.	class2	OK	
51	111	63	W	111/51.jpg	3	16:31:45	0,7223598	0,093324219	0,00286106	0,07038221	0,000538635	0,000807738	0,002167108	positive	n.a.	positive	n.a.	class2	OK	
52	111	63	W	111/52.jpg	3	16:31:55	0,4819602	0,08002857	0,005152681	0,087159306	0,001554756	0,001255546	0,000548969	positive	n.a.	positive	n.a.	class2	OK	
53	111	63	W	111/53.jpg	3	16:32:05	0,6279858	0,065799944	0,003020537	0,169564322	0,001814251	0,008649813	0,007507186	positive	n.a.	positive	n.a.	class2	OK	
54	111	63	W	111/54.jpg	3	16:32:15	0,569176435	0,04697587	0,003134762	0,051338412	0,00091976	0,000743498	0,002721293	positive	n.a.	positive	n.a.	class2	OK	
55	113	57	W	113/55.jpg	1	16:32:25	0,08552291	0,002726589	0,012037964	0,018232286	0,018635519	0,001348087	0,8511856	positive	n.a.	positive	n.a.	class2	OK	
56	113	57	W	113/56.jpg	1	16:32:35	0,9456792	0,000827894	0,001351568	0,03320021	0,002192192	0,004689114	0,010399138	positive	n.a.	positive	n.a.	class2	OK	
57	113	57	W	113/57.jpg	1	16:32:45	0,702238858	0,025165748	0,00377014	0,030732526	0,00300858	0,002701852	0,003974254	positive	n.a.	positive	n.a.	class2	OK	
58	113	57	W	113/58.jpg	1	16:32:55	0,85904556													

61	113	57	W	113/61.jpg	1	16:33:25	0,142121166	0,000932914	0,001816953	0,00819141	0,010301528	0,001535502	0,821832836	positive	n.a.	positive	n.a.	class2	OK
62	113	57	W	113/62.jpg	1	16:33:35	0,897044837	0,005604972	0,00097861	0,05193997	0,004716201	0,00163515	0,001833473	positive	n.a.	positive	n.a.	class2	OK
63	113	57	W	113/63.jpg	1	16:33:45	0,759529233	0,000766465	0,001734931	0,01992552	0,014625334	0,003777222	0,003345131	positive	n.a.	positive	n.a.	class2	OK
64	113	57	W	113/64.jpg	1	16:33:55	0,759842753	0,000577999	0,042583458	0,008318308	0,009147774	0,164016977	0,005546141	positive	n.a.	positive	n.a.	class2	OK
65	113	57	W	113/65.jpg	1	16:34:05	0,920670152	0,004751091	0,003862702	0,022520363	0,004017893	0,001707466	0,000507161	positive	n.a.	positive	n.a.	class2	OK
66	113	57	W	113/66.jpg	1	16:34:15	0,917762339	0,004856076	0,009914239	0,018760331	0,010146513	0,00414426	0,001631808	positive	n.a.	positive	n.a.	class2	OK
67	113	57	W	113/67.jpg	1	16:34:25	0,960321665	0,000955072	0,006164696	0,01370263	0,005049071	0,001805055	0,001813297	positive	n.a.	positive	n.a.	class2	OK
68	113	57	W	113/68.jpg	1	16:34:35	0,883538842	0,006252264	0,003592891	0,036818508	0,007786339	0,003323746	0,001982129	positive	n.a.	positive	n.a.	class2	OK
69	113	57	W	113/69.jpg	1	16:34:45	0,5581032	0,143605247	0,009781145	0,054025862	0,011171686	0,00250475	0,000138382	positive	n.a.	positive	n.a.	class2	OK
70	113	57	W	113/70.jpg	1	16:34:55	0,757284045	0,017425839	0,014313067	0,097195104	0,03922613	0,005087771	0,00188483	positive	n.a.	positive	n.a.	class2	OK
71	113	57	W	113/71.jpg	1	16:35:05	0,569037	0,064870924	0,003113596	0,03757679	0,019449476	0,000937806	0,000177994	positive	n.a.	positive	n.a.	class2	OK
72	113	57	W	113/72.jpg	1	16:35:15	0,6914	0,021709888	0,009300618	0,159783989	0,050850965	0,006840093	0,004219065	positive	n.a.	positive	n.a.	class2	OK
73	113	57	W	113/73.jpg	1	16:35:25	0,916860938	0,003045738	0,012961021	0,018762613	0,003357541	0,003166158	0,030271549	negative	A	negative	A	class2	OK
74	113	57	W	113/74.jpg	1	16:35:35	0,9335644	0,001761843	0,007012692	0,019573407	0,004526543	0,005063288	0,010275277	positive	n.a.	positive	n.a.	class2	OK
75	113	57	W	113/75.jpg	1	16:35:45	0,857119	0,0104099	0,002962586	0,09324609	0,003131234	0,003239401	0,002884592	positive	n.a.	positive	n.a.	class2	OK
76	113	57	W	113/76.jpg	1	16:35:55	0,8428659	0,009443129	0,015809728	0,028213091	0,030200008	0,009521051	0,006619444	positive	n.a.	positive	n.a.	class2	OK
77	113	57	W	113/77.jpg	1	16:36:05	0,682411551	0,001857975	0,002423897	0,216283768	0,004773603	0,079143465	0,010615354	positive	n.a.	positive	n.a.	class2	OK
78	113	57	W	113/78.jpg	1	16:36:15	0,609296739	0,012001454	0,000848664	0,362937748	0,002559057	0,002698596	0,003347409	positive	n.a.	positive	n.a.	class2	OK
79	113	57	W	113/79.jpg	1	16:36:25	0,9295671	0,002133924	0,003359923	0,024501178	0,008710898	0,002523693	0,002044277	positive	n.a.	positive	n.a.	class2	OK
80	113	57	W	113/80.jpg	1	16:36:35	0,7860313	0,025629487	0,002698004	0,137809917	0,003046322	0,002476	0,001205264	positive	n.a.	positive	n.a.	class2	OK
81	115	44	W	115/81.jpg	1	16:36:45	0,955550849	0,000107782	0,000143856	0,004086062	0,000385722	0,002968116	0,03288381	negative	A	negative	A	class2	OK
82	115	44	W	115/82.jpg	1	16:36:55	0,5614036	0,032616705	0,001038845	0,3648567	0,002699092	0,005432894	0,004933331	positive	n.a.	positive	n.a.	class2	OK
83	115	44	W	115/83.jpg	1	16:37:05	0,8742548	0,007050076	0,000373863	0,033282977	0,000984307	0,004919738	0,008806866	positive	n.a.	positive	n.a.	class2	OK
84	115	44	W	115/84.jpg	1	16:37:15	0,7362417	0,001264806	0,004046093	0,239143074	0,002880303	0,008854241	0,005307275	positive	n.a.	positive	n.a.	class2	OK
85	115	44	W	115/85.jpg	1	16:37:25	0,908146739	0,000763316	0,000317402	0,04677805	0,001406762	0,003462484	0,031226702	negative	A	negative	A	class2	OK
86	115	44	W	115/86.jpg	1	16:37:35	0,918117642	0,002212343	0,000321908	0,01768021	0,000794492	0,003364979	0,02838041	negative	A	negative	A	class2	OK
87	115	44	W	115/87.jpg	1	16:37:45	0,426377952	0,09317614	0,009005914	0,242377475	0,021444153	0,013096955	0,045760192	negative	A	negative	A	class2	OK
88	115	44	W	115/88.jpg	1	16:37:55	0,00304675	5,89955E-09	1,2221E-05	6,8487E-06	1,31748E-05	5,19608E-06	0,9969153	positive	n.a.	positive	n.a.	class2	OK
89	115	44	W	115/89.jpg	1	16:38:05	0,431231946	0,07655426	0,001029703	0,4468016	0,003251296	0,003946725	0,001816165	positive	n.a.	positive	n.a.	class2	OK
90	115	44	W	115/90.jpg	1	16:38:15	0,8035552	0,017340843	0,000372142	0,07425744	0,001416037	0,003814258	0,004286109	positive	n.a.	positive	n.a.	class2	OK
91	115	44	W	115/91.jpg	1	16:38:25	0,923078656	0,001419664	0,000651167	0,05518205	0,001146938	0,007444939	0,004247954	positive	n.a.	positive	n.a.	class2	OK
92	115	44	W	115/92.jpg	1	16:38:35	0,564072967	0,05729318	0,001563077	0,298080027	0,004628405	0,005126911	0,00416131	positive	n.a.	positive	n.a.	class2	OK
93	115	44	W	115/93.jpg	1	16:38:45	0,7149941	0,044017736	0,00074238	0,167826474	0,001792837	0,003964862	0,008213121	positive	n.a.	positive	n.a.	class2	OK
94	115	44	W	115/94.jpg	1	16:38:55	0,721936941	0,047228258	0,000860214	0,14545913	0,001798731	0,003639096	0,003314158	positive	n.a.	positive	n.a.	class2	OK
95	115	44	W	115/95.jpg	1	16:39:05	0,7669776	0,008930452	0,000863639	0,08409903	0,003230505	0,004458322	0,110376693	positive	n.a.	positive	n.a.	class2	OK
96	133	28	W	133/96.jpg	1	16:39:15	0,132966474	0,016115688	0,013313403	0,38634795	0,029500479	0,021384541	0,383476466	positive	n.a.	positive	n.a.	class2	OK
97	133	28	W	133/97.jpg	1	16:39:25	0,531117558	0,004816356	0,001863491	0,289998323	0,000928749	0,004096142	0,15799959	positive	n.a.	positive	n.a.	class2	OK
98	133	28	W	133/98.jpg	1	16:39:35	0,626552939	0,00343257	0,018884376	0,271889776	0,026035002	0,010450348	0,03681632	negative	A	negative	A	class2	OK
99	133	28	W	133/99.jpg	1	16:39:45	0,670714855	0,002480167	0,00873193	0,269818932	0,011765963	0,006145713	0,027817449	negative	A	negative	A	class2	OK
100	133	28	W	133/100.jpg	1	16:39:55	0,6990123	0,004226863	0,030549789	0,112934932	0,030269237	0,012221028	0,103873089	positive	n.a.	positive	n.a.	class2	OK
101	133	28	W	133/101.jpg	1	16:40:05	0,7733592	0,00071819	0,005723431	0,035743244	0,006294886	0,011939968	0,1638215	positive	n.a.	positive	n.a.	class2	OK
102	133	28	W	133/102.jpg	1	16:40:15	0,386955261	0,004278885	0,050755937	0,497819662	0,027125677	0,010153317	0,02147351	negative	A	negative	A	class2	OK
103	133	28	W	133/103.jpg	1	16:40:25	0,416104734	0,000344396	0,08882722	0,484715	0,004692757	0,004417873	0,000510768	positive	n.a.	positive	n.a.	class2	OK
104	133	28	W	133/104.jpg	1	16:40:35	0,488471121	0,00218791	0,13986747	0,304897726	0,042927716	0,016249592	0,002955542	positive	n.a.	positive	n.a.	class2	OK
105	133	28	W	133/105.jpg	1	16:40:45	0,315722018	0,001880437	0,0530843	0,5800604	0,026500277	0,015364106	0,006855505	positive	n.a.	positive	n.a.	class2	OK
106	133	28	W	133/106.jpg	1	16:40:55	0,404570669	0,000660929	0,039132554	0,537824869	0,006327708	0,00623935	0,004752214	positive	n.a.	positive	n.a.	class2	OK

## Appendix G

This appendix shows the test results of the inferring engine rules for men under/equal to 27 years old.

User					UI	Detection time		Detected Emotions							Expected		Observed			test
# image	userid	age	gender	image	web	time	neutral	fear	anger	sadness	disgust	contempt	happiness	emotion	UI issue	emotion	UI issue	class	results	
1	85	25	M	85/1.jpg	1	18:49:25	0,668826461	7,03903E-06	0,001098851	0,288583577	0,002403932	0,03786523	0,001178515	negative	A	negative	A	class1	OK	
2	85	25	M	85/2.jpg	1	18:49:35	0,695480347	2,08699E-05	0,001261444	0,278736949	0,001566925	0,019781446	0,003058379	negative	A	negative	A	class1	OK	
3	85	25	M	85/3.jpg	1	18:49:45	0,8984025	1,29407E-05	0,000865863	0,085201725	0,000624549	0,011794151	0,003000459	positive	n.a.	positive	n.a.	n.a.	OK	
4	85	25	M	85/4.jpg	1	18:49:55	0,917089641	1,32307E-05	0,002314151	0,054697853	0,00099713	0,023221903	0,001572666	negative	A	negative	A	class1	OK	
5	85	25	M	85/5.jpg	1	18:50:05	0,740574658	9,46214E-06	0,000525801	0,237185448	0,00107988	0,016592886	0,003987453	positive	n.a.	positive	n.a.	n.a.	OK	
6	89	23	M	89/6.jpg	1	18:50:15	0,6380276	0,00567131	0,002236966	0,3350122	0,001183846	0,004693738	0,006395353	positive	n.a.	positive	n.a.	n.a.	OK	
7	89	23	M	89/7.jpg	1	18:50:25	0,587749243	0,000931324	0,000186004	0,404392779	0,000123739	0,000526145	0,001087763	negative	A	negative	A	class1	OK	
8	89	23	M	89/8.jpg	1	18:50:35	0,5089926	0,013437641	0,000813262	0,346314847	0,001420814	0,003545447	0,00148252	negative	A	negative	A	class1	OK	
9	89	23	M	89/9.jpg	1	18:50:45	0,710871458	0,002760782	0,000152724	0,203805834	2,3385E-05	0,00048039	0,07768918	positive	n.a.	positive	n.a.	n.a.	OK	
10	89	23	M	89/10.jpg	1	18:50:55	0,304952234	0,010284023	0,001190177	0,06291617	0,000438555	0,040319566	0,566156149	positive	n.a.	positive	n.a.	n.a.	OK	
11	89	23	M	89/11.jpg	1	18:51:05	0,5634923	0,002369782	0,00021129	0,06787534	5,01529E-05	0,002851797	0,359510422	positive	n.a.	positive	n.a.	n.a.	OK	
12	155	21	M	155/12.jpg	1	18:51:15	0,9796668	5,97049E-06	0,006953313	0,011547138	0,000799795	0,000885214	3,62465E-05	positive	n.a.	positive	n.a.	n.a.	OK	
13	155	21	M	155/13.jpg	1	18:51:25	0,924277842	1,07186E-05	0,0515507	0,020614233	0,001532091	0,001867686	3,77234E-06	negative	A	negative	A	class1	OK	
14	155	21	M	155/14.jpg	1	18:51:35	0,995125	6,86133E-06	0,000894001	0,002691416	7,31507E-06	0,000246701	0,000852387	negative	A	negative	A	class1	OK	
15	155	21	M	155/15.jpg	1	18:51:45	0,9005278	2,43343E-05	0,037572123	0,050664954	0,005364911	0,000539225	8,4924E-05	positive	n.a.	positive	n.a.	n.a.	OK	
16	155	21	M	155/16.jpg	1	18:51:55	0,8564496	7,00832E-06	0,1184276	0,02084437	0,002413997	0,001766742	5,92434E-06	positive	n.a.	positive	n.a.	n.a.	OK	
17	155	21	M	155/17.jpg	1	18:52:05	0,818789959	2,68955E-05	0,104121193	0,041451834	0,004412842	0,03097912	5,90819E-05	positive	n.a.	positive	n.a.	n.a.	OK	
18	155	21	M	155/18.jpg	1	18:52:15	0,9460237	1,72194E-06	0,05059025	0,002057627	0,000277638	0,001028224	3,48564E-07	negative	A	negative	A	class1	OK	
19	155	21	M	155/19.jpg	1	18:52:25	0,9345074	0,000123071	0,046990767	0,00872015	0,001413675	0,00722112	6,34622E-05	negative	A	negative	A	class1	OK	
20	155	21	M	155/20.jpg	1	18:52:35	0,589204848	0,000100341	0,002167749	0,02483085	0,01622451	0,016236072	0,350353	positive	n.a.	positive	n.a.	n.a.	OK	
21	132	24	M	132/21.jpg	4	18:52:45	0,999639663	9,22267E-07	2,36197E-06	0,000246467	1,07892E-06	4,04958E-05	4,03101E-06	positive	n.a.	positive	n.a.	n.a.	OK	
22	132	24	M	132/22.jpg	4	18:52:55	0,978989859	0,000200374	0,000130871	0,018803887	1,09438E-05	0,000204902	2,95124E-07	positive	n.a.	positive	n.a.	n.a.	OK	
23	132	24	M	132/23.jpg	4	18:53:05	0,991290867	1,80733E-06	3,86406E-05	0,008566651	4,265E-06	6,55532E-05	4,90655E-08	positive	n.a.	positive	n.a.	n.a.	OK	
24	132	24	M	132/24.jpg	4	18:53:15	0,9942417	1,27301E-05	1,96391E-05	0,005484271	1,74696E-06	3,71013E-05	1,72272E-07	positive	n.a.	positive	n.a.	n.a.	OK	
25	132	24	M	132/25.jpg	4	18:53:25	0,9558048	5,05554E-05	0,000339498	0,042163517	4,77545E-05	0,001106649	5,54613E-07	negative	U	negative	U	class2	OK	
26	132	24	M	132/26.jpg	4	18:53:35	0,9763825	0,000303316	0,000827762	0,01987289	6,60605E-05	0,000484281	3,21953E-06	positive	n.a.	positive	n.a.	n.a.	OK	
27	132	24	M	132/27.jpg	4	18:53:45	0,9284785	0,000115916	0,000363105	0,06874674	7,94111E-05	0,001538415	1,10457E-06	negative	U	negative	U	class2	OK	
28	87	21	M	87/28.jpg	3	18:53:55	0,3214063	0,00030655	0,000665324	0,007082577	0,001170872	0,015859947	0,6470377	positive	n.a.	positive	n.a.	n.a.	OK	
29	87	21	M	87/29.jpg	3	18:54:05	0,9621638	0,001035697	0,000305266	0,002378233	7,93036E-05	0,003853446	0,024345378	negative	AU	negative	AU	class3	OK	
30	87	21	M	87/30.jpg	3	18:54:15	0,9791004	0,002102085	7,71182E-05	0,003312157	3,76501E-05	0,005512164	0,001113508	positive	n.a.	positive	n.a.	n.a.	OK	
31	87	21	M	87/31.jpg	3	18:54:25	0,9361993	0,012108387	0,000109744	0,006116146	0,000112989	0,002362678	0,004564481	positive	n.a.	positive	n.a.	n.a.	OK	
32	87	21	M	87/32.jpg	3	18:54:35	0,985647559	0,002941504	0,000224881	0,005233287	2,49115E-05	0,000459448	2,89309E-05	positive	n.a.	positive	n.a.	n.a.	OK	
33	87	21	M	87/33.jpg	3	18:54:45	0,9435874	0,010137474	0,000128711	0,00341937	9,13847E-06	9,41456E-05	3,46242E-05	positive	n.a.	positive	n.a.	n.a.	OK	
34	87	21	M	87/34.jpg	3	18:54:55	0,8406447	0,0617063	0,001314345	0,012814315	0,000156723	0,000138481	0,001387399	positive	n.a.	positive	n.a.	n.a.	OK	
35	87	21	M	87/35.jpg	3	18:55:05	0,4280099	0,027446147	2,66839E-05	0,000561251	5,55648E-06	1,43127E-05	0,000106049	negative	AU	negative	AU	class3	OK	
36	87	21	M	87/36.jpg	3	18:55:15	0,9645784	0,017510904	0,000134599	0,003803598	1,06187E-05	0,000139821	0,000295534	negative	AU	negative	AU	class3	OK	
37	147	20	M	147/37.jpg	3	18:55:25	0,599615	0,021752007	0,00167806	0,132645726	0,000515326	0,000558472	0,017446104	negative	AU	negative	AU	class3	OK	
38	147	20	M	147/38.jpg	3	18:55:35	0,8332204	0,007709653	0,001123525	0,018590923	0,000327623	0,002570952	0,084962055	positive	n.a.	positive	n.a.	n.a.	OK	
39	147	20	M	147/39.jpg	3	18:55:45	0,8536356	0,011632705	0,000343621	0,056892894	5,49751E-05	0,000209476	0,003784443	positive	n.a.	positive	n.a.	n.a.	OK	
40	147	20	M	147/40.jpg	3	18:55:55	0,9916827	7,72451E-05	0,000473252	0,002510403	2,83862E-05	0,000356519	0,002026358	positive	n.a.	positive	n.a.	n.a.	OK	
41	147	20	M	147/41.jpg	3	18:56:05	0,994573	2,46795E-05	2,99662E-05	0,000704472	5,55865E-06	0,000318585	0,002179786	positive	n.a.	positive	n.a.	n.a.	OK	
42	147	20	M	147/42.jpg	3	18:56:15	0,9962444	7,51994E-06	3,96565E-06	0,000114559	9,04999E-07	8,24199E-05	0,000401663	positive	n.a.	positive	n.a.	n.a.	OK	
43	147	20	M	147/43.jpg	3	18:56:25	0,3263338	2,35973E-06	0,012254679	0,000788995	0,06681362	0,5825862	0,011044151	negative	AU	negative	AU	class3	OK	
44	147	20	M	147/44.jpg	3	18:56:35	0,995719	2,93942E-06	3,58415E-06	7,6428E-05	5,36917E-07	5,45825E-05	0,000719349	positive	n.a.	positive	n.a.	n.a.	OK	
45	147	20	M	147/45.jpg	3	18:56:45	0,998146653	2,81965E-06	8,14702E-06	0,000109689	9,01997E-07	0,000133868	0,000220712	positive	n.a.	positive	n.a.	n.a.	OK	
46	147	20	M	147/46.jpg	3	18:56:55	0,9516951	0,001240349	0,000128838	0,003865646	4,24824E-05	0,00171028	0,000587142	positive	n.a.	positive	n.a.	n.a.	OK	
47	147	20	M	147/47.jpg	3	18:57:05	0,9675474	0,000566175	7,68115E-05	0,004134403	4,05898E-05	0,003575047	0,001650387	positive	n.a.	positive	n.a.	n.a.	OK	
48	147	20	M	147/48.jpg	3	18:57:15	0,9732507	0,000120056	7,43788E-05	0,004302297	3,86956E-05	0,001824259	0,000951309	positive	n.a.	positive	n.a.	n.a.	OK	

## Appendix H

This appendix shows the test results of the inferring engine rules for men over 27 years old.

User					UI	Detection time		Detected Emotions						Expected		Observed			
# image	userid	age	gender	image	web	time	neutral	fear	anger	sadness	disgust	contempt	happiness	emotion	UI issue	emotion	UI issue	class	test results
1	105	32	M	105/1.jpg	3	21:49:25	0,3923791	0,052749746	0,128740773	0,113830678	0,052712333	0,0072	0,00031	positive	n.a.	positive	n.a.	n.a.	OK
2	105	32	M	105/2.jpg	3	21:49:35	0,3923791	0,052749746	0,128740773	0,113830678	0,052712333	0,0072	0,00031	positive	n.a.	positive	n.a.	n.a.	OK
3	105	32	M	105/3.jpg	3	21:49:45	0,1725436	0,011995383	0,419384331	0,173670158	0,199285164	0,0075	2,1E-05	positive	n.a.	positive	n.a.	n.a.	OK
4	105	32	M	105/4.jpg	3	21:49:55	0,9583537	0,000208527	0,000164698	0,03400255	5,11059E-05	0,00193	0,00499	positive	n.a.	positive	n.a.	n.a.	OK
5	105	32	M	105/5.jpg	3	21:50:05	0,3923791	0,052749746	0,128740773	0,113830678	0,052712333	0,0072	0,00031	positive	n.a.	positive	n.a.	n.a.	OK
6	105	32	M	105/6.jpg	3	21:50:15	0,634842157	0,001199211	0,2698038	0,06375885	0,013199536	0,01201	0,00011	negative	AU	negative	AU	class2	OK
7	105	32	M	105/7.jpg	3	21:50:25	0,815341	0,000113935	0,131570667	0,022070039	0,003861703	0,02504	0,00125	positive	n.a.	positive	n.a.	n.a.	OK
8	105	32	M	105/8.jpg	3	21:50:35	0,803820252	3,40404E-05	0,171683	0,009242504	0,00139245	0,01335	0,0001	positive	n.a.	positive	n.a.	n.a.	OK
9	105	32	M	105/9.jpg	3	21:50:45	0,7505294	0,000278706	0,1969555	0,024492102	0,007394208	0,01732	0,00042	negative	AU	negative	AU	class2	OK
10	105	32	M	105/10.jpg	3	21:50:55	0,7505294	0,000278706	0,1969555	0,024492102	0,007394208	0,01732	0,00042	negative	AU	negative	AU	class2	OK
11	105	32	M	105/11.jpg	3	21:51:05	0,7505294	0,000278706	0,1969555	0,024492102	0,007394208	0,01732	0,00042	negative	AU	negative	AU	class2	OK
12	105	32	M	105/12.jpg	3	21:51:15	0,7059841	0,036972422	0,07212752	0,1340626	0,005940445	0,00584	0,00302	positive	n.a.	positive	n.a.	n.a.	OK
13	105	32	M	105/13.jpg	3	21:51:25	0,6340183	0,003051425	0,030992076	0,2783255	0,004499442	0,04515	0,00145	positive	n.a.	positive	n.a.	n.a.	OK
14	105	32	M	105/14.jpg	3	21:51:35	0,957530439	1,55909E-05	0,00590143	0,027404511	0,00065097	0,00578	0,00258	positive	n.a.	positive	n.a.	n.a.	OK
15	105	32	M	105/15.jpg	3	21:51:45	0,957530439	1,55909E-05	0,00590143	0,027404511	0,00065097	0,00578	0,00258	positive	n.a.	positive	n.a.	n.a.	OK

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<sup>1</sup> [www.noldus.com/facereader](http://www.noldus.com/facereader)

<sup>2</sup> [azure.microsoft.com/id-id/services/cognitive-services/emotion/](https://azure.microsoft.com/id-id/services/cognitive-services/emotion/)

<sup>3</sup> [www.affectiva.com/product/emotion-sdk/](http://www.affectiva.com/product/emotion-sdk/)

<sup>4</sup> [www.angularjs.org/](http://www.angularjs.org/)

<sup>5</sup> [www.jquery.com](http://www.jquery.com)