INTRODUCTION

NeuroIS uses neurotechnology tools such as galvanic skin response (GSR) and Electroencephalogram (EEG) for research in Information Systems (IS) (Dimoka et al 2010). High brainwave frequencies can be linked to human anxiety and neurotechnology can be used to measure these frequencies (Valverde 2015). Past research showed that computer anxiety influences how users perceive ease of use of a learning management system (Saade & Kira 2009). Although computer anxiety has been used successfully to evaluate the usability of learning management systems, the main data collection mechanisms proposed for its evaluation has been questionnaires. Questionnaires suffer from possible problems such inadequate to understand some forms of information such as emotions, lacks validity, possible lack of thought and honesty in the responses (Ackroyd & Hughes 1981).

Learning management systems (LMS) are designed to facilitate the learning process and have been used in recent years extensively in Business Schools (Condon & Valverde 2014). However, it has been reported that as many as fifty percent of adults, including first-year University students, have some sort of computer-related phobia and previous studies have shown that computer anxiety influences how users perceive ease of use and computer self-efficacy an information system (Saade & Kira 2009). Much effort has been devoted to creating user friendly interfaces in resent years (Venkatesh & Morris, 2000) in particular with the use of NeuroIS (Dimoka et al 2010). Motivated by previous computer-anxiety studies and the lack of studies that incorporate data collection and analytical techniques using neuroscience that can better capture the perception of computer users for the purpose of usability evaluations, the objective of this study is to provide an understanding on how to use neuroscience techniques for data collection of the use of a LMS and provide the analytical tools that can process computer anxiety measurements for usability testing.

Quantum based approaches to consciousness have been very popular in the last years. Some of the approaches include the Quantum emission probabilities (Eccles, 1986), where the two-way mental-neural interaction (with the electric/magnetic fields as a link) is supposed to be realized in a manner analogous to probability fields in quantum Mechanics, the Photon-corticon interaction (Jibu & Yasue, 1995), where consciousness was reduced to the creation and annihilation dynamics of photons (as quanta of an electromagnetic field) and corticons (as quanta of a rotational field of water dipoles) and the quantum model reduction in microtubules (Hameroff, 1998;Penrose & Hameroff, 1995), where quantum coherence occurs by exciting quasicrystalline water molecules as dipoles buried in microtubules.

The objective of the chapter is to propose an architecture based on a NeuroIS that collects data by using neurotechnology from users and then use the collected data to perform analytics by using the quantum consciousness model proposed by Pop-Jordanov & Pop-Jordanova (2010) for computer anxiety measurements that can be used for the usability testing of a learning management system. This model proposes a theoretical approach to explain the characteristic empirical interdependence between the states of arousal (representing the level of consciousness) and EEG activity.

As a NeuroIS does not use surveys for data collection and instead uses direct brain wave measurements from the user's brain, the proposed approach contributes to the literature by incorporating data collection techniques based on neuroscience that can better capture the perception of computer users and also propose a set of analytical tools by using a quantum based approach that can be used for the purpose of usability evaluations of LMS.

LITERATURE REVIEW

Quantum Neural Network

Quantum Neural Networks (QNNs) are models, systems or devices that combine features of quantum theory with the properties of neural networks. Neural networks (NNs) are models of interconnected units based on biological neurons feeding signals into one another. A large class of NNs uses binary McCulloch-Pitts neurons, thus reducing the complex process of signal transmission in neural cells to the two states 'active/resting'. The analogy with the two-level qubit serving as the basic unit in quantum computing gives an immediate connection between NN models and quantum theory. The majority of proposals for QNN models are consequently based on the idea of a qubit neuron (or 'quron' as we suggest to name it), and theoretically construct neurons as two-level quantum systems. Although close to discussions about the potential 'quantumness of the brain, QNNs do not intend to explain our brain functions in terms of quantum mechanics. Neurons are macroscopic objects with dynamics on the timescale of microseconds, and a quron's theoretically introduced two quantum states refer to a process involving millions of ions in a confined space, leading to estimated decoherence times in the order of $10-13$ sec and less , thus making quantum effects unlikely to play a role in neural information processing. However, QNNs promise to be very powerful computing devices. Their potential lies in the fact that they exploit the advantages of superposition-based quantum computing and parallel-processed neural computing at the same time. QNN research can furthermore be seen as a part of a growing interest of scientist and IT companies to develop quantum machine learning algorithms for efficient big data processing. Artificial neural networks thereby play an important role as intelligent computational methods for pattern recognition and learning (Schuld & Petruccione 2014).

Brain-computer interface (BCI) has been identified to function as an extra channel between brain and external environment to transmit information bypassing the spinal and peripheral neuromuscular systems and has also found applications in rehabilitation, neuroscience and cognitive psychology. Existing research in applications of BCI is composed of two main areas. For assistive technology, BCI makes it possible for people with motor disabilities to regain the interactions with external environment in order to improve the quality of their lives. The second area aims at training the subject to emit a specific brain activity. In this application, BCI is called as Neurofeedback (NFB), it becomes a therapy tool which helps subjects recover their cognitive function by consciously altering some features of their electroencephalographic (EEG) signals in order to stay in certain brain state. These features can be used to activate a certain action, including visual/ auditory representations. By continuous neurofeedback training humans can learn how to change their brain electrical activity in a desired direction. It can assist individuals with a variety of conditions and disabilities in which the brain is not working as well as it might be (Wang et al. 2007).

Memory for learning

Replication of the outstanding functions of the human brain in a computer, based on analysis and modeling of the essential functions of a biological neuron and its complicated networks has recently become an active research field. Several studies in this field have revealed successful developments of learning and memory which inspired by neural architectures in the brain. In general, from the engineering view, quantum mechanics (QM) has been developed as a theory to explain the fundamental principles of substance. QM provides several mathematical concepts, such as duality of waves and particles, complementarity, and nonlocality, to improve the comprehension of the microworld. From the biological perspective, on the other hand, it is hypothesized that QM is based on mesoscopic features in the physical and biological or physiological processes of the brain, and it has the potential to illustrate the dynamics of neurons in the human brain by the quantum information. In fact, in the internal structure of neuron in the brain, the presence of the two quantum states in tubulin, which are proteins of the size 4 nm×8 nm and having a 20-nm gap between the synapse, suggest that artificial neural networks would be handled as a descriptive subject from QM perspective. In other words, the QIC is expected to be possible to bring a new standpoint for cognitive process of brain from a biological viewpoint.

Memory Capacity is a significant factor for performance in associative memory. The memory capacity, in general, is responsive to the number of neurons, e.g., the memory capacity of model is directly affected by the magnitude of number of neurons. Moreover, the differences in number of neurons between layers is another significant factor for the performance of memory capacity. Therefore, in regards to memory capacity, the two types of conditions are considered; the constant number of neurons being set in layers, and different number of neurons applied to layers. From the above-mentioned two conditions, it can be evaluated that the sensitivity of the memory capacity from the viewpoint number of neurons. Here, the layer 1 is assigned with desired information while others are assigned the random bipolar patterns as the initial conditions (Masuyama et. al 2017).

The early quantum model of brain

In the quantum model, the brain elementary constituents are not the neurons and the other cells (which cannot be considered as quantum objects), but, in analogy with the QFT approach to living matter, they have been identified with the vibrational electric dipole field of the water molecules and other biomolecules present in the brain, and with the NG bosons (called the dipole wave quanta (dwq)) generated in the breakdown of the rotational symmetry of the electrical dipoles.
Memory printing is achieved under the action of external stimuli producing the breakdown of the continuous phase symmetry. In the quantum model of brain it is thus imported all the machinery of the spontaneous breakdown of symmetry introduced in the previous Section. The information storage function is thus represented by the coding of the ground state (the lowest energy state, or vacuum) through the coherent condensation of dwq collective modes. The memory capacity can be enormously enlarged by considering the intrinsic dissipative character of the brain dynamics: the brain is an open system continuously coupled to the environment. The dissipative quantum model seems to imply that the conscious identity emerges at any instant of time, in the present, as

the minimum energy brain state which separates the past from the future, that point on the mirror of time where the conjugate images A and Ã join together. In the absence of such a mirroring there is neither consciousness of the past, nor its projection in the future: the suggestion is that consciousness does not arises solely from the subject (first person) inner activity,
without opening to the external world. In the dissipative quantum model the intrinsic dissipative character of the brain dynamics strongly points to consciousness as dialogue with the inseparable own Double (Vitiello 2003).

Stochastic neurodynamics

Stochastic dynamics of relative membrane potential in the neural network is investigated. It is called stochastic neurodynamics. The least action principle for stochastic neurodynamics is assumed, and used to derive the fundamental equation. It is called a neural wave equation. A solution of the neural wave equation is called a neural wave function and describes stochastic neurodynamics completely. As a simple application of stochastic neurodynamics, a mathematical representation of static neurodynamics in terms of equilibrium statistical mechanics of spin system is derived (Yasue et. al. 1988).

Quantum Neural Computing

A quantum neural computer is a single machine that reorganizes itself, in response to a stimulus, to perform a useful computation. Selectivity offered by such a reorganization appears to be at the basis of the gestal style of biological information processing. Clearly, a quantum neural computer is more versatile than the conventional computing machine.
Paradigm of science and technology draw on each other. Thus Newton's conception of the universe was based on the clockworks of the day; thermodynamics followed the heat engines of the 19th century; and computer followed the development of telegraph and telephone. From another point of view, modern computers are based on classical physics. Since classical physics has been superseded by quantum mechanics in the microworld and animal behavior of being seen in terms of information processing by neural networks, one might ask the question if a new paradigm of computing based on quantum mechanics and neural networks can be constructed. (Kak 1995)
We define a quantum neural computer as a strongly connectionist system that is nevertheless characterized by a wavefunction. In contrast to a quantum computer, which consists of quantum processes are supported. The neural network is a self-organizing type that becomes a different measuring system based on association triggered by an external or an internally generated stimulus. We consider some characteristics of a quantum neural computer and shoe that information is not a locally additive variable in such a computer (Kak 1995).

Virtual learning environment

Virtual learning environments and quantum mechanics efforts have made possible the virtual learning environment StudentResearcher proposed by Pedersen et al. (2016) for the learning of Quantum mechanics. Learning management systems (LMS) are designed to facilitate the learning process and have been used during many years in the academic environment (Condon & Valverde 2014). It has been reported that as many as fifty percent of adults have some sort of computer-related phobia (Saade & Kira 2009). Past research shows that computer anxiety influences how users perceive ease of use of an information system. Saade & Kira (2009) identified several variables of computer self-efficacy and computer anxieties. Self-efficacy is determined by levels of anxiety such that reduced anxiety and increased experience improves performance indirectly by increasing levels of self-efficacy (Saade & Kira 2009). Saade & Kira (2009) investigated the influence of computer anxiety on perceived ease of use and the mediating effect of computer self-efficacy on this relationship, within an e-learning context.

Although Saade & Kira (2009) contributed with computer anxiety effect in computer systems usability, the studied relied mainly in a survey methodology approach. Ackroyd and Hughes (1981) acknowledge some of the main disadvantages of surveys as:

- Is argued to be inadequate to understand some forms of information - i.e. changes of emotions, behaviour, feelings etc.
- Lacks validity
- There is no way to tell how truthful a respondent is being
- There is no way of telling how much thought a respondent has put in
- The respondent may be forgetful or not thinking within the full context of the situation
- People may read differently into each question and therefore reply based on their own interpretation of the question - i.e. what is 'good' to someone may be 'poor' to someone else, therefore there is a level of subjectivity that is not acknowledged
- There is a level of researcher imposition, meaning that when developing the questionnaire, the researcher is making their own decisions and assumptions as to what is and is not important...therefore they may be missing something that is of importance

Given the arguments of Ackroyd and Hughes (1981), surveys might not be the best way to measure levels of anxiety among computer users. Although computer anxiety has been proven as effective in the measurement of computer usability, biofeedback and neuro biofeedback might have better solutions to measure computer anxiety. Demoka et al (2010) highlighted the potential of cognitive neuroscience for IS research in particular for the domain of human-computer interaction (HCI).

Biofeedback and neuro biofeedback instruments measure muscle activity, skin temperature, electro-dermal activity (sweat gland activity), respiration, heart rate, heart rate variability, blood pressure, brain electrical activity and blood flow. These technologies are able to capture analog electrical signals from the body and translate those signals into meaningful information through complex algorithmic software that a technician can then decipher. Biofeedback is also used by computer scientists in order to build human computer interactions (Valverde, 2011).

Bioofeedback has been applied in the field of psychology for the measurement of anxiety. (Valverde 2015). Biofeedback uses sensors to monitor physiological relaxation indicators, like skin temperature and muscle tension. It expands classical biofeedback by using galvanic skin response (GSR) together with modern computer technology to detect the response of the built-mind-spirit body to a large array of stress indicators (Valverde 2015). Galvanic skin response is one measurable quantity generated involuntarily by the body. It's well known as the basis for the polygraph, or lie detector. The theory behind is that a user sweats more when stressed, and that telling a lie is stressful (Valverde 2011).

The brain and muscles generate small electrical signals that can be picked up by electrodes strapped to the body (Valverde 2011). Neuro biofeedback is based on electroencephalographic (EEG) measurements taken from the frontal cortex of the brain. This EEG information is presented to the user who then tries to consciously change their internal reactions to modify their brainwave state (Valverde 2015). Our brain works primarily with bioelectrical energy. Although the power of electricity that handles our neurons is low (measured in mill volts), this power processes, manage, distribute and use vast amounts of information and generates multiple answers (almost infinite in possibilities). So by using micro electricity, we can conclude that the brain is a machine of low frequencies. The first types of brain frequencies that were discovered were the “alpha” and “theta”. Later, these findings were complemented by research in the range frequencies captured by the electroencephalograph (Valverde 2015). Each type of wave results in a different neuropsychological state. That is, our mind, our body and our physical and physiological activity are completely different in each of these states or frequencies. The most common consciousness are wakefulness and sleep; however, changes in expressing both cerebral and psycho states change according to conscious or subconscious feelings of each person are distinguished. These changes are directly related to the electrical activity of the brain. This activity can be measured by the number of oscillations per second (Hz) that are linked to different states of consciousness in the brain: our brain only perceives a limited range of frequencies indispensable to operate with ease in this three-dimensional medium. 20 to 20,000 vibrations per second are perceptible by our ears, the colors perceived by our eyes range from red to violet (although extending beyond, up and down), all possible smells and tastes (which are also vibrations) and the endless textures that we can distinguish with our skin. But the brain is not only receiver but also is sends vibrations. It has been proven thanks to the EEG that the brain emits waves of varying intensity and frequency depending on the mental state of the person being observed (Valverde 2015). These waves are classified according to table 1.

Table 1. Types of Brainwaves (Valverde 2015).

TYPES OF BRAIN WAVES	STATES OF CONSCIOUSNESS
BETA WAVES: 14 Hz to 30 Hz	This type of waves is recorded when the person is awake in a state of normal activity. Correspond to states of conscious attention, anxiety, surprise, fear, stress.
GAMMA WAVES: 25 and 100 Hz	They express pathological conditions of maximum tension, excitement and the individual enters a state of STRESS in which the coordination of ideas and normal physical activity are seriously altered.
ALPHA WAVES: 8 Hz to 13 Hz	Relaxation and rest, calm, reflective state. Reduction of bodily sensations. The subconscious begins to emerge: Abstraction, suggestibility. Assimilation of the study. Ease of visualization of mental images.

THETA WAVES: 3.5 Hz to 7 Hz	During sleep or in deep meditation, autogenous training, hypnosis, yoga (whenever the formations of the subconscious act). The state stimulates creative inspiration. Considered a state for maximum capacity of learning. Fantasy, imagination. Hypnagogic images.
DELTA WAVES: 1 Hz to 3 Hz	It arises mainly in the states of deep sleep and unconsciousness. Very rarely can be experienced being awake unless with a very hard training (Yoga, Meditation, Zen, Hypnosis, Self-hypnosis) or with a synchronizer of hemispheres. It corresponds to deep sleep, hypnotic trance, REM sleep. It corresponds to sleep without dream, trance, deep hypnosis. Delta waves are very important in the healing process and strengthening the immune system.

As table 1 indicates, beta brain waves can be associated with stress and anxiety while alpha waves are associated with calmness and relaxation.

NeuroIS

During the past decade, increasingly more scholars from the social and economic sciences and from computer science have started to use methods and tools from Neuroscience. This development is expected to result in a better theoretical understanding of human behavior such as decision making. Moreover, using Neuroscience methods and tools may contribute to the design and development of innovative information systems as demonstrated. (Hevner 2014).
Physiological reactions of humans in IS contexts (e.g., human interaction with computers) are usually measured by sensors placed on the body surface, even though the bodily reaction actually occurs "in" the body. The unit of signal frequency used is Hertz (Hz). The HZ is equivalent to cycles per second (Riedl, Davis, & Hevner, 2014).

Over the past decade, many scholars from various disciplines of social, economic science, computer science have started to pay particular attention to methods used and tools in neuroscience, to measure and conduct research in their respective fields (Riedl, Davis, & Hevner, 2014). In this vein, scholars in the field of Information Systems, have also incorporated on how to incorporate the neuroscience tools and measurement methods, in order to understand the human behavior by directly getting the results from the brain of human body.

Scholars in Information Systems have introduced the concept of NeuroIS into the IS literature (Dimoka et al., 2010; Dimoka, Pavlou, & Davis, 2007). The base of this concept of NeuroIS is to use neuroscience and neurophysiological methods, tools and theories to better understand, design, develop, and use of information communication technologies (ICT) in the society (Riedl et al., 2014).

Traditionally, IS researchers conduct data collection from various means and methods, notably from surveys, lab experiments, interviews, secondary data collection, ethnography, and many more methods (Dimoka et al., 2010; Dimoka et al., 2007). Considering that these methods of data collection are indeed useful, and have contributed importantly on the advancement of this field (IS research), asking directly the brain, and not the person opens an entirely new era of data collections, which is not biased, interpreted, and does not interfere with the subjectivity of human being. In other words, these methods, by means of directly asking the brain (data directly collected), tools offer unbiased measurements of decision-making, cognitive, emotional and social processes (Dimoka et al., 2010; Dimoka et al., 2007).

Moreover, one of the keys figures of neurological data collection is the advantage of continuous real-time measurement that allows collecting data continuously (Dimoka et al., 2010). In addition, this type of data collection, enables a level of precision, on a given period of time, permitting powerful time-series analysis and comparison (Loos et al., 2010). Applications of these types of data collection have been tested and conducted on various processes, for example on decision-making processes, understanding emotional processes (by capturing pleasure, enjoyment, displeasure, happiness, sadness, anxiety, sadness, disgust and etc.), understanding social processes (by capturing series of feelings, such as trust/distrust, cooperation/competition and etc.) and many more.

There are numerous opportunities provided by NeuroIS tools and its measurements in IS. According to Dimoka et al., (2010), these opportunities are illustrated as of the followings: 1) localize the various brain areas associated with IS constructs (neural correlates of IS constructs) and link them to the cognitive neuroscience literature to map IS constructs into specific brain areas, learn about the functionality of these brain areas, and better understand the nature and dimentionality of IS constructs. 2) Capture hidden (automatic and unconscious) mental processes (e.g. habits, ethics, deep emotions) that are difficult or even impossible to measure with existing measurement methods and tools. 3) Complement existing source of data with brain imaging data that can provide objective responses that are not subject to measurement biases (e.g., subjectivity bias, social desirability bias, common method bias). 4) Identify antecedents of IS constructs by examining how brain areas are activated in response to IT stimuli (e.g., designs, systems, websites) that intend to enhance certain outcomes (use behaviours, productivity). 5) Test consequences of IS constructs by showing whether, how, and why brain activation that is associated with certain IS constructs can predict certain behaviours (e.g., system use, online purchasing). 6) Infer causal relationships among IS constructs by examining the temporal order of brain activations (timing of brain activity) stimulated by common IT stimulus that activates two or more IS constructs. 7) Challenge IS assumptions by identifying differences between existing IS relationships and the brain's underlying functionality, thus helping to build IS theories that correspond to the brain's functionality.

There are numerous tools in NeuroIS which enable to the point measurements. These tools, according to Dimoka et al. (Dimoka et al., 2010; Riedl et al., 2014) are categorized under neurophysiological tools and focus measurement tools. The examples are these tools are Eye Tracking, Skin Conductance Response (SCR), Facial Electromyography (eEMG), Electrocardiogram (EKG), Functional Magnetic Resonance Imaging (fMRI), Positron Emission Tomography (PET), and many more (Dimoka et al., 2010). As mentioned above, there are various advantageous of using these devices in order to conduct the research directly from the brain (body) of human. However, these devices are very expensive, and require extensive laboratory settings.

Moreover, these experiments are conducted in artificial settings, and scholars might have validity concerns about whether neurophysiological data captured are the construct that they are intended to measure (Dimoka et al., 2010; Dimoka et al., 2007).

The Pop-Jordanov and Pop-Jordanova Quantum Consciousness Model

In the quantum approach to consciousness model, the brain elementary constituents are not the neurons and the other cells (which cannot be considered as quantum objects), but, in analogy with the quantum field theory approach to living matter (Del Giudice et al. 1985), they have been identified (Jibu & Yasue, 1995) with the vibrational electric dipole field of the water molecules and other biomolecules present in the brain, and with the NG bosons (called the dipole wave quanta) generated in the breakdown of the rotational symmetry of the electrical dipoles.

The description of the observed non-locality of brain functions, especially of memory storing and recalling, was the main goal of the quantum brain model proposed in the 1967 by Ricciardi and Umezawa (Ricciardi and Umezawa 1967). This model is based on the Quantum Field Theory of many body systems and its main ingredient is the mechanism of spontaneous breakdown of symmetry. Spontaneous symmetry breaking is a spontaneous process of symmetry breaking, by which a physical system in a symmetrical state ends up in an asymmetrical state.

In Quantum Field Theory the spontaneous breakdown of symmetry occurs when the dynamical equations are invariant under some group, say G , of continuous transformations, but the minimum energy state (the ground state or vacuum) of the system is not invariant under the full group G. When this occurs, the vacuum is an ordered state and massless particles (the Nambu-Goldstone bosons (NG) also called collective modes) propagating over the whole system are dynamically generated and are the carriers of the ordering information (long range correlations): order manifests itself as a global, macroscopic property which is dynamically generated at the microscopic quantum level (Vitiello 2003).

According to the model, memory recording is achieved under the action of external stimuli producing the breakdown of the continuous phase symmetry. In the quantum model of brain, it is thus imported all the machinery of the spontaneous breakdown of symmetry. The information storage function is thus represented by the coding of the ground state (the lowest energy state, or vacuum) through the coherent condensation of dipole wave quanta collective modes (Stuart et al. 1978). The non-locality of the memory is therefore derived as a dynamical feature rather than as a property of specific neural circuits, which would be critically damaged by destructive actions or by single neuron death or deficiency.

According to Pop-Jordanov & Pop-Jordanova (2010), based on their initial assumptions, the present quantum approaches to consciousness can be separated into four groups:

- Quantum emission probabilities (Eccles, 1986), where the two-way mental-neural interaction (with the electric/magnetic fields as a link) is supposed to be realized in a manner analogous to probability fields in quantum mechanics.
- Photon-corticon interaction (Jibu & Yasue, 1995), where consciousness was reduced to the creation and annihilation dynamics of photons (as quanta of an electromagnetic field) and corticons (as quanta of a rotational field of water dipoles) mechanics.

- Objective reduction in microtubules (Hameroff, 1998; Penrose & Hameroff, 1995), where quantum coherence occurs by exciting quasicrystalline water molecules as dipoles buried in microtubules.

- Virtual photons (Romijn, 2002), where the fleeting patterns of electric and magnetic fields, substituted by virtual photons, encode for conscious experiences.

Reviewing these approaches it can be inferred that, although being mainly conceptual and lacking numerical results, practically all of them have identified electric field and cortical dipoles as crucial elements of neural-mental correlation. With this in mind, the Pop-Jordanov and Pop-Jordanova Quantum Consciousness Model (2010) applies a field-dipole approach as a starting assumption.

Quantum transitions model

The transitions between the states of dipole water molecules as quantum rotators interacting with the time-dependent electric field have been studied recently, both analytically and numerically (Pop-Jordanov & Pop-Jordanova 2010). The corresponding nonstationary Schrödinger equation is not solvable analytically and it is too complicated for abinitio numerical calculation. Applying the adiabatic approach from the theory of atomic collisions, Pop-Jordanov & Pop-Jordanova (2010) proposes the solution in the following form:

$$\psi(\hat{d},\, t) = \varphi_a\left(\hat{d}, F(wt)\right) e^{-\frac{i}{h}\int^{t} E_\alpha(F(wt))dt}$$

Where F is the electric field, $\hat{d}$ is the direction of direction of the dipole vector, while φ_a are the eigenfunctions of the stationary Schrödinger equation. Adiabatic approximation requires the signal frequency to be much less than rotational frequency W rot=10^{13}Hz, which is obviously fulfilled in the case of EEG frequency (Pop-Jordanov & Pop-Jordanova 2010). The periodic variation of the electric field F = F0 sin(t) leads to transitions with exponential probabilities as indicated in the formula below:

$$P_{ab} = e^{\frac{2C_{ab}F0}{F0w}}$$

Where *a* and *b* are sets of quantum numbers specifying the initial and the final state of the system, while *Cab* is a parameter that depends on physical characteristics of the system (magnitude of the dipole and its moment of inertia). Thus, the probability of transition from one to another quantum energy state appears to be independent of the amplitude of the periodic external field, i.e., this mechanism is related to transition of information content rather than energy (Pop-Jordanov & Pop-Jordanova 2010).

In the case of a system of N dipoles, each energy level splits into N sublevels (because of interaction between di-poles) with the distance between sublevels being approximately N-times smaller. Hence, the probability of transitions for such a system is (Pop-Jordanov & Pop-Jordanova 2010).

$$P_{ab} = e^{\frac{2C_{ab}}{Nw}}$$

The Correlation of the Quantum transitions With Consciousness Level

To examine the eventual correlation of the transition probability P_{ab} with the probability of mental/neural excitations related to consciousness level (arousal), it is of interest to analyze the variation of P_{ab} with the spectral variable f = w/2π for a neuron with N = 10^{12} dipole molecules. This indicates that the arousal sensitivity to EEG frequency may be correlated to the transition probability variation for a system of quantum dipoles in the cortical electric field. The obtained theoretical result, suggesting the correlation of consciousness level with quantum transition probabilities, seems to be reasonable, since wakefulness can be conceived as a general activation, tonic state, and non-focused readiness to change the state, here identified as the probability of transitions between quantum states (Pop-Jordanov & Pop-Jordanova, 2009).

The basic dependence of mental arousal on EEG frequency, established empirically by Pop-Jordanov & Pop-Jordanova, (2005), is summarized in Fig. 1 and establishes the level of consciousness that ranges from deep sleep, drowsy, relax, alert, anxiety and peak performance.

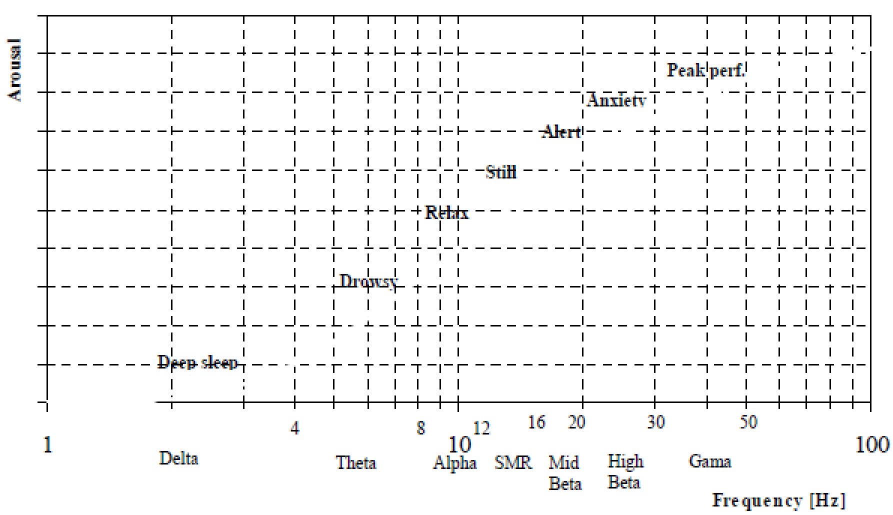

Figure 1 Mental arousal (Pop-Jordanov & Pop-Jordanova 2005)

A possible objection could be that mental acts cannot be reduced to one neuron. However, since only synchronized neurons of neuronal assemblies contribute to EEG, the relevant frequency is just the one-neuron (representative) frequency we are dealing with, when considering the consciousness level. The obtained formula connecting arousal (*A*) and field frequency (*f*) may be rewritten in the form:

$$P_{ab} = A = 2^{-\frac{f_e}{f}}$$

Where the equilibrium frequency fe actually corresponds to the dominant frequency with eyes closed, known to be age dependent – ranging from around 6 Hz to around 10 Hz, for children and adults, respectively (Thompson & Thompson, 2003).

The variable *f*, related to the dominant frequency band, can be identified as a spectrum weighted mean frequency(Pop-Jordanov & Pop-Jordanova, 2005). Characterizing the EEG spectrum, it may serve as a quantitative indicator of the general brain activation, and it is term as "brainrate" (in analogue to e.g. heart-rate). As such, it can contribute to the gross, initial assessment, not substituting the subtle, differential investigations of disorders corresponding to the same general level of arousal.

Being defined as the mean frequency of brain oscillations weighted over the all bands of the EEG potential (or power) spectrum, the brain-rate (fb) may be calculated as:

$$\cdot f_b = \sum_i f_i P_i = \sum_i f_i \frac{V_i}{V}$$

$$\text{With } V = \sum_i V_i$$

where the index *i* denotes the frequency band (for delta $i = 1$, for theta $i = 2$, etc.) and Vi is the corresponding mean amplitude of the electric potential. Following the standard five-band classification, one has $fi = 2, 6, 10, 14$ and 18, respectively.

Quantitative electroencephalography

EEG technology generates raw data, this data can be broken into different frequencies (alpha, theta, etc) by using Fourier analysis. The Fourier analysis decomposes the EEG time series into a voltage by frequency spectral graph commonly called the "power spectrum", with power being the square of the EEG magnitude, and magnitude being the integral average of the amplitude of the EEG signal, measured from(+) peak-to-(-)peak), across the time sampled, or epoch. The epoch length determines the frequency resolution of the Fourier, with a 1-second epoch providing a 1 Hz resolution (plus/minus 0.5 Hz resolution), and a 4-second epoch providing ¼ Hz, or plus/minus 0.125 Hz resolution (Kececi & Degirmenci 2008). The Fourier equation to transform time dependent raw date can be defined by the equation below:

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-i2\pi f t} dt$$

ARCHITECTURE

The proposed architecture is mainly to support usability testing for a selected learning management system. Usability testing helps to determine how people use systems and where they may encounter difficulty of use (Valverde 2011).

Dumas and Redish (1999) identify five tasks must be completed for a usability test:

1. Define goals and concerns.
2. Determine who your test participants are.
3. Select, organize, and create test scenarios.
4. Determine to measure usability.
5. Prepare test materials.

In the first step of a usability test, goals are identified from the task analysis and quantitative usability goals for the LMS used for the study. For the second step, a sample of user should be selected. In the third step, test scenarios should be designed to detect potential usability problems. Test scenarios are normally prepared based on the HCI designer‘s experiences on what the user will do with the product (Valverde 2011).

Test scenarios should identity the activities to perform the tasks. The test case should number each task to complete it and provide and a description for each task that is clear enough for the user to perform it. Each task should show the time it will take and the high-level instructions and procedures required to complete the task (Valverde 2011).

The fourth step of defining usability tests requires determining usability measures performance and subjective measures. Performance measures are quantitative measures of specific actions and behaviours that are observed during the test. The subjects performing the usability test will be wearing a EEG device as indicate in figure 2 in order to measure computer anxiety. The Quantum NeuroIS acquires de EEG signal and applies a Fourier analysis in order to brake the data into different frequencies (alpha, theta, etc) (figure 2). The different levels of power of the different frequencies is used to calculate a bit rate that is related to the dominant frequency band in the brain as an indicator of the main level of consciousness (Pop-Jordanov & Pop-Jordanova, 2005). The quantum level of arousal sensitivity is calculated based on the bit rate, this level of arousal is correlated to the consciousness level given its quantum transition probabilities (Pop-Jordanov & Pop-Jordanova, 2009). The brain rate and arousal level are used to establish a particular level of consciousness (deep sleep, drowsy, relax, alert, anxiety and peak performance) as indicated in figure 1.

The time taken to perform each task and task will be recorded as part of the usability test with a video camera that is part of the NeuroIS. This will help the researcher to log each time a user exhibits a certain behaviour during the test, like expressing frustration with a criterion for performance measures (Valverde 2011). The task time and actions are linked to a particular level of consciousness calculated by the NeuroIS and recorded in a permanent storage for further analysis (figure 2).

The collected data from the NeuroIS are a video that records the different activities required to complete a set of tasks associated with a consciousness level that is intended to measure Computer Anxiety. It is expected that there is a linear relation between Computer Anxiety and Ease of Use and Computer Anxiety and Computer Self-Efficacy. The NeuroIS can produce two regression models with the collected data. The first regression will have Ease of Use as a dependent variable and Computer Anxiety as the independent variable. The model can be prepared with the Computer Anxiety measurements in terms of the different level of consciousness. The Ease of Use data that will be used for the regression model will be the log for the behaviour during the test with a four-point scale that evaluates the task from positive to negative ease of use (figure 2).

A second regression model will be produced with Computer Self-Efficacy (CSE) as dependent variable and Computer Anxiety as the independent variable. The CSE data will be computed by calculating the difference between the time taken to perform a task and the expected time to complete the task for each test. A lower CSE factor means a more efficient task while a higher factor means a less efficient task (figure 2).

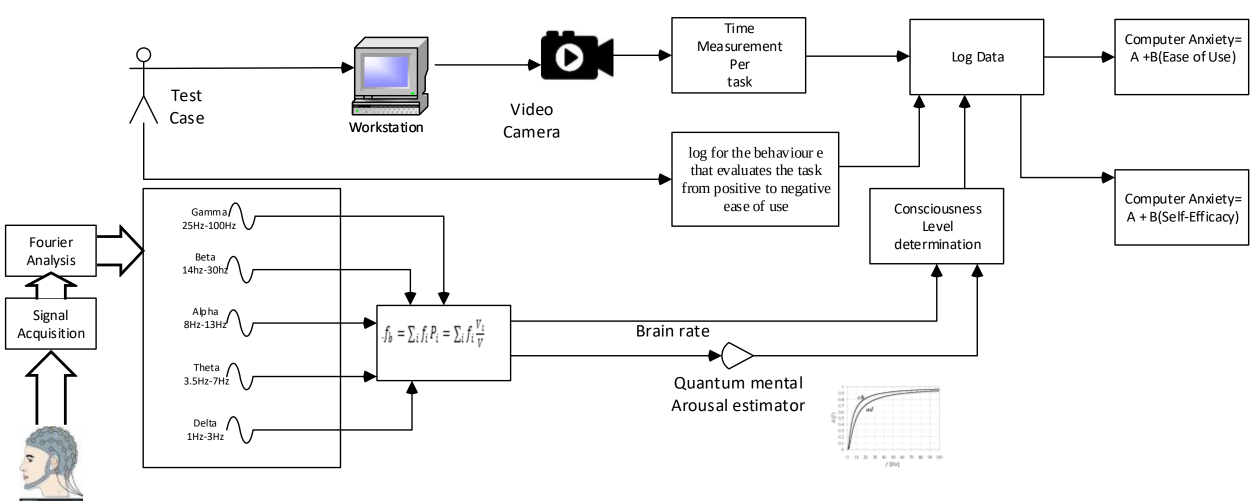

Figure 2 Quantum NeuroIS data analytics architecture

Figure 3 shows a prototype of the Quantum NeuroIS, the figure shows an image capturing the video recording of the user interacting with the LMS at a particular time on the top right. The first graph on the top displays the raw data collected from the EEG by displaying amplitude in time. The second graph is displaying the Power Spectrum of the raw data signal displaying the concentration of power over the different frequencies, the graph at the bottom displays the Gamma, Beta, Alpha, Theta and Delta signals that are the result of the Fourier analysis.

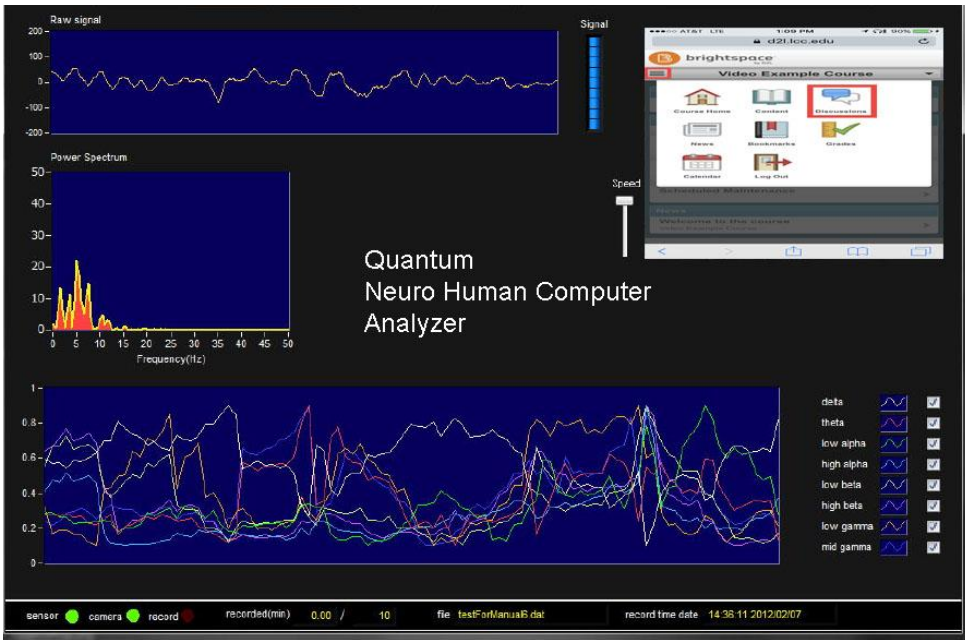

Figure 3 Quantum NeuroIS Prototype

Test results

A test was conducted with the prototype, an online course given at Concordia University in Introduction to Information Technology was used for the pilot test. Five users followed a usability test protocol for usability for about 15 minutes by using an EEG device and raw data was recorded for all the sessions. Raw data was used to calculate dominant frequencies and arousal rates and videos were recorded for the sessions. The average of these results for the five students are given figure 4 and 5.

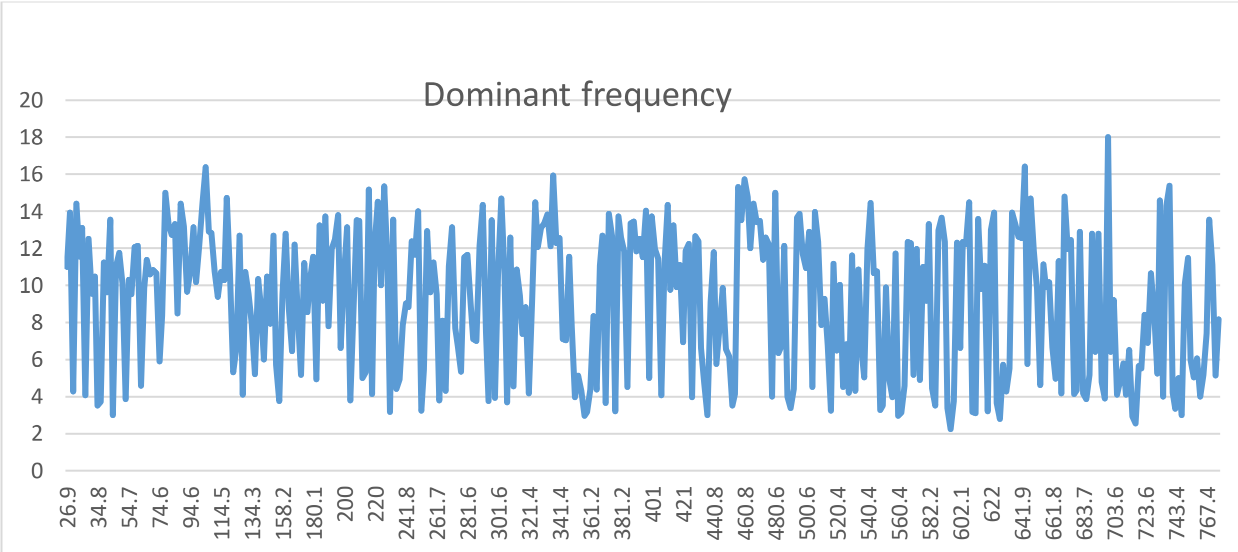

Figure 4 Dominant frequency

Figure 4 shows that dominant frequencies ranges from 18 Hz (Beta state) to 2 Hz (Delta state). It seems that some parts of the course caused stress and there were jumps of frequencies that go from very calm to stress. Videos need to be examined and change of frequencies would help to detect the areas that cause stress to users.

Figure 5 shows arousal rates. Arousal rates go from 0 to 1. A sudden jump in the arousal indicates a sudden change of state of consciousness that can indicate problems of with the usability. Videos would need to be examined in order to detect the tasks that generated sudden changes of states as possible indication of problems with usability.

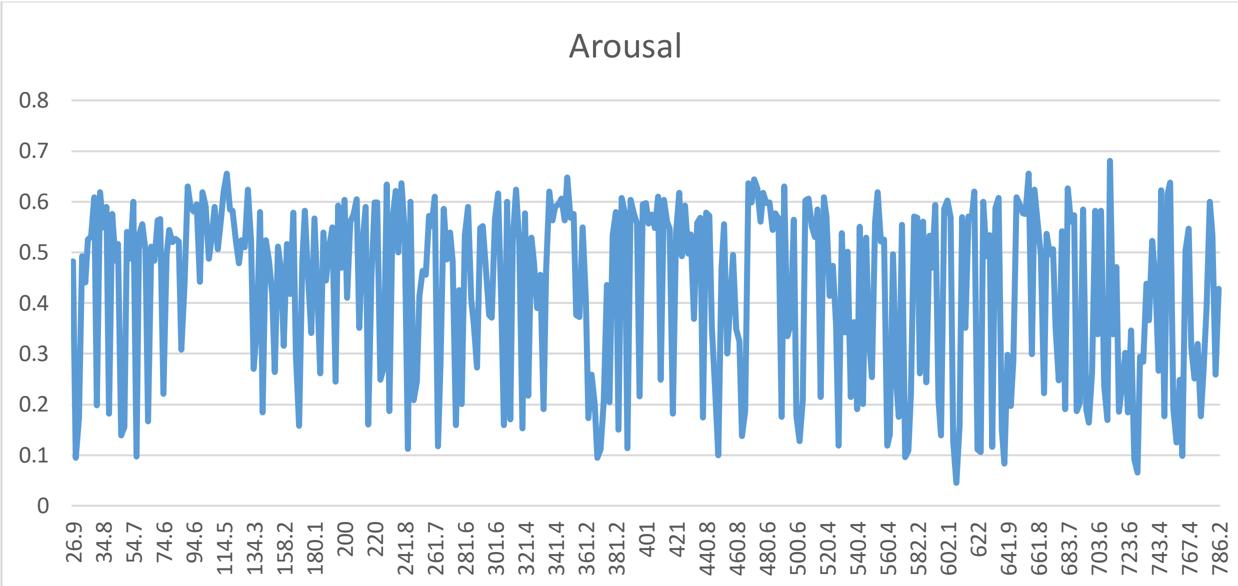

Figure 5 Arousal

CONCLUSIONS

The proposed NeuroIS is based on a quantum approach to measure consciousness proposed by Pop-Jordanov & Pop-Jordanova (2010), this model captures the levels of anxiety of the user from very relaxed to very stressed. An architecture with the different required components for the NeuroIS and the mathematics to make it work were identified. A software prototype with a possible interface was developed in order to show the feasibility of this architecture. A test with five students was performed in order to show the feasibility of the architecture and use in detecting problems with usability. The NeuroIS provides a tool for the measurement of computer anxiety can help to improve the usability of an LMS. The main advantage of the NeuroIS is that it does not use surveys for data collection and instead uses direct brain wave measurements from the user's brain. Future research should focus on the development of a software based on the proposed architecture for the validation of this design including the implementation of different usability tests for several LMS. In general, the research shows the potential of quantum consciousness research in the development of computer evaluation systems, quantum consciousness models can not only measure state of consciousness but also mental arousals that can detect changes of these states of consciousness. This type of models could have many other applications including NeuroIS for marketing and financial applications and any type of application that can benefit the with the measurement of consciousness and anxiety levels.

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