Ongoing Challenges of Evaluating Mulsemedia QoE

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Multimedia applications are usually limited to stimulating only two human senses: vision and hearing. Recent studies seek to expand the definition of multimedia applications to include stimuli for other human senses. In this way, sensory effects that should be triggered in synchrony with the audiovisual content being presented are included in the applications. By including sensory effects in multimedia, we aim to improve the Quality of Experience (QoE) with these mulsemedia environments. Usually, two approaches are being used for performing QoE evaluations these environments. The first, more common, is performed by subjective evaluation approaches, i.e. through questionnaires, interrogations, oral responses, etc. The second, rarer but growing, uses objective approaches by collecting physiological data from the user when dealing with the system being evaluated. Such data is gathered in real time or not, however, it is considered objective because it is "involuntary", that is, data is not the result of the user's intention. This paper will address both the these methods to evaluate QoE and what the respective obstacles are when dealing with in mulsemedia systems.

CCS Concepts: • **Human-centered computing → Interaction paradigms**; **HCI design and evaluation methods**; • **Information systems → Multimedia information systems**.

Additional Key Words and Phrases: Mulsemedia, Quality of Experience, Objective Evaluations, Subjective Evaluations

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1 INTRODUCTION

For many years, multimedia were limited to stimulating only two of the human senses: sight and hearing. This situation is at odds with the fact that 60% of human communications are non-verbal, and that most of us perceive the world through the combination of the five senses: sight, hearing, touch, taste and smell [12]. Based on this, efforts have been made to study and understand how to expand the definition of multimedia to include other sensory stimuli besides sight and hearing [3].

The last decade has witnessed a growing shift in emphasis from studying the senses alongside other media devices. Calvert and Thesen [4] say that the adoption of a multisensory perspective on human sensory perception has evolved in part as a consequence of developments in both technology and sensory neurophysiology. These advances in technology have coincided with the increasing knowledge about the mechanisms involved in the sensory systems. A natural extension of this was the realization that a complete understanding of our perceptual systems would require the inclusion of how each sense was integrated with input from different sensory systems. Thus, the basis of mulsemedia capabilities is clear: the integration multiple sensory sources besides audio and video to improve user feeling of presence.

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However, to understand how mulsemedia works, evaluations of QoE are necessary. There are two ways to acquire QoE data: *subjective* and *objective*.

Subjective measures refer to self-report methods that are typically combined with a task during which participants are asked to indicate how they are feeling during the evaluation. These are the most common method of user evaluation, which compromises of user questionnaires, think A loud methods, interrogation, etc. Subjective measures, however, are not without problems [19, 22] as they can suffer from what is called "response bias", which is a phenomenon that participants respond inaccurately or falsely to said questions. For example, participants often set their own criteria for assessing what they are feeling, and those who are not sure what to feel may not report that they are confident unless they are absolutely right [19]. However, as these self-reported measures are relative ease of use, they can be easily applied in a multitude of environments without much cost.

Objective measures was proposed to address the problem aforementioned about the imprecision of voluntary and self-report methods. This view is not new, authors such as Huynh et al. [16] and Ciolacu and Svasta [6] have proposed models and architectures for evaluating QoE using objective measures. Lin et al. [17] also has already stated that, although subjective evaluation is an essential element in the usability evaluations, they are not enough and may need an objective method for physiological measures to be integrated in traditional usability evaluations. Object measures e.g. EMG, accelerometers, video recordings and biosiginals [22], are more costly and, so far, only being applied in academics and laboratory environment. For instance, *EngageMon* [16] is a system that uses a combination of sensors from the smartphone, a wristband, and an external camera to accurately determine the engagement level of a mobile game. Aiming at learning and education, Ciolacu and Svasta [6] presented a model that uses biofeedback to measure and control learning processes during user interaction with learning content, as the authors argue that the process of teach-learning should not be measured only at the end of the exam, but also during the learning experience.

In summary, objective measures are those information captured from the user biofeedback and biosignal response. To avoid misunderstandings about these terms, it's important to make clear what they are. According to McKee [20], biofeedback is as much a process as the instrumentation used in that same process. For the first, it is taking physiological information that is monitored and returning it to be used elsewhere through biofeedback instruments. The latter refers to biofeedback instruments that are capable of monitoring one or more physiological processes, measuring what is monitored and transforming that measurement into an understandable information, such as images or audio cues, to present what is monitored and measured simply, direct and immediate. Biosignals are closely related to biofeedback data. Giannakakis et al. [13] state that biosignals are measures of human body processes that can be divided into two main categories: physical signals and physiological signals. The former are measurements of body tension as a result of muscle activity, such as pupil size, eye movements, blinking, head, body and semi-voluntary position/movements, breathing, facial expressions, and voice. As part of it is not a subject of the Autonomic Nervous System (ANS), it is not a entirely objective measurement. Thus, physiological signals are more directly related to the ANS, such as cardiac activity, brain function, exocrine activity, and some muscle excitability assessed by electromyography. These are closely related to the ANS and are seen as objective metrics. However, objective measurements are not easy to collect. Almost always expensive, they are usually limited to controlled environments and is not commonly applied in real situations.

Biofeedback is an umbrella term for capturing physiological data from biosignals and returning it for another purpose. With the advent of the Internet of Things (IoT) and a more ubiquitous computing world with mobiles, smart watches, heart rate monitors, etc., we believe that the data collected through this multitude of connected devices and new ways to interact with information can, in addition to being used for evaluations, also be used as a control mechanism for the delivery of mulsemedia (multiple sensorial media) content, as IoT improvements are increasing the ubiquity of the Internet by integrating all objects for interaction between systems leading to a highly distributed network of devices that communicate with humans and other devices, opening up opportunities for a host of new applications that promise to improve the quality of our lives [30].

What this paper proposes is to highlight some of the ongoing problems and challenges of objective and subjective approaches for mulsemedia QoE evaluation. This work is divided into the following sections. Section 2 is subdivided in three subsections: 2.1 Subjective Measures will address approaches such as questionnaires, think-A-loud, etc. 2.2 Objective Measures will address approaches such as biosignals gathering, involuntary data, etc. The last subsection 2.3 Challenges will address the ongoing current challenges of both approaches. Finally, Section 3 our conclusions.

2 EVALUATION APPROACHES

2.1 Subjective Measures

Evaluation of QoE refers to a collection of methods and tools used to discover how a person perceives a system (product, service, non-commercial item, or a combination thereof) before, during, and after interacting with it. When investigating momentary user experiences, we can evaluate the level of positive affect, negative affect, joy, surprise, frustration, etc. via vocal statements (i.e Think Aloud protocol) or post-experience (i.e. User experience questionnaire or UEQ). It is not trivial to assess user experience, as user experience is subjective, context-dependent, dynamic over time and when dealing with mulsemedia, the challenge is magnified by the plethora of multisensory devices.

Murray et al. [21] stated that user perceived QoE capture of mulsemedia is non-trivial mainly due to the number and various types of media components that are presented synchronously. As there are no standardized methodologies to conduct subjective assessment of mulsemedia quality, researchers use different approaches to assess user QoE of mulsemedia applications, mostly of them with questionnaires. Which questionnaires were administered depends on the mulsemedia environment being assessed, with no standard questionnaire found to date. Furthermore, according to Murray et al. [21] review on QoE evaluation of Olfaction-Based Multisensorial Media, only 20% of the experiments provided details on questionnaires, allowing very few repeatability opportunity.

There are, however, already tested Subjective Methods involving Mulsemedia content, such as Covaci et al. [7] which proposed a method to improve subjective QoE in 360° Virtual Reality (VR) Videos through a QoE questionnaire that comprised a series of questions focused on the user experience. The answer to each question was expressed on a 5-point Likert scale. In addition, participants also answered a set of 8 more questions aimed at olfactory and wind effects.

2.2 Objective Measures

When dealing with objective measurements, there is a plethora of devices being used. The most common and easier to use is the measurement of Electrodermal activity (EDA) or Galvanic Skin Response (GSR). Mostly are being used to measure various psychological states, including arousal, attention, and stress. Because of its low cost, being non-intrusive, and sensitivity to psychological processes, EDA is one of the most popular response systems in psychophysiology [1]. Being measure by the skin, it is also common that the Heart Rate (HR) is measured along with EDA. The mostly common method it is with Photoplethysmogram (PPG). An optically obtained plethysmogram that can be used to detect changes in blood volume in the microvascular bed of tissue. PPG is usually obtained using a pulse oximeter that illuminates the skin and measures changes in light absorption.

A conventional pulse oximeter monitors blood perfusion in the dermis and subcutaneous tissue of the skin. As EDA and PPG are non-invasive, they hold promise for stress detection because they rely on passive sensors to provide pulse and electrodermal data that can be analyzed and have been shown to be reliable alternatives for easy and inexpensive objective user evaluations. Houzangbe et al. [15], Wang et al. [29] stated however that both are only able to show "arousal", which is the physiological and psychological state of being awake or of sense organs stimulated to a point of perception, leading to increased heart rate, electrodermal activity and blood pressure. This means that arousal triggered by fear or happiness are detected equally and difficult to differentiate by data collected.

To this end, and because being more capable of detecting emotions with greater precision, Electroencephalography (EEG) is preferred. EEG is a method of recording an electrogram of electrical activity in the scalp that has been shown to represent the macroscopic activity of the surface layer of the brain. This measure can be used to explore physiological information about the user and can be a useful tool for user experience as EEGs can be taken as an indicator to assess user perception when using products without interruption [9]. However, they are expensive to collect, to analyze and EEG suffers from high variability between subjects and requires a long setup of high expert specialists to acquire good quality signal [11]. Because they are increasingly being used for QoE evaluations, with EEG-based emotion recognition studies gaining popularity in many disciplines [8], there are now commercial EEG products that promise to make your data easier to measure and understand, such as Emotiv EPOC X, Emotiv EPOC+ , Emotiv INSIGHT, Emotiv EPOC FLEX, OpenBCI and NeuroSky MindWav. Some of these EEG devices have one or more extra channels for capturing physiological signals, such as Electrocardiogram (ECG), Electrooculography (EOG) and Electromyography (EMG) [28], capable of collecting psychological (brain) and physiological (blood pressure, muscle activity, heart rate, etc.) data, being an improvement over the cheaper devices mentioned earlier. EMG and EOG, however, are not always necessarily "objective" biosignals, as some of the bio-data recorded are a result of the user's intention to do so, and are not a product of our autonomic nervous system (ANS), which would jeopardize the "objectivity" of these data.

2.3 Challenges for Mulsemedia Quality of Experience Evaluations

Subjective and objective approaches for QoE evaluations are prone to problems. Subjective measurements, although cheaper, are also a source of criticism: questionnaires and surveys can break user immersion when dealing with immersive experiences as in VR because the transition from the virtual world to the physical world to respond to VR experience questionnaires can lead to systematic biases [23, 24]. A better approach was proposed by Schwind et al. [27] who stated that applying questionnaires directly in the VR environment is better because, although the results indicate that, in addition to reducing the duration of a study and decreasing disorientation, filling out questionnaires in RV does not change the measured presence, but it can increase the consistency of variance. Almost the same conclusions were reached by Putze et al. [23] who stated that the application of VR questionnaires (inVRQs) is becoming more common in contemporary research. This builds on the intuitive notion that inVRQs can facilitate participation, reduce Break in Presence (BIP), and avoid bias. Also, Safikhani et al. [24], despite not having reached a definitive conclusion, highlighted that users preferred to use inVRQs designs to the traditional ones. Also for that reason, a Think-A-Loud method is more suitable for evaluations of mulsemedia environments, as it indicates the user's feeling in real time, rather than a post-report carried out after the user's interaction with the environment, thus, avoiding biases and false statements. What we are trying to say is that traditional approaches may not be suitable for mulsemedia QoE evaluation because they explore new fields of experience that cannot be reached by such methods.

While objective measurements seek to be accurate, when dealing with mulsemedia environments, the devices and sensors used may lack synchronization and latency, which is a current challenge of using these devices altogether. Synchronization and latency are a major challenge for the inclusion of other sensory stimuli than audio and video in these environments, which depends on a complete synchronization between traditional multimedia and devices that deliver haptic, olfactory or taste sensations [26, 33]. When wearable devices are used to capture and detect biosignals, the problem is magnified.

Some sensory effects such as olfactory and gustatory effects are gradual, whereas using EDA or PPG is a highly responsive body signal. Synchronize these devices can be challenging as Ho et al. [14] claimed that electrodermal activity increased rapidly within seconds in response to small physiological and mental stimuli. This means that correctly choosing which devices to measure biosignals when evaluating multisensory environments can be tricky. For example, when dealing with emotions such as fear and excitement, both produce an increase in heart rate and electrodermal skin activity. This means that trying to identify them with just EDA and PPG devices can lead to confusion. As noted before, both positive ("happy" or "joyful") and negative ("threatening" or "saddening") stimuli can result in an increase in arousal, and by it, in an increase in skin conductance and heart rate. That said, EDA and PPG signals are therefore not representative of the type of emotion, but the intensity of it.

Another challenge is how to adapt these devices for "real time environments", this mean, outside of a controlled area. EDA devices, for instance, can have their data compromised by outside temperatures. That's because while EDA have a strong association has with emotional arousal, it also shares a link to the regulation of our internal temperatures [2]. Since PPG is dependent of light, its signals can be affected by the light spectra and intensity of the environment [18].

When dealing with even more complex devices such as the EEG, the range of problems is widened. EEG devices, even commercial ones, can be uncomfortable [5]. Other still ongoing challenges are costs, accuracy of sensors (EEG sensors often need a saline solution or gel to facilitate skin conduction), data transfer errors or inconsistency, and ease of use for devices [10, 31, 32].

However, some challenges are about to be faced with 5G, which has the potential to create new interfaces for our everyday devices and network components. With 5G being able to connect more users to provide smarter and faster communications we are about to see a boom in wearables. How 5G will work together with mulsemedia devices is an object of research [25], but we can assume that 5G technology will provide faster and more reliable communication with high data rate and low latency rates, partially dealing with the ongoing challenge of synchronization and latency on mulsemedia devices, as cited by work by Yuan et al. [33].

Table 2.3 summarizes advantages and disadvantages of each approach.

Evaluation Approaches in Mulsemedia Environments

Subjective	**Advantages**		
		1.1	Cheap
		1.2	It can be done anywhere, without the need for a lot of resources, compared to other evaluation approaches.
		1.3	Very explored and diverse field, with high number of references and standardizations.
	Disadvantages		
		1.4	Questionnaires and surveys can break user immersion when dealing with immersive experiences
		1.5	Can suffer from “response bias” and subject to inaccuracies
		1.6	Mulsemedia explores new fields of experience that cannot be evaluated by this method.
Objective	**Advantages**		
		2.1	More accurate data
		2.2	Does not suffer from user bias or inaccuracies presented in subjective approaches.
		2.3	Can detect hidden information, usually not detected with subjective methods.
	Disadvantages		
		2.4	Expensive
		2.5	Requires resources and controlled environment.
		2.5	Inherent complexities of mulsemedia environments can interfere with the execution of objective approaches.
		2.6	Wearable data collection devices can be uncomfortable.

3 CONCLUSION

For conclusions, we can agree that the usability evaluation of mulsemedia environments presents a higher level of difficulty than the standard multimedia. The interaction of multiple systems makes it difficult to evaluate sensory stimuli in isolation, compromising the standard forms of usability evaluation, especially the subjective ones.

Growing alternatives currently are the use of wearable devices for real time analysis of the user's level of satisfaction when interacting with the system, and with the advancement of 5G networks, it is expected that challenges such as latency and synchronization will be mitigated and that better machine user interaction is reached.

However, the plethora of available devices makes it difficult to generalize how evaluations of QoE should be performed, as each device has different peculiarities and structures: some use Peltier heating systems, others simulate haptic effects by "tricking" the human senses (such as using a mint scent to give the impression of being cold). This said, it's not just a technical issue of the devices, but how the human senses are stimulated by them. This increases the scope of usability evaluations, expanding the field to psychology, medicine, design, etc.

Furthermore, seeing how this area of study is growing every day, even more so with the arrival of 5G, we assume that this will be a fertile field of research, even outside academia, as we can see with the advent of Virtual Reality environments, as META.

We also do not seek to substitute one method for the other, as both can be mutual complementary. What we want to say in this paper is the opportunity to use objective data collection devices to better understand the functioning of mulsemedia systems.

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