A Smart Mirror to Promote a Healthy Lifestyle

Sara COLANTONIO, Giuseppe COPPINI, Danila GERMANESE, Daniela GIORGI, Massimo MAGRINI, Paolo MARRACCINI, Massimo MARTINELLI[1], Aurora MORALES, Maria Antonietta PASCALI, Giovanni RACCICHINI, Marco RIGHI and Ovidio SALVETTI

National Research Council of Italy, Pisa, Italy

Nomenclature

AGEs	Advance Glycation End-products
ECG	Electrocardiography
EEG	Electroencephalography
EMG	Electromyography
HUI	Health Utilities Index
HRQOL	Center for Disease Control and Prevention's health-related quality-of-life
NIR	Near Infra-Red
PGM	Personalized Guidance Module
PGS	Personalized Guidance System
PSS	Personalized Support Systems
SEMEOTICONS	SEMEiotic Oriented Technology for Individual’s CardiOmetabolic risk self-assessmeNt and Self-monitoring
SF12-PCS	Short Form12 – Physical Component Summary
SF12-MCS	Short Form12 – Mental Component Summary
UV	Ultraviolet
VIM	Virtual Individual Model
WI	Wellness Index
WM	Wize Mirror

[1] Corresponding Author: Massimo Martinelli, Institute of Information Science and Technologies, National Research Council of Italy, Via G. Moruzzi, 1, 56124, Pisa, Italy; E-mail: massimo.martinelli@isti.cnr.it phone:+39 050.621.2803.

Abstract.
ICT solutions to foster behavioral change have shown to be effective in implementing primary prevention in terms of a healthy lifestyle. Primary prevention is the most viable solution to reduce the socio-economic burden of chronic and widespread diseases, such as cardiovascular and metabolic diseases. In this paper, we present a novel multisensory device, the Wize Mirror, which is under development in the EU FP7 Project SEMEOTICONS. The Wize Mirror detects and monitor over time semeiotic face signs related to cardio-metabolic risk, and encourage users to reduce their risk by improving their lifestyle.

Keywords. User profiling, personalized guidance systems, wellbeing evaluation.

Introduction

It is well-known that prevention is the best strategy to limit the spread of cardio-metabolic diseases, which are the leading cause of mortality worldwide (Mathers, Fat, & Boerma, 2008). Indeed, cardio-metabolic risk factors are mainly related to modifiable factors pertaining to people's lifestyle, such as dietary habits, physical activity, tobacco and alcohol use, stress and psychological conditions. New perspectives on primary prevention rely on the *empowerment* of individuals, in terms of their ability to self-monitor their health status and act upon their lifestyle. Nowadays people are aware of the importance of a correct lifestyle, and they want to be active actors in the acquisition and maintenance of wellbeing.

Over the last few years, supportive technological instruments invaded the market, mainly in the form of wearable devices (wristbands, smartwatches, eyewear, wearable bio-monitors) and applications on smart devices (such as Runtastic or Melarossa). According to an Internet-based survey of thousands of Americans (Ledger & McCaffrey, 2014), as of September 2013 one in ten US consumers over the age of 18 owns a modern activity tracker. Interestingly, there is a bimodal distribution of users by age: the adopters are divided into youngsters (25-34 years), who focus on fitness optimization, and older users (55-64), who focus on improving overall health and extending their lives. But what contrasts with the increasing adoption of wearables is that the majority of consumers stops using the device within six months of receiving it. In other words, most of the devices on the market fail to drive long-term, sustained engagement. As a consequence, they fail to make a long-term impact on their users' health.

We believe the key to success is sustained engagement, based on the promotion of behavior change towards *wellness* as a whole and long-term health objectives. Enhancing wellness is an effective way to promote participation and motivate people to change their habits. In a year-long research study from the University of Michigan (Segar, Eccles, & Richardson, 2011), participants who adhered to a long-time exercise regime did not want to lose weight, but rather to "enhance their daily life and wellness".

It is in this direction that the European project SEMEOTICONS ("SEMEiotic Oriented Technology for Individual's CardiOmetabolic risk self-assessmeNt and Self-monitoring") is moving (SEMEOTICONS FP7 European Project, 2013). SEMEOTICONS started in November 2013 to develop a multisensory device in the form of a mirror, called the "Wize Mirror", which comfortably fits the home as a piece of house-ware, but also the pharmacies and fitness centers. By analyzing data acquired unobtrusively via a suite of contactless sensors, the Wize Mirror detects on a regular basis any physiological change relevant to cardio-metabolic risk factors. The computation and delivery of a comprehensive Wellness Index enables individuals to estimate and track over time their health status and their cardio-metabolic risk. Finally, the Wize Mirror offers personalized guidance towards the achievement of a correct lifestyle, via tailored coaching messages.

The Wize Mirror is designed to meet a two-faced objective: stimulating *initial adoption and utilization*, by providing a pleasant usage experience; and supporting *long-term engagement*, by helping people to establish new positive habits. To this aim, the main features of the Wize Mirror are the provision of day-by-day monitoring in an unobtrusive way; the automatic assessment of physiological conditions via advanced data processing algorithms; the promotion of sustained behavior change towards long-term wellness objectives. These functionalities are developed by taking into account theories belonging to different disciplines (psychology, motivation and communication science, social marketing, behavioral theories, and economics).

1. The Wize Mirror at a glance

The inspiring idea behind the Wize Mirror is that the face is the preeminent channel of communication among humans: it is a mirror of status, emotions and mood. As such it is the base of *medical semeiotics*, which reveals the healthy status of an individual through a combination of physical face signs (e.g., skin color, subcutaneous fat), and facial expressions. Dating back to as far as Aristotle's times, medical semeiotics is still used today by medical doctors. The Wize Mirror moves medical semeiotics to the digital realm: it translates the semeiotic code of the face into cardio-metabolic risk-related computational descriptors and measures automatically extracted from videos, images, and 3D scans of the face of people standing in front of the mirror.

The Wize Mirror is a multisensory platform that offers (Figure 1):

- an *advanced sensing framework* for acquiring physiological data over time: the Wize Mirror seamlessly integrates contactless sensors (3D optical sensors, multispectral cameras, gas detection sensors) which collect heterogeneous data of individuals standing in front of the mirror (Section 3);
- a *multimodal data processing module*, with dedicated algorithms which extract a number of morphometric, colorimetric, and compositional descriptors correlated with cardio-metabolic risk. These descriptors define a Virtual Individual Model (Section 4);
- a *data fusion and synthesis module*, which derives a composite Wellness Index (WI) out of the huge amount of data computed. The WI is an index of the health status of an individual, to be traced over time and reported in a health diary, thus enabling users to relate their lifestyle to their wellbeing (Section 5);
- a *profiling module*, which identifies specific users' clinical history, attitudes, habits, and context, so as to tailor the system and ensure long-lasting engagement (Section 6);
- a *personalized user guidance module*, which acts as a kind of health navigator to support users in the achievement and maintenance of a correct life-style (Section 7).

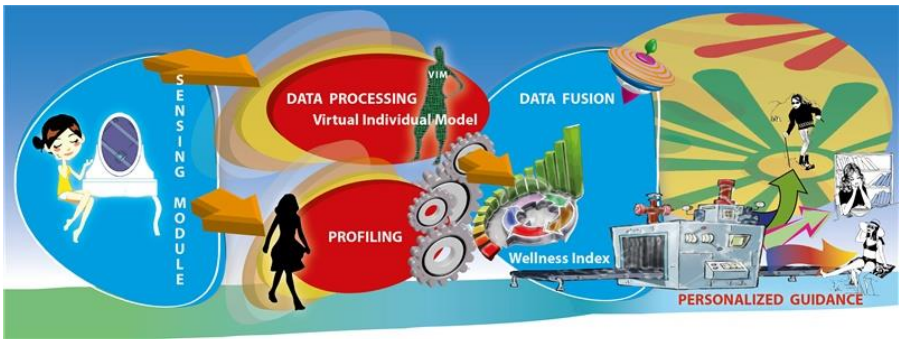

Figure 1: The schema of the Wize Mirror.

The development of the Wize Mirror raises significant scientific and technological challenges. After a brief review of the state-of-the-art in Section 2, Sections 3-7 give details on the approaches under development, for all the modules listed above. Section 8 describes the human population study designed for the validation of the Wize Mirror. Section 9 draws conclusions about the current state and the potential of the system.

2. State of the art

Over the last decades, the growing demand for telemedicine and health care has been met by many systems for automating medical data collection and diagnosis, monitoring physiological conditions, and performing diagnosis and treatment. In most cases, these systems are equipped with sophisticated and expensive medical machinery (like ECG or EEG) and they are not intended for common-day residential use.

One of the emerging solutions for the integration of monitoring systems in common residential settings are smart mirrors: mirrors are no longer simple reflecting surfaces, but are becoming more and more functional tools. Most of the smart mirrors are realized covering a LCD display with a reflecting surface, or using a semi-reflective display. They usually offer vocal, touch screen or gesture-based interaction, and let the user display various information: from the internet (e-mail, calendar, news, social networks, shopping on-line, etc.) to environmental (bathroom water temperature/pressure) and individual (fat mass, muscle mass, bone mass) information.

The Smart Mirror for home environment in (Hossain, Atrey, & Saddik, 2007) is endowed with a facial recognition module and allows users to control all the smart devices of their home environment. The Medical Mirror in (Poh, McDuff, & Picard, 2011) detects user's heart rate in real time without using contact sensors. The Non Contact Health Monitoring System (Yang, Zhao, & Zhang, 2012) analyses facial expressions, posture and voice changes.

As for other monitoring devices, the Biomotion sensor (De Chazal, et al., 2011) uses low-power radiofrequency wave reflection to monitor user's movements and breathing during sleep. The system in (Chekmenev, Farag, & Essock, 2006) allows the monitoring of blood pressure by means of thermal imaging of face and neck.

Despite this long list of monitoring platforms, an unobtrusive system capable of monitoring multiple individuals day after day, and evaluating a comprehensive list of psycho-physical parameters related to cardio-metabolic risk, does not exist yet. The development of a beyond-the-state-of-the-art device requires bending advances in several fields, from unobtrusive tele-monitoring to wellness estimation, from decision support systems to user engagement strategies.

3. Touch-less data acquisition

The Wize Mirror features an advanced sensing framework for unobtrusive acquisition of videos, images, and 3D scans of individuals standing in front of the mirror. The imaging devices include a visible camera, a multispectral imaging system, and 3D optical sensors. The platform also includes a device for breath analysis (Figure 2).

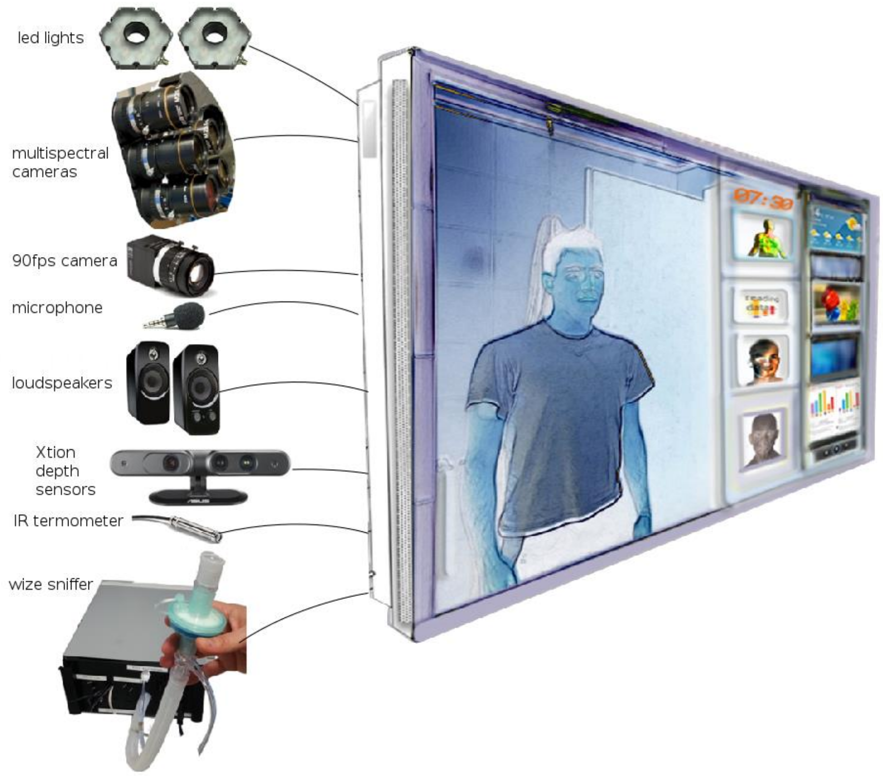

Figure 2: The multisensory Wize Mirror.

Visible cameras are used for emotional analysis: video sequences are captured to look for signs of stress, fatigue and anxiety. The prototype under development includes a high-resolution camera at a maximum frame-rate of 90 fps.

The multispectral imaging system serves to analyze the skin tissue and the microcirculation. The main challenge is the set-up of a system of reasonable cost and sufficient accuracy. In its current configuration, the system comprises five compact cameras with filters at selected wavelengths (monochrome 3.2 MP USB 3.0 CMOS cameras) controlled by a computer, computer controllable LED light sources (white and UV), and a remote skin heater for thermal stimulation.

A scanner for 3D face reconstruction supports the extraction of bio-morphometric descriptors of face shape changes, due for example to weight gain and swelling. The use of laser-scanners or similar solutions is not practicable as these scanners are too big and expensive for the Wize Mirror. Therefore, an inexpensive, compact scanner is under development, based on two Xtion depth sensors and the visible camera mentioned above.

The breath analysis device, called the Wize Sniffer, captures breath samples to detect the presence of molecules related to noxious habits and cardio-metabolic risk. It features a 600ml store chamber with an array of commercial semiconductor gas sensors, and a hardware platform with a micro-controller board. The breath gases reach the store chamber through a corrugated tube.

To facilitate an unobtrusive data acquisition and synchronization of the different sensors, the WM can also perform user detection, user recognition, 3D head pose tracking, and face image segmentation.

Having an unobtrusive, lifestyle-compatible acquisition procedure is essential to drive initial adoption and mid-term utilization. Indeed, the less interaction and habits change the acquisition procedure requires, the more likely users will keep using the mirror. The Wize Mirror acquires data of users just standing in front of it, possibly as a part of their daily routine. In the current implementation, most of the acquisitions require a very short time, from just a couple of seconds for 3D reconstruction, to one minute for emotion recognition. Moreover, acquisitions are done in parallel. These facts, along with the need of short processing times impose severe computational requirements that cannot be addressed relying on a single processor. To ensure the needed computational power still maintaining the flexibility of general purposes architectures, we resorted to adopt a multiprocessor modular architecture where a main processor controls the operation of a set of slave processors each being dedicated to specific acquisition and processing tasks. The main processor controls the overall processing flow, hosts the user interface and the database with users' diaries. Three slave processors are responsible of face recognition and tracking, multispectral imaging, and emotional analysis of face signs, respectively. Only some analysis involving multispectral imaging require up to seven minutes, in the current implementation; in this case, our strategy is to make users aware of the overall utility of the analysis, and of how it will help them avoiding longer and potentially more invasive analysis.

Fundamental to the user experience is also the design of the interface, which is designed to be intuitive and familiar for a seamless experience. The interface is also responsible for the presentation of results to users (about this point see Section 5).

4. Multimodal data processing

The multimodal data acquired by the sensors are processed to extract reliable computational measures correlated with clinical risk factors.

The clinical partners in SEMEOTICONS produced a *semeiotic model* of the face for cardio-metabolic risk (Coppini, Favilla, Gastaldelli, Colantonio, & Marraccini, 2014), defining cardio-metabolic risk factors and the set of parameters that the Wize Mirror can produce as surrogate risk indicators. Table 1 shows the risk factors (which include physical, psychological, and life-style parameters), their translation into computational face descriptors, and the data source they are extracted from. The challenge is the development of algorithms that measure the parameters above with reasonable accuracy, yet in quasi real time, and robust against environmental conditions in the utilization scenarios.

More in detail, the multispectral imaging of facial skin helps assessing endothelial function, skin cholesterol concentration, and AGE accumulation in specific regions of interest of the face. The idea of analyzing the skin composition and function remotely is innovative. The first results are promising, as they demonstrate a correlation between parameters measured on the images and physiological parameters (Strömberg, Karlsson, Fredriksson, Nyström, & Larsson, 2014) (Ewelof, Salerud, Stromberg, & Larsson, 2015). The main criticality is with the remote heating of facial skin at a controlled temperature.

The analysis of high-resolution, high-frame rate videos supports emotional analysis for the detection and monitoring of adverse psychological states (anxiety, stress, fatigue). Facial expressions are the preeminent channel for non-verbal communication of human emotions. Whereas several studies have been published, using facial expressions in the recognition of the six basic emotions (anger, disgust, fear, happiness, sadness, and surprise), fewer studies exists on stress, anxiety and fatigue recognition, despite their frequency, intensity, and debilitating effects (Chiarugi, et al., 2014).

The research in SEMEOTICONS started with a deep investigation on facial signs of anxiety, stress, and fatigue, which resulted in a list of parameters to be detected: they are mainly related to movements of the head, the eyebrows, the eyelids, and the mouth.

RISK FACTOR	MEASURED PARAMETER	DATA SOURCE
Endothelial dysfunction	Blood volume Skin perfusion and thermal vasodilation	Multispectral imaging
Dyslipidemia	Estimate of skin cholesterol accumulation	Multispectral imaging
	Xantelasmas: presence and size	Standard color imaging/ multispectral imaging
	Arcus cornealis: measure at the iris boundary	Standard color imaging/ multispectral imaging
Glucose metabolism abnormalities	Skin AGE concentration	Multispectral imaging
Smoke	Exhaled gas: *CO* *H* *Ethanol*	Breath analysis (Wize Sniffer)
Alcohol intake	Exhaled gas *Ethanol*	
Overweight/Obesity	Face geometry	3D face reconstruction
Neurovegetative unbalance	HR HR variability	Skin Colorimetric changes (high speed camera) Head motion (high speed camera)
	Respiratory Rate	
Anemia/Plethora/Jaundice	Face colorimetry	Standard Color imaging / Multispectral imaging
Stress, anxiety, fatigue	Descriptors of: *head movement* *eyebrow movement* *lip movement* *yawns* *eyelid movement* *gaze distribution* *blushing* *reddening* *pallor*	Color imaging

Table 1: Cardio-metabolic risk factors and related parameters from the Wize Mirror

The detection algorithms were developed and showed promising results concerning the accuracy of detection and measurements of parameters. The main challenge from now on will be the definition of an integrated model for recognizing the emotional state from individual signs.

Concerning bio-morphological 3D face analysis, the focus is on quantifying patterns in face shape variation, and especially changes due to weight gain, overweight and obesity being major cardio-metabolic risk factors. The signs must be computed on a 3D face model reconstructed from range data acquired by the 3D scanner. Though several authors studied the application of anthropometric analysis through 3D body scanner to classify normal weight, overweight, and obese individuals, most of the methods in the literature are based on measurements taken on the 3D scanned *body* of subjects, rather than on their *face*, as foreseen in SEMEOTICONS' Wize Mirror. Moreover, most of the techniques that consider faces are based on measures computed on 2D images rather than on 3D models. This makes our goal a challenging one. Two strategies are under investigation. On the one hand, we are taking advantage of modern 3D shape analysis techniques to define descriptors and similarity measures for the quantitative investigation of changes in the configuration of anthropometric face landmarks (Giorgi, Pascali, Raccichini, Salvetti, & Colantonio, 2015). On the other hand, since locating landmarks with optimal accuracy could be difficult, especially for poorly geometrically characterized landmarks, we are also developing landmark-independent techniques, based on the computation of shape features such as surface curvature and section lengths.

The analysis of data from the gas sensors aims to calculate in real-time the percentage of different molecules in the exhaled breath. The molecules are those related to noxious habits for cardio-metabolic risk, like alcohol intake and smoking (Carbon Monoxide, Hydrogen, Ethanol, Oxygen, Carbon Dioxide, Ammonia). The main difficulty is the cross-sensitivity of the gas sensors. The foreseen solution is the development of ad-hoc sensors using polyaniline nano-fibers as sensing element. Nano-fibers are expected to increase the sensor sensitivity, thanks to their high surface/volume ratio. The use of nano-fibers will also support the detection of other compounds such as Nitric Monoxide (related to endothelial function) and Nicotine.

As the sensor measurements are collected and processed day-by-day, the set of computational descriptors of face signs are gathered into a Virtual Individual Model (VIM). Basically, the VIM collects in a digital and machine understandable form all the data describing users and their cardio-metabolic risk. The VIM is made up of a huge amount of multimodal data, therefore it is not suited for communicating with the user. SEMEOTICONS' solution is exploiting the VIM to synthesize a Wellness Index (WI) for the sake of the user, as described in the next section.

5. Data fusion and synthesis

The WI is a composite measure of the health status of an individual, which is traced over time and reported in a health diary for the user to consult.

There are many definitions of wellbeing indices in the literature, though there is no standard measurement of the health status of individuals or population groups. The health status may be measured either by an observer (e.g., a physician), or by asking people to report their health perception (about physical functioning, emotional well-being, pain or discomfort, and overall perception of health). To the best of our knowledge, an index combining both objective components and subjective impressions has not been developed yet.

The first attempts of giving a simple measure of health status date back to the 1940s (Karnofsky & Burchenal, 1949) (Steinbrocker, Traeger, & Battman, 1949). More recent health-related quality of life utility scores are (Torrance, Boyle, & Howood, Application of Multi-Attribute Utility Theory to Measure Social Preferences for Health Status, 1982) (Torrance, et al., 1996) (Horsman, Furlong, Feeny, & Torrance, 2003) (Health Related quality of Life, 2014). A simple index measuring the health status, in a scale from 7 to 21 and based on seven factors, was presented in (Lee, Rampersaud, & Brown, 2008); the study investigated the relationship between the index and nutrient intakes, lifestyle and demographics, via regression methods.

The majority of the measures used up to now to assess the health status require people to fill out lengthy questionnaires, many of which were developed for specific health problems (Fries, Spitz, & Young, 1982) (Tughwell, et al., 1987) or meant for a subjective evaluation of the health status of respondents. Moreover, most of the wellness indices in the literature have been designed to be used for statistics about large communities or states. As a consequence, our research for a Wellness Index based on automatically acquired biophysical individual data is quite innovative, in both concept and method.

In developing our WI, we are addressing two main challenges. The first challenge is the construction of a proper wellbeing space where the index lives, and the analysis of trajectories in space which characterize the health status over time (Section 5.1). The second challenge is the visual representation of the WI: as the hard data may be difficult for many users to absorb, the index visualization has to be immediately intuitive and familiar, also possibly subject-dependent (Section 5.2).

5.1. Wellbeing space and Wellness Index

The values of the parameters monitored by the Wize Mirror can be seen as the components of a state vector in a multidimensional space, the *wellbeing space*. Following our semeiotic model (Coppini, Favilla, Gastaldelli, Colantonio, & Marraccini, 2014), we decided to divide the wellbeing space into three separate wellbeing sub-spaces: *physical*, *emotional*, and *lifestyle* wellbeing space. This reduces the dimensionality of the problem. More importantly, since the three spaces refer to the various facets of an individual's status, they introduce a semantic characterization of data that is well suited for user interaction and guidance.

The wellbeing space(s) can be seen as phase space(s), where the state of an individual is a point in the space, and the temporal evolution is given by trajectories in the space. The starting point of a trajectory is the individual baseline condition, that is, the individual risk according to the medical and psychological characterization at the beginning of self-monitoring (see also Section 6 about profiling). The exploitation of clinical knowledge provides a mechanism to label points in the wellbeing space and attribute them a meaning in term of cardio-metabolic risk. Consequently, we have an interpretative key to establish how the user risk is varying during self-monitoring.

Machine learning methods, including nonlinear mapping techniques, are under investigation to implement the above processes. The idea is to compute the WI as a multidimensional entity capturing both the overall wellbeing status and the details of the many aspects, both physical and psychosocial, that concur to an individual health status. In this respect, a major challenge is to ensure the WI is responsive to real differences and changes in the health status, while allowing a certain degree of flexibility to deal with possible limitations related to data availability (the user will be allowed to skip some measurements or postpone longer tests) and quality (e.g. due to environmental interferences).

5.2. Visualization of the Wellness Index

The Wellness Index is the main communication challenge with users: its purpose is to make users understand at a glance their current status, and whether things are going better or worse. Therefore, the visual representation of the WI has to be tailored on the subject's peculiarities, preferences and attitudes (cf. Section 6 about profiling). Though no definite decisions have been taken at the current project state, different solutions are under study. According to the literacy and numeracy of the subject (i.e., her ability to understand messages with figures and scientific terms), the presentation of the Wellness Index could vary from a very simple and friendly visualization – like a comic – to a more scientific one – like a sort of augmented photorealistic visualization of the subject.

Another challenge is the representation of changes in the wellness status over time. The solutions under study include image sequences with exaggerated or false color to highlight the observed changes, and image animation or morphing sequences that condense in a few seconds changes occurred over time.

The communication with users will also benefit from the creation of an individual *wellbeing diary*, which documents the wellbeing trend over time. The diary proactively helps people to identify evolving physiological conditions: it can help determine when a symptom or change manifested itself and how it changed over time or after lifestyle changes, thus helping people relate their wellbeing with their lifestyle. The diary can be supplied as an electronic document, and shared with health professionals, in accordance with the individual privacy settings.

6. User profiling

The Wize Mirror is designed to ensure a comprehensive and long-lasting approach to lifestyle changes. The main requirement is that the support is strongly tailored. Tailored information has been proved to be effective in giving consumer information and is generally preferred by patients. Tailoring means to reach one specific person based on characteristics that are unique to that person, related to the outcome of interest and derived from an individual assessment. Therefore, *profiling* the individual user is essential to tailoring.

SEMEOTICONS profile is twofold, as we define a baseline profile and an action profile. The *baseline profile* is a snapshot of the page-zero health status of users, that is, when they start using the Mirror: it includes all the information pertaining to one’s health behaviors and clinical risk factors for cardio-metabolic disease (Section 6.1). The *action profile* identifies users’ characteristics, attitudes, habits and preferences; it serves to provide customized suggestions and coaching messages, so as to engage the individual to undertake and sustain behavior change, working out the barriers (Section 6.2).

6.1. **Baseline profile**

According to the semeiotic model of cardio-metabolic risk, medical doctors and psychologist made the hypothesis that the baseline profile was a combination of both *objective* parameters. That is, clinical findings, and *subjective*, psychosocial parameters, derived from questions asked to users. The clinical variables include validated cardio-metabolic risk scores, namely Heart SCORE, HOMA Index, Fatty Liver Index, and FINDRISC (Coppini G., 2014). The subjective parameters were selected from a series of well-assessed questionnaires and tests. They include the physical components score and the mental components score from the SF12 generic quality of life instrument, which asks subjects their personal views about their health, and the PSS, which measures how unpredictable, uncontrollable, and overloaded respondents find their lives. The PSS predicts both objective biological markers of stress and increased risk for disease for individuals which feel highly stressed.

It was assumed that the variables above could define different risk profiles in a population. A preliminary test was carried out on SEMEOTICONS reference dataset (cf. Section 8.1). Both objective and subjective variables were used to profile the dataset population, then a clustering analysis was performed. Three well-distinguished clusters corresponding to three approximately increasing levels of cardio-metabolic risk could be detected. The groups were homogeneous in terms on size, but they did show differences in their content for both objective clinical variables and subjective scores (Table 2). This fact confirmed the soundness of the clinical hypothesis.

Cluster	Subject number	HEART SCORE	HOMA INDEX	FATTY LIVER INDEX	FINDRISC	SF-12 PCS	SF-12 MCS	PERCEIVED STRESS
1	8	0,46	1,41	20,78	5,63	52,71	47,33	16,13
2	6	2,89	2,13	45,28	7,33	53,60	54,62	10,17
3	9	0,45	3,90	66,17	8,11	48,64	57,18	8,78

Table 2 Clusters observed in the reference dataset population when subjects are characterized by objective (cardio-metabolic risk scores Heart Score, Home index, Fatty liver Index, FINDRISC) and subjective (Physical Component Summary SF-12 PCS and Mental Component Summary SF-12 MCS from the SF12 questionnaire, and Perceived Stress Scale questionnaire[2]) parameters.

[2] For more information about questionnaires, please see: http://goo.gl/IuKoqT for SF12, and http://goo.gl/I7Mjpm for the Perceived Stress Scale

Whereas the subjective variables can be accessed by administering questionnaires, the four cardio-metabolic risk scores will not be available directly in the Wize Mirror, because they need blood samples. Therefore, we selected a minimum set of variables, which can be collected by the Wize Mirror and are able to reproduce the same assignment to risk clusters as the theoretical profile. The variables are summarized in Table 3, and include: age, which the user can input by just typing in; weight, height and waist circumference, which can be approximated via morphological analysis on the reconstructed 3D face; hearth rate variability, which is measurable through colorimetric analysis of images; Advanced Glycation Endproducts and blood cholesterol which are being studied via multispectral imaging; and perceived stress and mental health, which can be estimated via the emotional analysis on video sequences.

Parameters	Data source
Age	Questionnaires
Weight Height Waist Circumference	Questionnaires & Morphological analysis
Heart rate variability	Colorimetry
Skin AGE Hemoglobin Skin cholesterol	Multispectral analysis
Perceived Stress SF12 PCS SF12 MCS	Questionnaires & emotional analysis

Table 3: User profile parameters in the Wize Mirror.

6.2. Action profile

The definition of the action profile presents two main issues. The first is the identification of *targets*, that is, of objectives of lifestyle intervention. The second issue is the study of *modulators*, which pertain to the way the intervention is managed.

We identified four potential target areas, related to lifestyle: tobacco use, alcohol consumption, physical training and dietary habits. For an individual user, targets will be identified via questionnaires and specific apps for gathering data from the users, but also indirectly via the sensors themselves, since the Wize Sniffer can identify noxious habits such as drinking and smoking.

The *modulators* describe user characteristics, attitudes, habits, psychological and cultural traits. Their study is crucial to make any lifestyle intervention effective and sustainable: their role is fundamental to ensure that the suggestions are well-received by the users, therefore more likely to be implemented. It is planned to define modulators by means of questionnaires which include: motivation to change; literacy (i.e., the ability of understanding data and messages); interior fracture and auto-efficacy (i.e., the gap between one's willingness to change and one's confidence in the possibility of success). Table 4 lists modulators and their related traits.

Modulator	Trait
Interior fracture & Auto-efficacy for nutrition	Motivation to change
Interior fracture & Auto-efficacy for exercise	Motivation to change
Literacy	Culture
Perceives stress	Affectivity

Table 4: Modulators and related traits.

7. Personalized guidance

The final goal of the Wize Mirror is to make people active actors in their health care. Decision support systems are gaining increasing attention as a solution to interpret data collected by tele-monitoring systems and to stimulate people changing behavior (Oinas-Kukkonen, 2010). Customized remote systems that monitor and assist users are usually called Personalized Guidance Systems (PGS) or Personalized Support Systems (PSS). Often, such systems are internet-, mobile-, or game-based (Krebs, Prochaska, & Rossi, 2010) (Honka, Kaipainen, Hietawitzla, & Saranummi, 2011) (Krishna, Boren, & Balas, 2009) (Riley, et al., 2011) (Kato, 2010) (Minutolo, Esposito, & De Pietro, 2012) (Pawar, Jones, Van Beijnum, & Hermens, 2012) (Kumar, et al., 2013). PGS have been proposed for disease management (Gibbons, et al., 2011) (Fjeldsoe, Marshall, & Miller, 2009), psychotherapeutic use (Andrews, Cuijpers, Craske, McEvoy, & Titov, 2010) (Barak, Hen, Boniel-Nissim, & Shapira, 2008) (Mitchell, Vella-Brodrick, & Klein, 2010), and health behavior change (Webb, Joseph, Yardley, & Michie, 2010) (Cugelman, Thelwall,

& Dawes, 2011). At any rate, these solutions have shown their limits once the intervention is concluded, thus suggesting the need for innovative techniques to help participants keep their good habits over time.

The Personalized Guidance System (PGS) of the Wize Mirror is under development. Techniques used in recommender systems are under investigation. A proactive decision support system is being studied, exploiting both computational models and procedural knowledge, formalized through ontologies and open standards provided by the Semantic Web community. The PGS will provide customized and personalized suggestions and messages, in accordance with the Wellness Index and its variation over time; the user's profile; and contextual information about the user's life circumstances. A lightweight inference engine is being designed to reason on the longitudinal record of the WI and watch for both subtle and dramatic changes in the index that can be indicative of physiologically significant changes related to cardio-metabolic risk. If the engine detects a potentially meaningful trend for a particular individual, then the system will notify the individual with a text or a visual clue displayed by the Graphical User Interface. The notification can have varying degrees of urgency, ranging from mild recommendations about lifestyle to the suggestion of contacting the general practitioner for a close examination. In case of a positive trend, the system could hearten the users to maintain their wellbeing status, and highlight how their efforts in changing their lifestyle resulted in the improvement of their wellbeing status. To promote health education, the PGS will also provide users with ad-hoc information and educational messages. Suggestions and coaching messages will be tailored to users' characteristics so as to influence information intake and user engagement, and maximize user acceptance.

As observed in (Varshney, 2014), PGS can be enhanced by context-awareness and processing. Context awareness and processing imply considering the rich context of subjects, which can be sensed, derived or explicitly provided. In the Wize Mirror, part of the context is taken into account in the user profile, part is sensed, and part is collected via questionnaires. Also, sensor and explicit information can be integrated for a better modelling of the context. For example, the Wize Mirror can administer personalized questionnaires concurrently with the detection of specific signs in the acquired data (e.g., signs of tiredness) or in correspondence of circumstances and situations the user can go through (e.g. emotional periods, stress at work). Taking context into account serves to reduce the number of alerts; for example, heavy smokers who are not willing to stop smoking should only be warned about relative excesses in their harmful habit, otherwise they will abandon the platform.

(Varshney, 2014) also includes improved presentation of information as a fundamental enhancement of PGS, since the presentation, visualization and linguistic style of messages are important moderators in communication modalities. Besides taking care of the visualization of the Wellness Index (as discussed in Section 5), the Wize Mirror will also personalize the style of suggestions, possibly drawing inspiration from game design strategies. Also, we plan to include the possibility for the user to act directly on the amount and type of messages to receive, that is, enable/disable coaching messages, or tune their frequency. For example, this would prevent the PGS keeping giving the subjects redundant suggestions that they are not going to follow and that could bias the user experience.

8. System validation

The Wize Mirror is being realized in a cycle made of development, test and validation phases. The cycle ends with a final verification of the ability of the system to estimate cardio-metabolic risk. The validation is based on a study population consisting of two groups: the *Reference Dataset* (Section 8.1), for the intermediate validation of individual algorithms, and the *Clinical Validation Dataset* (Section 8.2), for the study of measurements reproducibility and final clinical validation. The study population includes healthy volunteers, wishing to assess their cardio-metabolic risk, and possibly aiming to act on their lifestyle to lower the risk. The eligibility criteria for inclusion include age in-between 25 and 60 years, no overt disease, and written informed consent. Exclusion criteria include history of overt disease, pregnancy or breast-feeding, claustrophobia, chronic medical treatment.

8.1. Reference dataset

The Reference Dataset was collected in May 2014 in Pisa, at the CNR premises. It includes 23 volunteers who underwent blood sample analysis and a comprehensive medical examination, including the assessment of anthropometric measurements (height, weight, waist and hip circumference); vital signs (hearth rate, respiratory rate, blood pressure); body composition (lean and fat mass) and energy expenditure; oxygen saturation and vasodilatation; and exhaled gas sampling. The volunteers were also asked to fill in validated psychological, knowledge and nutrition questionnaires, which measure psychological wellbeing; depression, anxiety, hostility; quality of life; lifestyle habits; motivation to change; health literacy and numeracy.

After the medical examination, the volunteers underwent an instrumental acquisition session, which served to collect:

- face still images and videos, both in visible light and infrared band, along with other reference signals (e.g., ECG) in a laboratory setup with controlled light conditions;
- multispectral images before and after thermal stimulation by heating panels to evoke vasodilation in the face, in a room with controlled temperature conditions;
- 3D reconstructions of the subjects;
- samples of exhaled gas.

The reference dataset is being used for the intermediate validation of the algorithms developed during the project, by allowing the comparison of the computational descriptors with routine clinical investigations and measurements. Moreover, the reference dataset supported the definition and test of the baseline and action profiles. To support these tasks, the subjects were selected so as to provide data in both normal and advanced cardio-metabolic risk states.

8.2. Clinical validation dataset

The Clinical validation dataset collection is foreseen in 2016. It will include 6 subjects for measurements of reproducibility, and 60 subjects for the clinical, prospective validation. The clinical validation will be carried out at three different clinical sites, in Italy and France

The measurements reproducibility serves to assess both the accuracy of measurements by the Wize Mirror, and the influence of environmental conditions such as temperature, light, post-prandial period.

The prospective validation will check whether changes in body composition and metabolism are reflected by changes in the parameters measured by the Wize Mirror. The subjects enrolled will be followed up for three months, after tailored medical prescription of lifestyle changes. The changes in the Wize Mirror measurements obtained at baseline and end of study will be correlated with changes in well-assessed cardio-metabolic risk scores, anthropometric measures, quality-of-life and wellbeing questionnaires, standard biochemistry and specific tests.

Finally, the feedback of clinicians will serve to evaluate the significance of the Wellness Index.

9. Discussion and conclusions

We presented the Wize Mirror, a platform for the estimation of cardio-metabolic risk from sensed facial data and the delivery of personalized user guidance towards lifestyle change. The platform is under development in the EU FP7 Project SEMEOTICONS.

Building the Wize Mirror implies responding to several challenges: *technological*, *scientific,* and *clinical* challenges.

The *technological* challenge is the development of a non-intrusive platform, seamlessly integrated in the daily-life environment. The focus is on touch-less data acquisition, temporal and spatial data synchronization, (quasi) real-time processing of multimodal data, and integration of different components (acquisition, processing, user interaction) in a single smart object. Additional requirements are low cost and acquisition accuracy compatible with clinical applications. In this respect, we believe the first Wize Mirror prototype meets these requirements, though it should be further engineered to reach the market.

The *scientific* challenge implies defining and integrating intelligent methods for translating face signs into repeatable, accurate, efficient computational measures. In this respect, we are half way through: reliable methods have been implemented that look for specific face signs, which now need to be integrated so as to optimize quantity and quality of information.

The *clinical* challenge is the development of solutions that are expected to find application into real settings, therefore have to be validated against traditional diagnostic examinations. In this respect, we have set up a clinical validation protocol and designed pilot experiments, which will take place in 2016 at different premises. In the meanwhile, mid-term validations of single components are being done on a reference dataset collected on volunteer subjects.

Last but not least, the major challenge is *impact*: facilitating people’s personal progress and helping them gaining control over their health is the key to improve health, user satisfaction and long-term engagement.

Acknowledgements

This work is partially supported by the EU FP7-ICT-2013.5.1-611516 Project SEMEOTICONS, started in November 2013.

The authors would like to thank all the partners of the Project Consortium. The authors would also like to thank Michela Carlino, Francesca Pardini and Elena Rossi from the Institute of Information Science and Technologies, National Research Council of Italy, and Prof. Massimo Ferri from the University of Bologna, for their precious help.

References

Andrews, G., Cuijpers, P., Craske, M. G., McEvoy, P., & Titov, N. (2010). Computer therapy for the anxiety and depressive disorders is effective, acceptable and practical health care: A meta-analysis. *PLoS ONE*.

Barak, A., Hen, L., Boniel-Nissim, M., & Shapira, N. A. (2008). A comprehensive review and a meta-analysis of the effectiveness of internet-based psychotherapeutic interventions. *Journal of Technology in Human Services*, pp. 109-160.

Chekmenev, S. Y., Farag, A. A., & Essock, E. A. (2006). Multiresolution approach for non-contact measurements of arterial pulse using thermal imaging. *Conference on Computer Vision and Pattern Recognition Workshop*, (pp. 129-137).

Chiarugi, F., Iatraki, G., Christinaki, E., Manousos, D., Giannakakis, G., Pediaditis, M., . . . Tsiknakis, M. N. (2014). Facial signs and psycho-physical status estimation for well-being assessment. *7th IEEE International Conference on Health Informatics (BIOSTEC 2014)*, (pp. 555-562). Angers, France.

Coppini, G., Favilla, R., Gastaldelli, M., Colantonio, S., & Marraccini, P. (2014). Moving Medical Semeiotics to the Digital Realm. SEMEOTICONS approach to Face Signs of Cardiometabolic Risk. *SUPERHEAL– HEALTHINF. INSTICC*, (pp. 606-613).

Cugelman, B., Thelwall, M., & Dawes, P. (2011). Online interventions for social marketing health behavior change campaigns: A meta-analysis of psychological architectures and adherence factors. *Journal of Medical Internet Research*.

De Chazal, P., Fox, N., O'Hare, E., Heneghan, C., A, Z., Boyle, P., & Smith, S. (2011). Sleep/wake measurement using a non-contact biomotion sensor. *Journal of Sleep Research*, pp. 356-366.

Ewelof, M., Salerud, E. G., Stromberg, T., & Larsson, M. (2015). Estimating skin blood saturation by selecting a subset of hyperspectral imaging data. *Imaging, Manipulation, and Analysis of Biomolecules, Cells, and Tissues XIII.*

Fjeldsoe, B. S., Marshall, A. L., & Miller, Y. D. (2009). Behavior Change Interventions Delivered by Mobile Telephone Short-Message Service. *American Journal of Preventive Medicine*, pp. 165-173.

Fries, J., Spitz, P., & Young, D. (1982). The Dimensions of Health Outcome, the Health Assessment Questionnaire: Disability and Pain Scales. *Journal of Rheumatology*, pp. 789-793.

Gibbons, M. C., Wilson, R. F., Samal, L., Lehmann, C. U., Dickersin, K., Lehmann, H. P., . . . Bass, E. B. (2011). Consumer health informatics: Results of a systematic evidence review and evidence based recommendations. *Translational Behavioral Medicine*, pp. 72-82.

Giorgi, D., Pascali, M. A., Raccichini, G., Salvetti, O., & Colantonio, S. (2015). Morphological analysis of 3D faces for weight gain assessment. *To appear in EG 3DOR 2015: Eurographics Workshop on 3D Object Retrieval.*

Health Related quality of Life. (2014, 05 26). Retrieved from Centers for Disease Control and prevention: http://www.cdc.gov/hrqol/

Honka, A., Kaipainen, K., Hietawitzla, H., & Saranummi, N. (2011). Rethinking Health: ICT-Enabled Services to Empower People to Manage Their Health. *IEEE Reviews in Biomed. Engineer.*, pp. 119-139.

Horsman, J., Furlong, W., Feeny, D., & Torrance, G. (2003). The Health Utilities Index. Concepts, Measurement Properties and Applications. *Healthy and Quality of Lifes Outcomes*, 1-54.

Hossain, M. A., Atrey, P. K., & Saddik, A. E. (2007). Smart mirror for ambient home environment. *3rd International Conference on Intelligent Environments (IE'07)*, (pp. 589-596). Ulm, Germany.

Karnofsky, D., & Burchenal, J. (1949). The Clinical Evaluation of Chemotherapic Agents in Cancer. *Evaluation of chemotherapeutic agents*, 199-205.

Kato, P. M. (2010). Video Games in Health Care: Closing the Gap. *Review of General Psychology*, pp. 113-121.

Krebs, P., Prochaska, J. O., & Rossi, J. S. (2010). Defining what works in tailoring: A meta-analysis of computer-tailored interventions for health behavior change. *Preventive Medicine*, pp. 214–221.

Krishna, S., Boren, S. A., & Balas, E. A. (2009). Healthcare via cell phones: A systematic review. *Telemedicine and e-Health*, pp. 231-240.

Kumar, S., Nilsen, W. J., Abernethy, A., Atienza, A., Patrick, K., Pavel, M., . . . Swendeman, D. (2013). Mobile health technology evaluation: The mHealth evidence workshop. *American Journal of Preventive Medicine*, pp. 228-236.

Ledger, D., & McCaffrey, D. (2014). Inside Wearables: How the science of human behaviour change offers the secret to long-term engagement. *Endeavour Partners: Cambridge, MA, USA.*

Lee, J. Y., Rampersaud, G. S., & Brown, M. G. (2008). An Index to Measure Health Status. *Florida Department of Citrus*.

Mathers, C., Fat, D. M., & Boerma, J. T. (2008). The global burden of disease: 2004 update. *World Health Organization*.

Minutolo, A., Esposito, M., & De Pietro, G. (2012). A pattern-based knowledge editing system for building clinical Decision Support Systems. *Knowledge-Based Systems*, pp. 120-131.

Mitchell, J., Vella-Brodrick, D., & Klein, B. (2010). Positive psychology and the internet: A mental health opportunity. *Sensoria: A Journal of Mind, Brain & Culture*, pp. 30-41.

Oinas-Kukkonen, H. (2010). Behavior change support systems: A research model and agenda. *Lecture Notes in Computer Science*, pp. 4–14.

Pawar, P., Jones, V., Van Beijnum, B. J., & Hermens, H. (2012). A framework for the comparison of mobile patient monitoring systems. *Journal of Biomedical Informatics*, pp. 544-556.

Poh, M. Z., McDuff, D., & Picard, R. (2011). A medical mirror for non-contact health monitoring. *ACM SIGGRAPH Emerging Technologies*.

Riley, W. T., Rivera, D. E., Atienza, A. A., Nilsen, W., Allison, S. M., & Mermelstein, R. (2011). Health behavior models in the age of mobile interventions: Are our theories up to the task? *Translational Behavioral Medicine*, pp. 53-71.

Segar, M., Eccles, J., & Richardson, C. (2011). Rebranding exercise: closing the gap between values and behaviour. *International Journal of Behavioural Nutrition and Physical Activity 8*.

SEMEOTICONS FP7 European Project. (2013). Retrieved from http://www.semeoticons.eu/

Steinbrocker, O., Traeger, C., & Battman, R. (1949). Therapeutic Criteria in Rheumatoid Arthritis. *J. Am. Med. Assoc.*, 765-770.

Strömberg, T., Karlsson, H., Fredriksson, I., Nyström, F., & Larsson, M. (2014). Microcirculation assessment using an individualized model for diffuse reflectance spectroscopy and conventional laser Doppler flowmetry. *Journal of Biomedical Optics*.

Torrance, G. W., Boyle, H. M., & Howood, S. P. (1982). Application of Multi-Attribute Utility Theory to Measure Social Preferences for Health Status. *Operational Research*, 1043-1069.

Torrance, G. W., Feeny, D. H., Furlon, W. J., Barr, R. D., Zhang, Y., & Wang, Q. (1996). Multiattribute Utility Function for a Comprehensive Health Status Classification System Health Utilities Index Mark 2. *Medical Care*, 702-722.

Tughwell, P., Bombardier, C., Buchanan, W., Goldsmith, C., Grace, E., & Hanna, B. (1987). The MACTAR Patient Preference Disability Questionnaier: an Individualized Functional Priority Approach for Assessing Improvement in Physical Disability in Clinical Trial. *J Rheumatol*, pp. 446-51.

Varshney, U. (2014). A model for improving quality of decisions in mobile health. *Decision Support Systems*, pp. 66-77.

Webb, T. L., Joseph, J., Yardley, L., & Michie, S. (2010). Using the internet to promote health behavior change: a systematic review and meta-analysis of the impact of theoretical basis, use of behavior change techniques, and mode of delivery on efficacy. *Journal of medical Internet research*, p. e4.

Yang, N., Zhao, X., & Zhang, H. (2012). A non-contact health monitoring model based on the Internet of things. *Eighth International Conference on Natural Computation (ICNC)*, (pp. 506-510).