Modeling User Quality of Experience of Olfaction-Enhanced Multimedia

Niall Murray, *Member, IEEE*, Gabriel-Miro Muntean, *Senior Member, IEEE*, Yuansong Qiao, *Member, IEEE*, Sean Brennan, and Brian Lee

***Abstract*—Research on modelling user quality of experience (QoE) to date has primarily focused the combination of traditional media components; audio and video, or the individual influence of each. However, multisensory experiences have recently gained significant traction in the research community as a novel method to enhance QoE beyond what is possible with traditional media. This paper presents a model developed based on empirical data. It estimates user QoE of olfaction-enhanced multimedia. A set of 12 olfaction enhanced video clips were viewed by 84 assessors. A strong age and gender balance produced 6048 user ratings across six questions. Employing this dataset, the proposed model considers the influence of: system factors, user factors and content factors on user perceived QoE. The model is instantiated and validated. The analysis indicates that: content factors have a 10% influence on user QoE; age factors have an 11% influence; and gender factors have an 8% influence on user QoE. Also, content factors had the highest number of statistically significant influences across all of the factors evaluated. These results suggest that human, and content in addition to system factors play a key role in perceptual multimedia quality of olfaction enhanced multimedia. Further work is required to understand the remaining factors as well as the relationship between the media components has on QoE.**

***Index Terms*—Mulsemedia, olfaction-enhanced multimedia, quality of experience, human factors, models.**

I. Introduction

TRADITIONAL multimedia content has stimulated two of the human senses: sight and hearing. Recently, motivated by the need to enhance user QoE, research and industry have reported works with respect to sensory experiences [1] or multiple sensorial multimodal media content (mulsemedia) [2], [3]. Such works generally stimulate three or more of the five human senses. In addition to audio-visual stimulation, such experiences may include olfaction (sense of smell) [4], tactile (sense of touch) [5] and taste [6]. It is assumed that addition of these media components will naturally enhance user QoE [7]. This has led to a significant increase in interest in this topic across a number of research domains; Human Computer Interaction (HCI), Multimedia, Psychology, Electronics/Sensor developers, as these multidisciplinary areas collaborate to make truly immersive multimedia experiences a reality.

The term quality of experience (QoE), as defined in the Qualinet White Paper, is the "user degree of delight or annoyance in relation to an application or service. It is determined by the level of fulfilment of user expectations and is dependent on user personality and current state. In the context of communication services, QoE is influenced by service, content, network, device, application, context of use, users' personality and current contextual state" [8].

A user's perception of quality of multimedia or mulsemedia experiences are affected by numerous influencing factors (IF). A number of documents exist in the literature that categorize such IF's in different manners [9]–[12]. Broadly speaking, there is commonality in the actual factors identified and explained, but there are differences in terms of classifications. In [10] as per Fig. 1, the IF's that effect user QoE are a function of the traditional QoS (device, network, content) metrics and social/psychological aspects. A different approach is taken in [12] where IFs are categorized under context, user, system and content. User models that can be employed to predict user Quality of Experience (QoE) are crucial for the broadcasting community. Such models can consider multiple system and human related IF's in particular and be used to estimate QoE levels based on varying conditions. In particular, the use of mulsemedia components as part of broadcasting experiences can mask the effects of numerous broadcasting related challenges as outline in [13].

In terms of olfaction-enhanced multimedia, the literature provides a number of key articles of how olfaction is and can be employed in future multimedia applications [14]–[21]. In [14], existing works in the areas of virtual reality and entertainment are highlighted with potential future research directions identified in terms of synchronization, olfactory display development and content association. Kovács *et al.* [15] and Murray *et al.* [16] presented the use of and potential for olfaction as a media component in less apparent domains such as health, tourism and education, whilst highlighting research challenges with respect to user QoE of olfaction-based multimedia applications and delivery challenges of multiple sensorial media over constrained communication networks. Murray *et al.* [17] presented a review of

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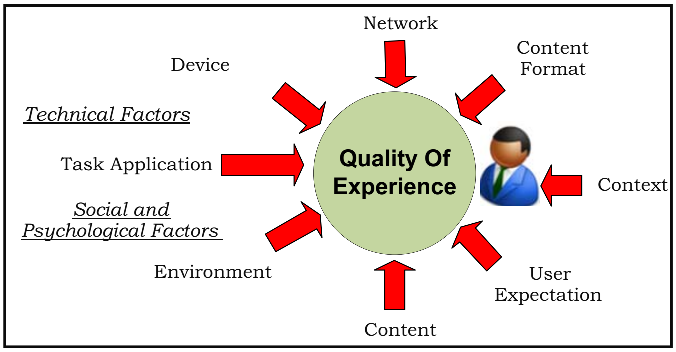

Fig. 1. Factors influencing user Quality of Experience [10].

assessment methodologies employed by the research community for olfaction based mulsemedia quality evaluations and concluded by making a number of recommendations for same considering the categories of screening, lab design, methodology as well as implicit and explicit analysis.

In [18], ten categories of smell experience were defined based on feedback obtained from over 400 participants in a user study. Considering the rapid development of olfactory sensor and display technology, olfaction-based multimedia applications are a realistic possibility technically and across a wide variety of application domains. Finally [19]–[21] highlighted opportunities and challenges around sensorial touch, taste and smell. They outlined key challenges around understanding sensory system processing within context of HCI: which tactile, olfactory and gustatory experiences HCI designers should design for; designing interfaces for sensory inputs, e.g., olfaction but also interfaces that integrate multisensory experiences, i.e., taste & smell. In addition to these, a related and key research challenge, as discussed in [22], is to understand how various factors influence user's perception of quality, and therein lies the focus of this work.

In this context, this paper presents a mathematical model that estimates user QoE of olfaction based mulsemedia. In addition, we provide statistical analysis to inform the influences of each of user, system and content factors on QoE.

II. Related Works

Solutions have been proposed for traditional multimedia content distribution to improve user perceived quality during multimedia delivery in wired [23]–[26], wireless [27], [28] and heterogeneous [29], [30] network environments. Several research works have been published that estimate user QoE of traditional multimedia components (audio and video), and influence of QoS characteristics [31], [32]. These approaches are based on the premise that there is a relationship between network QoS and QoE. Hence they aim to understand the correlation between the two. The IQX hypothesis [31], as per eq. (1), is derived from two key sets of parameters (a) QoE parameters (based on user satisfaction) and (b) QoS parameters (based on level of network disturbance). The assumption is that if satisfaction is high, the level of disturbance should be low (e.g., low delay or packet loss). Their results indicate that an exponential relationship between QoS and QoE existed, and that minimal drops in QoS could lead to high fall in QoE ratings. It was also reported that if QoE was already low, additional disturbances did not have any significant impact.

$$\partial \text{QoE}/\partial \text{QoS} \sim -(\text{QoE} - \gamma)$$

which can be represented as an exponential function:

$$\text{QoE} = \text{e}\alpha \cdot e^{(-\beta \cdot \text{QoS})} + \gamma \tag{1}$$

where α, β and $+\gamma$ are unknown parameters used in this model for accuracy tuning.

There has been a growing interest on the influence of human factors on perceived quality of multimedia experiences. These works [33]–[36], suggest that human factors play an important role in perceptual media quality. Scott *et al.* [33], [34] analysed the role of personal and culture on perceptual multimedia quality. They reported that approximately 9% variance in perceived quality was attributed to human factors. Zhu *et al.* [35] also considered human factors to predict user visual experience quality in addition to affective content. The user factors analysed were interest in the content, gender, cultural background, personality and immersive tendency. Similar to the model proposed here, Pereira [37] proposed a triple user characterization model factor for user QoE of multimedia experiences. This tuple include sensorial, perceptual and emotional dimensions.

More closely related to modelling user perception of mulsemedia, although not considering olfaction, Timmerer *et al.* [38] and Rainer and Timmerer [39] took an interesting approach to modelling the effect of enhancing traditional media with a number of sensory effects on QoE. They proposed a utility model based on subjective evaluation of effects such as wind, light, vibration and combinations thereof with audio-visual media. The model was based on the assumption that the addition of sensory effects linearly enhanced user QoE. As such they compared user QoE of multimedia with and without sensory effects. Their linear utility model is reflected by eq. (2):

$$QoE_{w=}QoE_{wo} * \left(\delta + \sum w_i b_i\right) \text{ [38], [39]} \tag{2}$$

In eq. (2), QoE_w reflects the user QoE with sensory effects; QoE_wo reflects the user QoE without any sensory effect components. W_i represents the weighting factor for a sensory media component of type $_\text{i}$ where $_\text{i}$ in [38] and [39] represented light, wind and vibration. b_i is a binary variable (i.e., has a value of 0 or 1) used to indicate whether a particular sensory effect is present or not. Finally, δ is used for fine-tuning. Jalal and Murroni [40] developed a nonlinear model from the dataset of [38] and [39]. Their model employed particle swarm optimization [41] for parameter estimation.

The closest work in the literature to what is presented in this paper was reported in [42] and [43]. Ademoye and Ghinea [42] and Ghinea and Ademoye [43]–[46], in their work on user perception of olfaction-enhanced multimedia, instantiated a model first proposed by Wikstrand [47]. That model proposed the consideration of multimedia quality from technical and user perspectives at three levels: *network*, *media* and *content*.

1) The network-level deals with data transmission over communications networks. Parameters include: bandwidth, delay, jitter and loss [47].
2) The media-level looks at how media is coded for transport of information over the network and / or whether the user perceives the video as being of good or bad quality. Media-level parameters include: frame rate, bit rate, screen resolution, colour depth and compression techniques [47].
3) The content-level is concerned with the transfer of information and level of satisfaction between the video media and the user, i.e., level of enjoyment [47].

Ademoye *et al.* focused on user perception at media and content levels. At the *media* level, the perceived quality was measured in terms of the combined media objects (audiovisual/olfaction) and they analyzed synchronization between the audiovisual/olfactory media streams. At the *content* level they focused on user perceived quality associated with olfaction and considered: Odor detection, acceptance, quality, context and influence on mood. They also investigated the impact of enhancing multimedia applications with olfactory media to inform and/or entertain users. To this end, the users' overall satisfaction and enjoyment of the multimedia experience, as well as the ability to assimilate and understand the information [46], [48] conveyed by the multimedia presentation was analyzed. Our previous work [6], [49]–[51] complimented and extended this work by defining a user profile based on age, gender and culture; and by analyzing the effect on the viewer's considering the scent type [13], audio masking [52] (both content level) and user QoE when multiple olfactory streams were presented. Finally, whilst Ademoye *et al.*, structured their analysis in the above mentioned "network->media->content" manner, no mathematical modeling of the user perception was performed.

User perceived mulsemedia QoE is a combination of the effect of all IFs discussed in Section I. Related to the content modalities, each contributes to the overall QoE as illustrated in Fig. 2. As such, the overall quality rating of an olfaction-enhanced multimedia experience is a combination of each of the multimodal streams. The individual contributions of the audio and video modalities to user QoE has been addressed in other works [53]. Here, the novelty lies in the fact that this is the first mathematical model, to the best of the author's knowledge, to estimate user QoE of olfaction-enhanced multimedia. The key concept of the model is that user QoE can be estimated based on 3 aspects: System Factors (user ability to detect inter-media skew (QoS)), Human Factors (the influence of user's age and gender on user ability to detect skew) and Content Factors (the impact of scent type on user ability to detect skew) as shown in Fig. 2.

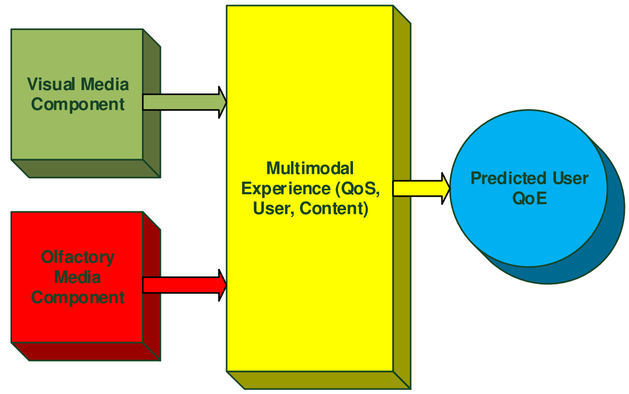

Fig. 2. Mulsemedia model (adapted from [33]).

III. Olfaction-Enhanced Multimedia Quality Experimental Setup, Content and Evaluation Methodology

A. Olfactory and Video Presentation System

The olfaction-based mulsemedia display system includes an audiovisual display in form of a 21 inch display screen with a resolution of 1024*768 with headphones, connected to a laptop. The olfactory component was supported via the SBi4 – radio v2 scent emitter from Exhalia [54]. It presents scents by blowing air (using 4 in-built fans) through scent cartridges (which are made from scented polymer balls). Presentation of scents is via the Exhalia JAVA-based SDK. The scent-emitting device is connected to the laptop via a USB port. The video content was played using the VLC media player 1.0.1 Goldeneye. The laptop had an Intel Core 2 Duo CPU @ 1.66GHz with 2GB RAM and run Windows 7 professional. A special control program was developed that controlled the synchronized presentation of olfactory data and video, including the introduction of artificial skews between the two media components presented in step sizes as per Table IV.

B. Olfactory and Video content

Assessors viewed a total of twelve video clips enhanced with olfactory components. Each clip was 90s in duration. Of the 90s video clip duration, the middle 30s block contained content related specifically to the olfactory component employed. The clips were in the form of documentaries, cookery programs and news shows as per Table III. The scents of *flowery*, *foul*, *fruity*, *burnt*, *resinous* and *spicy* reflect a "fair distribution" between what users might refer to as pleasant and unpleasant smell categories [55], [56].

C. The Assessors

A total of 84 assessors took part in the study. This group included subjects between 19 and 60 years old from a wide variety of backgrounds with a reasonable balance of age and gender as indicated in Table I. The assessors were screened according to the methodology recommended in the ISO standard 5496:2006 on assessor training for detection and recognition of odours [57] and generally had to be in good health.

D. Assessment Methodology, Questionnaire and Rating Scales

A number of approaches exist to capture user perceived quality of experience of multimedia applications. Broadly speaking, these efforts fall within capturing user QoE as

TABLE I
BREAKDOWN OF ASSESSORS BASED ON AGE AND GENDER

Gender	Age	Totals
Female	20-30	13
Female	30-40	9
Female	40-60	12
Total Female		34
Male	20-30	23
Male	30-40	14
Male	40-60	13
Total Male		50
Totals		84

TABLE II
RATING SCALES FOR EACH OF THE STATEMENTS/QUESTIONS (LIKERT SCALE)

Score	Statement 1	Question 2	Statements 3,4,5
5	Too Late	Imperceptible	Strongly Agree
4	Late	Perceptible but not annoying	Agree
3	Neither Early or Late	Slightly annoying	Neither Agree or Disagree
2	Early	Annoying	Disagree
1	Too Early	Very annoying	Strongly Disagree

the participant experiences the event or gathering the user QoE post event. With respect to the latter, a number of solutions exist in the literature for offline subjective evaluations of multimedia applications. The selected approach was the Degradation Category Rating (DCR) or Double Stimulus Impairment Scale method described in ITU-T P.910 [57]. This selection was justified based on two points: feedback from assessors during preliminary testing indicated that the "novelty" of olfactory media made even large errors temporarily acceptable, hence we wanted an approach that would introduce assessors to these types of experiences and to act as a training step. Secondly, Huang *et al.* [58] highlight the issue of non-uniform distribution of results associated with the Absolute Category Rating [59] whereby just one sample is presented to assessors for quality ratings. The implementation of DCR included a reference sample which was always a synchronized presentation of olfactory and video media and a sample under test which was either olfaction-enhanced multimedia synchronized or with synchronization error. The entire testing time took for a single subject was approximately 1 hour. This comprised of 250 seconds per test sequence (i.e., reference sample, break, sample under test and voting). In addition, at the mid-point of the test, each assessor was given a ten-fifteen minute break to address any concerns over olfactory adaptation or assessor fatigue.

The samples being tested included inter-media skew of varying degrees (shown in Table IV) as well as the synchronized presentation of olfactory and video media. For all questions, assessors chose one answer from the Likert scale, shown in Table II. The first statement aimed to determine assessor ability to **detect** the existence of a synchronization error, "*Relative to the content of the video clip, the smell was released:*". Assessors answered by selecting one of the five possible answers as shown under statement 1 in Table II. Question 2 aimed to determine how **tolerant** assessors were to different levels of skew. Hence they were asked to qualify their annoyance of the inter-media skew by answering; "*In the event that you may have perceived the video clip and smell being out of sync, please indicate the extent to which it impacted upon you. Please select the appropriate option below that reflects how you would qualify it?*" As per answers for question 2 in Table II, assessors had the option of selecting one of five values that reflected how they perceived the synchronization error (if it existed) in terms of its annoyance. The mean opinion score (MOS) of respondents was used to determine the tolerable level of skew.

The final three statements were included to analyze the impact of inter-media skew on the user experience. Assessors were asked to select one of five possible answers in terms of their agreement with the statements. The statements were ordered from general to being more specific. To determine the impact of inter-stream skew, assessors' agreement with "*You enjoyed watching the video clip*" evaluates assessor level of **enjoyment** of olfactory data as a media when in sync and explores any deterioration in this perception with the introduction of inter-media skew. "*The smell when presented, was relevant to what I was watching"* queried the **relevance** olfactory media had to the video when skews existed as opposed to synchronized presentation. By examining the assessors' agreement with "*The smell contributed to a heightened sense of reality whilst watching the video clip*", the aim was to determine the impact the level of skew has on assessors' sense of **reality** of an olfaction enhanced multimedia clip.

IV. OLFACTION-ENHANCED MULTIMEDIA QUALITY MODELING

This section explains how the proposed model to estimate user QoE of olfaction-enhanced multimedia considering system, human and content factors was designed and formalised. As outlined in Section II, user QoE affected by numerous IFs (I_i) is represented by eq. (3):

$$QoE \approx \Phi(I_1, I_2, \ldots, I_n) \tag{3}$$

In this context, the IFs considered in the proposed model are system factors: inter-media skew for olfaction enhanced multimedia; content factors: impact of scent type (pleasant vs. unpleasant); human factors: the influence of age and gender (human factors) on the user ability to detect skew. The proposed approach considering these three criteria is reflected

TABLE III
VIDEO CATEGORIES AND SCENTS USED [43] ©ACM 2012

SMELL CATEGORY	BURNT	FLOWERY	FRUITY	FOUL	RESINOUS	SPICY
VIDEO CLIP #	CLIP 1	CLIP 2	CLIP 3	CLIP 4	CLIP 5	CLIP 6
VIDEO DESCRIPTION	DOCUMENTARY ON BUSHFIRES IN OKLAHOMA	NEWS BROADCAST FEATURING PERFUME	COOKERY SHOW ABOUT MAKING FRUIT COCKTAIL	DOCUMENTARY ABOUT ROTTING FRUIT	DOCUMENTARY ON SPRING ALLERGIES & CEDAR WOOD	COOKERY SHOW ABOUT MAKING A CURRY
SCENT USED	BURNING WOOD	WALLFLOWER	STRAWBERRY	RANCID ACRID	CEDAR WOOD	CURRY
						

by eq. (4), which instantiates a multiplicative exponential weighting method (MEW). In a MEW method parameters between which there is certain level of dependency can be combined and weights can be such set not to allow for a poor value to outweigh or be outweighed by a very good value of any other component.

$$U_{QoE} \approx \alpha\left(U_S^{W_S} * U_{H_{(\mathrm{a,g})}}^{W_H} * U_C^{W_C}\right) \tag{4}$$

U_{QoE} is an aggregate utility function reflecting user QoE, U_S is the utility of the general user detection of inter-media skew, where s is the skew levels between -30s and $+30$s. $U_{H(\mathrm{a,g})}$ is a utility function representing how age "a" and gender "g" of the user affect their ability to detect inter media skew. U_C is a utility function representing how scent types affects user detection of inter-media skew. The weights w_S, w_H, w_C are associated with each of the criteria, respectively and reflect the importance of the different criteria in the algorithm. The α value is a reduction factor, with a range from 0 to 1, required for increased accuracy in user QoE estimation. For the design of each of the utilities, 35% (model design group) of the MOS ratings captured during the subjective testing was randomly selected [7], [51] within the categories of age, gender and scent type, i.e., 35% of the results from each of the criteria of age, gender and scent type. The remaining 65% of MOS ratings was used in the evaluation of the proposed models (model evaluation group). Cross validation between the different potential "design" datasets was performed to determine any effects of how the design dataset was selected. The analysis indicated minor differences between potential design group datasets, but these differences were comfortable within error ranges of 95% confidence levels. The datasets for this work are available in [60].

The following sections provide further explanations on the design of the utilities for each of the criteria outlined in eq. (4). All of the models defined in this section were generated based on non-linear regression by using the *originpro* [54] curve fitting tool. This tool supported the input of the model design group subjective data and generated the mathematical models described below. *Originpro* supports a large number of regression models. For each dataset, we preformed analysis across all available models and selected the most accurate on a case by case basis, with the goal of minimizing the mean square error (MSE).

A. *Utility Model for Inter-Media Skew*

U_S is a major utility function to evaluate the effect of skew on user QoE. The subjective ratings from the model design group were reported in [48], specifically; the assessor ability to detect skew was used to inform the model. The rating scale for detection of inter-media skew was 1 through 5 in terms of the scent being delivered "too early", "early", "at the correct time", "late" or "too late", respectively. Hence if assessors perceived the scent to be presented correctly, a rating of "3" was selected. However for the QoE related questions on enjoyment, relevance and reality, the highest possible rating was "5". Hence to provide alignment between assessor detection of skew and QoE, a mapping to calculate the mapped MOS (mMOS), was achieved using eq. (5) and presented in Fig. 3.

$$mMOS = \left\{ \begin{array}{l} 5-(3-MOS),\ \mathit{if}\ MOS \leq 3 \\ \\ 5-(MOS-3),\ \mathit{if}\ MOS \geq 3 \end{array} \right\} \tag{5}$$

For accuracy reasons in modelling the assessor detection of inter-media skew for olfaction enhanced multimedia, we split the assessor ratings into two distinct regions, (a) when olfaction is presented before video (i.e., -30s to 0s) and (b) when olfaction is presented after video (i.e., 0s to $+30$s). For each region, an exponential quality utility function is defined as this was the most accurate when computing the mean square error using the *originpro* software [54]. The "before" video utility function U_{Sb} for region (a) was calculated based on non-linear regression, using the *originpro* curve fitting tool. Based on the skew levels from -30s through to 0s, (in step sizes of 5s) the resultant function is provided by eq. (6):

$$U_{Sb} = y + ae^{rx} \tag{6}$$

where $y = 3.08374$, $a = 1.76394$ and $r = 0.08189$. These three parameters have no unit and are used to determine the shape of the utility curve. The adjusted resultant coefficient of

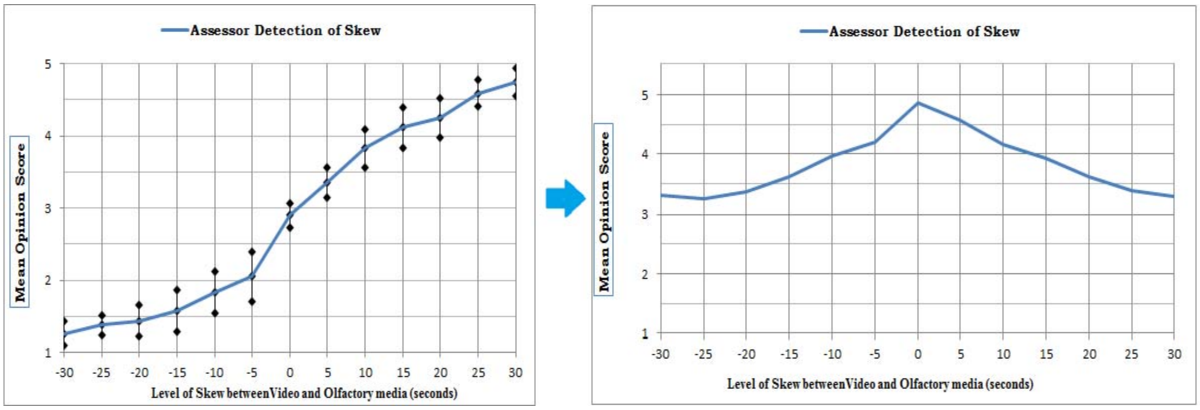

Fig. 3. Mapping from assessor detection (MOS) to MOS (mMOS) scale.

determination R^2, is used to validate the accuracy [61] and has a value very close to 1 at adj. $R^2 = 0.97983$. This indicates the accuracy of the model compared with the subjective ratings.

The "after" video utility function U_{Sa} for region (b) was calculated based on the skew levels from 0s through to +30s again in step sizes of 5s and is provided by eq. (7):

$$U_{Sa} = y + ae^{rx} \tag{7}$$

where $y = 1.95523$, $a = 22.93471$ and $r = -0.02757$. Again these have no units and are used to determine the shape of the utility curve. The adj. R^2, has a value very close to 1 at $R^2 = 0.99186$ indicating the accuracy of the model.

Considering eq. (6) and eq. (7), the model for U_S is provided by eq. (8) for all inter-media skew levels from −30s to +30s.

$$U_S = \left\{ \begin{array}{l} U_{Sb}, -30s \le x \le 0s \\ \\ U_{Sa}, 0 \le x \le 30s \end{array} \right\} \tag{8}$$

Fig. 4 graphically compares U_S with the assessor detection of skew ratings from the subjective results (mMOS of the model evaluation group) across all the skew levels from −30s to +30s. Generally speaking it is an excellent fit to the assessor MOS ratings, with minor discrepancies at skew levels of −25s, −20s, −15s and +5s. The error range of these discrepancies comfortably fall within the confidence levels for the subjective MOS values as reported in [48].

B. Utility Model for User Profile

This section describes the building of the user profile utility function, $U_{H(a,g)}$, which considers the influence of some human factors on the ability to detect skew and as a result, the overall QoE rating. As reported in previous works [7], [51], the variables of age and gender each had an impact (to varying degrees) on the assessor ability to detect inter-media skew between the olfactory and video media components and user QoE of olfaction enhanced multimedia. $U_{H(a,g)}$ is proposed as a multi-component utility function considering the impact of each of the variables as per eq. (9).

$$U_{H(a,g)} = f(Age, Gender) \tag{9}$$

where $\left\{ \begin{array}{l} Age = (20 - 30yrs, 30 - 40yrs, 40 + yrs) \\ Gender = (Male, Female) \end{array} \right\}$

Modelling $U_{H(a,g)}$ using an analytical approach is non-trivial, and would require further substantial subjective evaluations. Therefore, a three-dimensional lookup table is employed which considers the age and gender influences with respect to detection of skew. Employing the design group subjective results, the mMOS equation illustrated above was applied to the respective assessor ratings of skew, i.e., user ratings of skew (grouped by age and gender combinations) were mapped. The results are presented in Table IV.

A one way ANOVA post hoc with least significant difference test with 95% confidence level was performed between the results for different age and gender subject groupings as per Table V. The results show how statistical significant differences existed for different skew levels and age/gender groupings. As per Table V, there were 20 statistically significant differences between the groups, indicated in the table as an entry with the skew level and ANOVA significance value (P). Further inspection indicates that seven of the statistically significant differences occurred when olfaction was presented before video, ten when olfaction was presented after video and finally three when olfaction and video were synchronized.

C. Utility Model for Scent Types

In this section, the utility function for impact of scent type on user ability to detect skew is defined. Our previous work [13] indicated that the enhancement of multimedia content with different scent types had different effects on the assessor QoE and also assessors detected skew differently based on scent type. In terms of modelling the impact of scent type on assessor QoE, the scent types are grouped based on the categories of "pleasant" or "unpleasant" scent types. The pleasant scent types were "flowery", "fruity" and "spicy". The unpleasant scent types were identified as "resinous", "burnt", "foul". The assessor MOS ratings from the assessors (model design group) for detection of skew were grouped based on this categorization and the mMOS mapping was applied as per eq. (5). As was the case for the

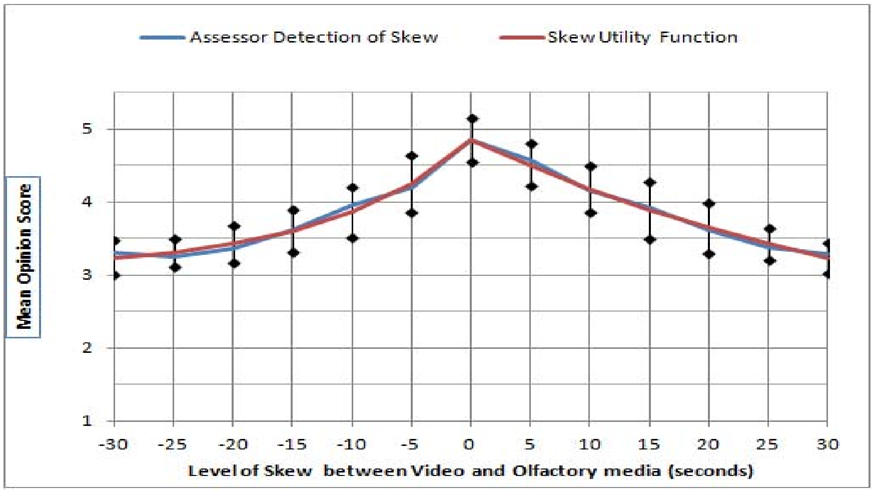

Fig. 4. Comparison of assessor detection of skew and skew utility model.

TABLE IV
ASSESSOR DETECTION OF SKEW (MMOS) PER AGE AND GENDER

Age & Gender	Skew (seconds)												
	-30	**-25**	**-2**	**-15**	**-10**	**-5**	**0**	**5**	**10**	**15**	**20**	**25**	**30**
Female 20-30 yrs.	3.25	3.25	3.42	3.42	3.75	3.67	4.58	4.08	4	3.42	3.75	3.42	3.25
Male 20-30 yrs.	3.24	3.24	3.48	3.62	3.95	3.95	4.76	4.38	4.1	3.9	3.71	3.33	3.48
Female 30-40 yrs.	3.22	3.44	3.56	3.22	4.11	3.33	4.78	4.67	4.11	4.22	3.56	3.33	3.22
Male 30-40 yrs.	3.31	3.23	3.15	3.62	3.46	3.92	4.54	4.31	4.31	3.62	3.54	3.46	3
Female 40+ yrs.	3.17	3.33	3.42	3.58	3.75	3.83	4.33	4.5	4.17	3.83	3.42	3.42	3
Male 40+ yrs.	3.62	3.23	3.46	3.38	3.08	4	4.15	4.54	3.85	3.62	3.77	3.31	3.23

TABLE V
STATISTICALLY SIGNIFICANT DIFFERENCES BETWEEN AGE AND GENDER GROUPS ON THEIR DETECTION OF SKEW (CONFIDENCE=95%)

		Statistically Significant Differences and Skew Level
Female 20-30 yrs.	**Male 20-30 yrs.**	@ +15s – P=0.032
	Female 30-40 yrs.	@ +5s – P=0.015, @ +15s – P=0.004,
	Male 40 + yrs.	@ -10s – P=0.016, @ +5s – P=0.036
	Female 40 + yrs.	@ +5s – P=0.058,
Male 20-30 yrs.	**Female 30-40 yrs.**	@ -5s – P=0.053,
	Male 30-40 yrs.	@ -10s – P=0.045, @ -10s – P=0.001, @ +30s – P=0.007
	Male 40 + yrs.	@ 0s – P=0.011, @ -30s – P=0.082, @ -10s – P=0.001
	Female 40 + yrs.	@ 0s – P=0.011, @ +30s – P=0.008
Female 30-40 yrs.	**Male 30-40 yrs.**	@ -10s – P=0.031, @ -5s – P=0.089, @ +15s – P=0.026
	Male 40 + yrs.	@ 0s – P=0.075, @ -10s – P=0.001, @ -5s – P=0.056, @ +15s – P=0.026
Male 30-40 yrs.	**Male 40 + yrs.**	@ +10s – P=0.081
Female 40 + yrs.	**Male 40 + yrs.**	@ -30s – P=0.068, @ -10s – P=0.016

model representing the general detection of skew, detection of skew based on scent category was divided into two distinct regions, (a) when olfaction was presented before video (i.e., -30s to 0s) and (b) when olfaction was presented after video, i.e., (0s to $+30$s) for both the pleasant and unpleasant groupings.

1) Utility Model for Unpleasant Scent Types: For the unpleasant category, an exponential quality utility function was defined for both regions (a) and (b). The "before" video utility U_{CUb} function for region (a) was calculated based on non-linear regression. Based the on skew levels from -30s through to 0s in steps of 5s, the resultant function is provided by eq. (10):

$$U_{CUb} = y + ae^{rx} \tag{10}$$

where $y = 2.82912$, $a = 1.94619$ and $r = 0.06538$. Again, these three parameters have no unit and are used to determine the shape of the utility curve. The resultant adj. R^2, has a value close to 1 at $R^2 = 0.89807$ indicating the high accuracy of the model.

The "after" video utility U_{CUa} function for the unpleasant scent group for region (b) was calculated based on non-linear

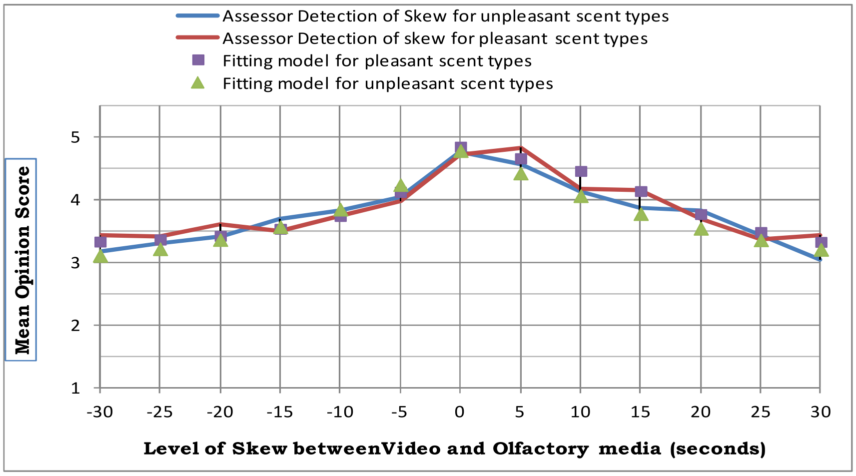

Fig. 5. Comparison of assessor detection of skew for pleasant and unpleasant scent types with associated utility model functions.

regression. Again the function was calculated based the on the skew levels from 0s through to +30s and again in steps of 5s; it is provided in eq. (11):

$$U_{CUa} = y + ae^{rx} \tag{11}$$

where $y = 2.58353$, $a = 2.27817$ and $r = -0.04358$. Again these are used to determine the shape of the utility curve. The resultant adj. R^2, has a value very close to 1 at $R^2 = 0.93547$ indicating the high accuracy of the model.

2) Utility Model for Pleasant Scent Types: In terms of the pleasant scent category model, interesting observations are made. In all the previous model values, the exponential model fitting returned high levels of accuracy. However, whilst performing the modelling on the pleasant scent category, the exponential model did not accurately fit for olfaction presented after video, with a sigmoid function selected subsequently. Again, two regions were defined, consistent with each of the models presented to date.

The model function for region (a) was calculated based on non-linear regression. Based the on skew levels from -30s through to 0s in step sizes of 5s as discussed in detail in [13], the resultant model function is:

$$U_{CPb} = y + ae^{rx} \tag{12}$$

where $y = 3.29041$, $a = 1.54626$ and $r = 0.12512$.

Again, these three parameters have no unit and are used to determine the shape of the utility curve. The resultant coefficient of determination R^2, has a value very close to 1 at $R^2 = 0.96747$ indicating the high accuracy of the model.

The model function for region (b) was calculated based on non-linear regression using *originpro*. Based the on skew levels from 0s through to +30s in steps of 5s, the resultant model function is:

$$U_{CPa} = \mathrm{A2} + (\mathrm{A1} - \mathrm{A2})/(1 + \exp((\mathrm{x} - \mathrm{x0})/\mathrm{z})) \tag{13}$$

where $\mathrm{A1} = 4.82618$, $\mathrm{A2} = 3.18731$, $x0 = 16.64647$ and $\mathrm{Z} = 5.46468$. Again, these parameters have no unit and are used to determine the shape of the utility curve. The resultant coefficient of determination R^2, has a value very close to 1 at $R^2 = 0.87224$ indicating the high accuracy of the model.

The overall utility for impact of scent type on user ability to detect skew, U_C, is provided in eq. (14). The accuracy is presented in Fig. 5. It always shows the accuracy of the respective models predicting the assessor ability to detect skew and the actual MOS scores of the model evaluation group captured via subjective testing for pleasant and unpleasant scent types.

$$U_C = \left\{ \begin{matrix} U_{CUb} \\ U_{CPb} \end{matrix} \quad -30\ s \le x \le 0\ s \atop \begin{matrix} U_{CUa} \\ U_{CPa} \end{matrix} \quad 0 \le x \le 30\ s \right\} \tag{14}$$

This section has highlighted the approaches to modelling the various criteria defined in eq. (4). Each of the utilities for inter-media skew, user profile influence on skew and scent type influence on skew were modelled. As such, the user QoE can be estimated considering each of these criteria. The estimated user QoE, U_{QoE}, is a multiplicative function such that the influence of each of the criteria is taken into consideration. In this next section, an instantiation of this model is performed with variable weightings per criteria. In addition, regression analysis is performed to evaluate the accuracy of the proposed model by comparing the estimated QoE with actual QoE ratings obtained via subjective testing.

D. Analysis and Evaluation

In this section, statistical analysis on the influence of various factors on user QoE is presented next. In addition, the proposed model for estimating user QoE of olfaction enhanced multimedia is instantiated and evaluated.

1) The Influence of the Factors on QoE: In this section, the authors analyse the influence of human and content factors on the ability to detect skew as well as their influence on user QoE. The analysis was performed using IBM SPSS Statistics package version 23. A Multivariate Analysis of Variance (MANOVA) was performed on the complete dataset (both design and evaluation groups) with 95% confidence level. The independent variables were the human (age, gender) and content (scent type) factors whilst the independent variables were detection of skew and user QoE rating. The overall QoE rating was captured via the post-test questionnaires. The average MOS values for user sense of enjoyment, sense of

TABLE VI
RESULTS OF MANOVA PERFORMED TO CONSIDER THE INFLUENCE OF HUMAN AND CONTENT FACTORS ON USER QoE (CONFIDENCE= 95%)

Skew Level	Box's Test of Equality of Covariance Matrices Sig.	Levene's Test of Equality of Error Variances Sig.	Multivariate Tests: Pillai's trace Sig.	Tests of Between-Subjects Effects: Sig.	Partial ETA
+30s	0.808	QoE =0.210 Detection =0.000	Age= 0.002 Gender = 0.575 Scent-type = 0.0041	Age and QoE = 0.012 Age and Detection = 0.049 Scent-type and QoE = 0.001	12% 8% 15%
+25s	0.797	QoE=0.733 Detection=0.004	Age=0.861 Gender=0.832 Scent-type=0.084	Scent-type and QoE =0.027	7%
+20s	0.941	QoE=0.264 Detection=0.000	Age=0.700 Gender=0.201 Scent-type=0.782	Age and QoE =0.834 Gender and QoE =0.125 Scent-type and QoE =0.565	N/A
+15s	0.509	QoE=0.886 Detection=0.742	Age=0.148 Gender=0.285 Scent-type=0.023	Scent-type and Detection=0.037	11%
+10s	0.277	QoE=0.136 Detection=0.077	Age=0.968 Gender=0.682 Scent-type=0.453	Age and QoE =0.972 Gender and QoE =0.638 Scent-type and QoE =0.229	N/A
+5s	0.991	QoE=0.289 Detection=0.001	Age=0.019 Gender=0.592 Scent-type=0.061	Age and Detection =0.05 Scent-type and QoE =0.044	9% 6% (*)
0s	0.868	QoE=0.431 Detection=0.001	Age=0.192 Gender=0.106 Scent-type=0.113	Gender and QoE =0.034	7% (*)
-5s	0.175	QoE =0.002 Detection =.255.	Scent-type=0.010	Scent-type and QoE =0.004	11% (*)
-10s	0.964	QoE =0.473 Detection =0.016.	Age=0.001 Gender=0.799 Scent-type=0.044	Age and QoE =0.048 Scent-type and QoE =0.033	9% (*) 10% (*)
-15s	0.091	QoE =0.226. Detection =0.000.	Age=0.959 Gender=0.225 Scent-type=0.168	N/A	N/A
-20s	0.172	QoE =0.020 Detection =0.125.	Age=0.856 Gender=0.065 Scent-type=0.580	N/A	N/A
-25s	0.234	QoE =0.276 Detection =0.000.	Age=0.014 Gender=0.025 Scent-type=0.046	Age and QoE =0.002 Gender and QoE =0.011 Scent-type and QoE =0.025	16% (*) 9% (*) 7% (*)
-30s	0.772	QoE =0.627 Detection =0.000.	Age=0.112 Gender=0.632 Scent-type=0.026	Age and QoE =0.030 Scent-type and QoE =0.009	10% (*) 10% (*)

(*) effect size is small

relevance and sense of reality were defined as a single digit representation of user QoE. The analysis is classified based on skew level. The results are presented in Table VI, which includes statistically significant results only, with the last column (partial ETA) indicating the percentage of the influence the factors contribute to either to detecting inter-media skew or user QoE, as reported. The effect of age on user QoE was found to have a small effect in four of the thirteen possible test cases. In terms of gender, it was found to have a small effect in just 2 of the thirteen scenarios tested whilst content factors, i.e., whether the scent type was pleasant or unpleasant, had a small effect in six of the possible scenarios. Interestingly, where statistically significance exists, the average influence levels for content age and gender were 10%, 11% and 8%, respectively. In terms of the influence of human and content factors on the user's ability to detect skew, two statistically significant results were reported at skew levels of +30s and +5s, with scent type reporting statistically significant results for just one of the skew levels.

2) Evaluation of the Proposed Model: The user QoE has been defined as a function of assessor sense of enjoyment, sense of relevance and sense of reality of olfaction enhanced multimedia. There was a consistency between assessor ratings for sense of enjoyment, relevance and reality. Indeed, no statistically significant differences exist between these three aspects [7]. The model proposed as per eq. (15), is evaluated by comparing estimated QoE with the MOS scores from the model evaluation group assessors ratings for sense of enjoyment, sense of reality and sense of relevance captured during the subjective testing. Eq. (16) defines the user QoE as a multiplicative utility function which considers user detection of inter-media skew, impact of user profile on user detection of inter-media skew and impact of scent type user detection of inter-media skew.

Fig. 6 presents the results of the QoE estimation model with the average QoE obtained during subjective testing. It shows the instantiated model with the same weightings for each of the criteria, 0.333 and an $\boldsymbol{\alpha} = .87$. The reduction

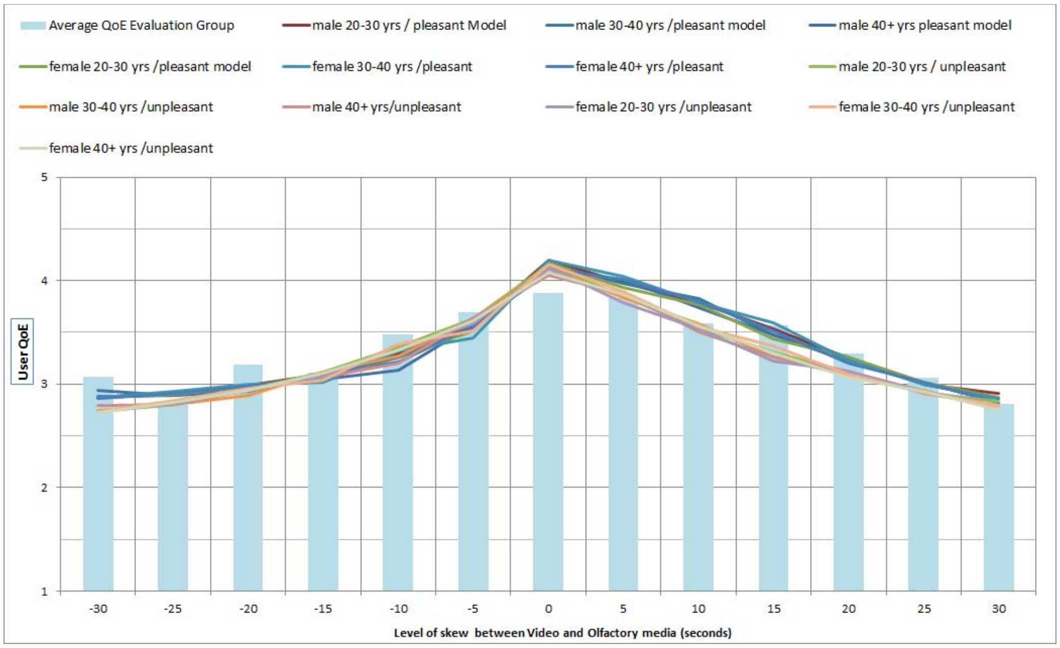

Fig. 6. Comparison of QoE rating from assessors with QoE utility with criterion weights of 0.333 and $\alpha = .87$.

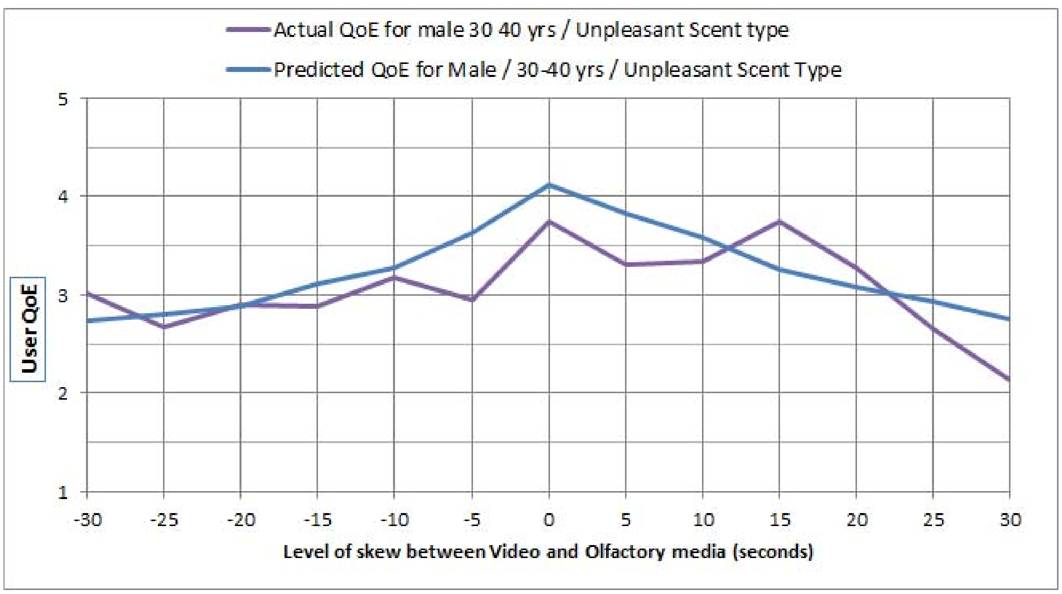

Fig. 7. Comparison of the predicted and actual QoE levels for male group of 30-40 yrs exposed to an unpleasant scent type.

factor $\boldsymbol{\alpha}$ was set at 0.87 so that the estimation model accurately matches the MOS values assessors provided during the subjective tests. The estimated QoE ratings achieved via the model are mapped reasonably well to the actual QoE ratings captured. In the next section, the model is evaluated for each of the possible weighting for each of the criteria and define the most suitable weightings accordingly.

$$U_{QoE(enjoyment,\, relevance,\, reality)} = U_{QoE} \tag{15}$$

$$U_{QoE(enjoyment,\, relevance,\, reality)} \approx \alpha\left(U_S^{W_S} * U_{H_{(a,g)}}^{W_H} * U_C^{W_C}\right) \tag{16}$$

In order to evaluate the accuracy of the proposed model and fine tune values for each of the criterion, we compared all possible combinations of assessors QoE based on the age, gender and scent type. Due to page limitations, we present two of our findings here in Fig. 7 and Fig. 8. These are male 30-40 with unpleasant scent type and female 30-40 with pleasant scent type respectively. Different weightings were applied to w_S, w_H and w_C. Analysis was performed between the actual and estimated QoE ratings via: correlation coefficient, "r"; the coefficient of determination "r^2"; and finally the mean square error ("MSE"). The correlation coefficient provides a measure of the relationship between the actual and predicted values and ranges between 0 and 1, where 1 indicates the strongest possible relationship. The coefficient of determination identifies the amount of variation in the actual data that is explained by variation in the predicted data. Hence, variations outside this

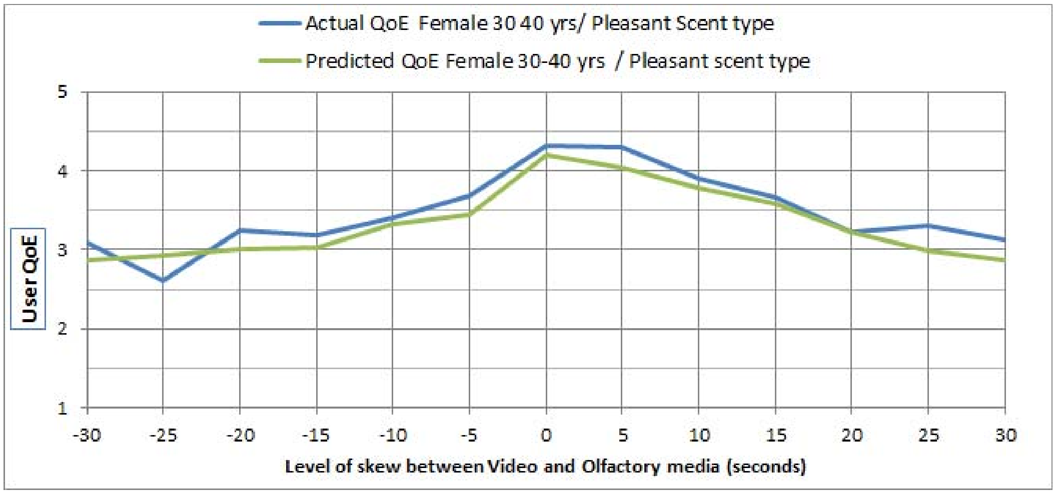

Fig. 8. Comparison of the predicted and actual QoE levels for female group of 30-40 yrs exposed to a pleasant scent type.

are caused by factors not considered in the model. Since both the linear regression and their accuracy for a non-linear model is questioned in some works [61], MSE was also employed. MSE is a measure of the average of the sum of the squares of errors between the predicted and actual values. Generally speaking, a trend emerges that the lowest MSE values are achieved when w_S has lower weights and w_H and correlation and coefficient are generally more applicable for w_C had higher weights. Based on the analysis, the following weighting generally resulted in the most accurate estimated QoE:

$$w_S = 0.1, w_H = 0.2 \text{ and } w_C = 0.7. \tag{17}$$

Given the weightings, the MSE values were 0.12 and 0.042 respectively. Whilst other weights that provide lower MSE and indeed higher r and r^2 exist, generally the chosen weights support on average the lowest MSE. Fig. 7 and Fig. 8 present a comparison between the estimated QoE from the model with the actual subjective ratings for males, 30-40 yrs exposed to unpleasant scents and females, 30-40 years dealing with pleasant scents. The accuracy of the model as presented in Fig. 7 and Fig. 8 is very encouraging. The accuracy of the estimated QoE as shown in Fig. 8 is very closely aligned with the actual MOS scores captured during the subjective test. Interestingly, where a reduction in α is required for greater accuracy with the unpleasant scent type, a minor increase in α is necessary for more accurate estimation of pleasant scent type QoE.

V. Conclusion

This paper has presented a model that estimates user QoE for olfaction-enhanced multimedia given a number of contextual criteria such as inter-media skew level, users' age and gender, as well as scent type. To the best of the authors' knowledge, this model is the first approach to estimate user QoE involving olfaction as a media component based on QoS metrics. Interestingly the findings are consistent with the impact similar QoS metrics have on QoE with respect to other media components as reported in. The accuracy of the model in terms of MSE is very encouraging. The model presented here, could be used as input into a recommender engine, which, based on context of user profile, skew levels and scent type on whether to present olfaction as part of a multimedia experience. The authors acknowledge the limitations of the proposed approach, specifically with regards to additional inputs that need to be considered. Such inputs could be: the number of olfactory streams (content utility function); genre of video content (content utility function); the influence of audio on olfaction based mulsemedia QoE (using the datasets available in [60] - content utility function); user preferences employing olfaction in multimedia experiences (user profile utility function) etc. Such efforts are identified as future work.

References

[1] C. Timmerer, M. Waltl, B. Rainer, and N. Murray, "Sensory experience: Quality of experience beyond audio-visual," in *Quality of Experience: Advanced Concepts, Applications and Methods*, S. Muller and A. Raake, Eds. Cham, Switzerland: Springer Int., 2014, pp. 351–365.

[2] G. Ghinea, S. R. Gulliver, and F. Andres, Eds., *Multiple Sensorial Media Advances and Applications: New Developments in MulSeMedia*. Hershey, PA, USA: IGI Glob., 2011.

[3] G. Ghinea, C. Timmerer, W. Lin, and S. R. Gulliver, "Mulsemedia: State of the art, perspectives, and challenges," *ACM Trans. Multimedia Comput. Commun. Appl.*, vol. 11, no. 1s, Oct. 2014, Art. no. 17. [Online]. Available: http://doi.acm.org/10.1145/2617994

[4] Z. Yuan, G. Ghinea, and G.-M. Muntean, "Beyond multimedia adaptation: Quality of experience-aware multi-sensorial media delivery," *IEEE Trans. Multimedia*, vol. 17, no. 1, pp. 104–117, Jan. 2015.

[5] F. Danieau *et al.*, "Toward haptic cinematography: Enhancing movie experience with haptic effects based on cinematographic camera motions," *IEEE Trans. Multimedia*, vol. 21, no. 2, pp. 11–21, Apr./Jun. 2014.

[6] T. Narumi, S. Nishizaka, T. Kajinami, T. Tanikawa, and M. Hirose, "Augmented reality flavors: Gustatory display based on edible marker and cross-modal interaction," in *Proc. ACM CHI Conf. Human Factors Comput. Syst.*, Vancouver, BC, Canada, 2011, pp. 93–102.

[7] N. Murray, Y. Qiao, B. Lee, and G.-M. Muntean, "User-profile-based perceived olfactory and visual media synchronization" *ACM Trans. Multimedia Comput. Commun. Appl.*, vol. 1, no. 10, 2014, Art. no. 11.

[8] P. Le Callet, S. Möller, and A. Perkis, "Qualinet white paper on definitions of quality of experience," Lausanne, Switzerland, Eur. Netw. Qual. Exp. Multimedia Syst. Services (COST Action IC 1003), White Paper, Mar. 2013. [Online]. Available: http://www.qualinet.eu/images/stories/QoE_whitepaper_v1.2.pdf

[9] S. Möller and A. Raake, *Quality of Experience?: Advanced Concepts, Applications and Methods*. Cham, Switzerland: Springer Int., 2014, doi: 10.1007/978-3-319-02681-7.

[10] T. Ebrahimi, "Quality of multimedia experience: Past, present and future," in *Proc. ACM Multimedia Conf. (MM)*, 2009, pp. 3–4.

[11] R. Stankiewicz, P. Cholda, and A. Jajszczyk, "QoX: What is it really?" *IEEE Commun. Mag.*, vol. 49, no. 4, pp. 148–158, Apr. 2011.

[12] U. Reiter *et al.*, "Factors influencing quality of experience," in *Quality of Experience?: Advanced Concepts, Applications and Methods*, S. Möller and A. Raake, Eds. Cham, Switzerland, Springer Int., 2014, pp. 55–72.

[13] N. Murray, B. Lee, Y. Qiao, and G.-M. Muntean, "The impact of scent type on olfaction-enhanced multimedia quality of experience," *IEEE Trans. Syst., Man, Cybern.*, vol. 47, no. 9, pp. 2503–2515, Sep. 2017, doi: 10.1109/TSMC.2016.2531654.

[14] G. Ghinea and O. A. Ademoye, "Olfaction-enhanced multimedia: Perspectives and challenges," *Multimedia Tools Appl.*, vol. 55, no. 3, pp. 601–626, 2011.

[15] P. T. Kovács, N. Murray, G. Rozinaj, Y. Sulema, and R. Rybárová, "Application of immersive technologies for education: State of the art," in *Proc. Int. Conf. Interact. Mobile Commun. Technol. Learn. (IMCL)*, Thessaloniki, Greece, 2015, pp. 283–288, doi: 10.1109/IMCTL.2015.7359604.

[16] N. Murray, Y. Qiao, B. Lee, A. K. Karunakar, and G.-M. Muntean, "Olfaction-enhanced multimedia: A survey of application domains, displays, and research challenges," *ACM Comput. Surveys*, vol. 48, no. 4, 2016, Art. no. 56.

[17] N. Murray, O. A. Ademoye, G. Ghinea, and G.-M. Muntean, "A tutorial for olfaction-based multisensorial media application design and evaluation," *ACM Comput. Surveys*, vol. 50, no. 5, 2017, Art. no. 67, doi: 10.1145/3108243.

[18] M. Obrist, A. N. Tuch, and K. Hornbaek, "Opportunities for Odor: Experiences with smell and implications for technology," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, Toronto, ON, Canada, 2014, pp. 2843–2852, doi: 10.1145/2556288.2557008.

[19] M. Obrist *et al.*, "Sensing the future of HCI: Touch, taste, and smell user interfaces," *Interactions*, vol. 23, no. 5, pp. 40–49, 2016.

[20] M. Obrist, E. Gatti, E. Maggioni, C. T. Vi, and C. Velasco, "Multisensory experiences in HCI," *IEEE Trans. Multimedia*, vol. 24, no. 2, pp. 9–13, Apr./Jun. 2017.

[21] C. Spence, M. Obrist, C. Velasco, and N. Ranasinghe "Digitizing the chemical senses: Possibilities & pitfalls," *Int. J. Human Comput. Stud.*, vol. 107, pp. 62–74, Nov. 2017, doi: 10.1016/j.ijhcs.2017.06.003.

[22] C. Zhang, A. S. Hoel, and A. Perkis, "Quality of alternate reality experience and its QoE influencing factors," in *Proc. 2nd Int. Workshop Alternate Realities*, Mountain View, CA, USA, Oct. 2017, pp. 3–8, doi: 10.1145/3132361.3132365.

[23] G.-M. Muntean, P. Perry, and L. Murphy, "A comparison-based study of quality-oriented video on demand," *IEEE Trans. Broadcast.*, vol. 53, no. 1, pp. 92–102, Mar. 2007.

[24] G.-M. Muntean, "Efficient delivery of multimedia streams over broadband networks using QOAS," *IEEE Trans. Broadcast.*, vol. 52, no. 2, pp. 230–235, Jun. 2006.

[25] G.-M. Muntean, P. Perry, and L. Murphy, "Objective and subjective evaluation of QOAS video streaming over broadband networks," *IEEE Trans. Netw. Service Manag.*, vol. 2, no. 1, pp. 19–28, Nov. 2005.

[26] G.-M. Muntean, P. Perry, and L. Murphy, "Subjective assessment of the quality-oriented adaptive scheme," *IEEE Trans. Broadcast.*, vol. 51, no. 3, pp. 276–286, Sep. 2005.

[27] G.-M. Muntean and N. Cranley, "Resource efficient quality-oriented wireless broadcasting of adaptive multimedia content," *IEEE Trans. Broadcast.*, vol. 53, no. 1, pp. 362–368, Mar. 2007.

[28] Z. Yuan and G.-M. Muntean, "A prioritized adaptive scheme for multimedia services over IEEE 802.11 WLANs," *IEEE Trans. Netw. Service Manag.*, vol. 10, no. 4, pp. 340–355, Dec. 2013.

[29] J. Huang, C. Xu, Q. Duan, Y. Ma, and G.-M. Muntean, "Novel end-to-end quality of service provisioning algorithms for multimedia services in virtualization-based future Internet," *IEEE Trans. Broadcast.*, vol. 58, no. 4, pp. 569–579, Dec. 2012.

[30] A.-N. Moldovan, I. Ghergulescu, and C. H. Muntean, "VQAMap: A novel mechanism for mapping objective video quality metrics to subjective MOS scale," *IEEE Trans. Broadcast.*, vol. 62, no. 3, pp. 610–627, Sep. 2016.

[31] A. Fielder, T. Hossfeld, and P. Tran-Gia, "A generic quantitative relationship between quality of experience and quality of service," *IEEE Netw.*, vol. 24, no. 2, pp. 36–41, Mar./Apr. 2010.

[32] F. Agboma and A. Liotta "QoE-aware QoS management" in *Proc. 6th Annu. Conf. Adv. Mobile Comput. Multimedia*, Linz, Austria, 2008, pp. 111–116.

[33] M. J. Scott, S. C. Guntuku, Y. Huan, W. Lin, and G. Ghinea, "Modelling human factors in perceptual multimedia quality: On the role of personality and culture," in *Proc. 23rd ACM Int. Conf. Multimedia*, Brisbane, QLD, Australia, 2015, pp. 481–490, doi: 10.1145/2733373.2806254.

[34] M. J. Scott, S. C. Guntuku, Y. Huan, W. Lin, and G. Ghinea, "Do personality and culture influence perceived video quality and enjoyment?" *IEEE Trans. Multimedia*, vol. 18, no. 9, pp. 1796–1807, Sep. 2016, doi: 10.1109/TMM.2016.2574623.

[35] Y. Zhu, I. Heynderickx, A. Hanjalic, and J. A. Redi, "Towards a comprehensive model for predicting the quality of individual visual experience," in *Proc. SPIE Human Vis. Electron. Imag. XX*, vol. 9394. San Francisco, CA, USA, Mar. 2015, Art. no. 93940A.

[36] N. Murray, B. Lee, Y. Qiao, A. K. Karunakar, and G.-M. Muntean, "The influence of human factors on olfaction based mulsemedia quality of experience," in *Proc. 8th Int. Workshop Qual. Multimedia Exp. (QoMeX)*, Lisbon, Portugal, 2016, pp. 1–6, doi: 10.1109/QoMEX.2016.7498975.

[37] F. Pereira, "A triple user characterization model for video adaptation and quality of experience evaluation," in *Proc. 7th IEEE Workshop Multimedia Signal Process.*, Shanghai, China, 2005, pp. 1–4.

[38] C. Timmerer, B. Rainer, and M. Waltl, "A utility model for sensory experience," in *Proc. 5th Int. Workshop Qual. Multimedia Exp. (QoMeX)*, 2013, pp. 224–229, doi: 10.1109/QoMEX.2013.6603241.

[39] B. Rainer and C. Timmerer, "A generic utility model representing the quality of sensory experience," *ACM Trans. Multimedia Comput. Commun. Appl.*, vol. 11, no. 1s, 2014, Art. no. 14.

[40] L. Jalal and M. Murroni, "A nonlinear quality of experience model for high dynamic spatio-temporal mulsemedia," in *Proc. 9th Int. Conf. Qual. Multimedia Exp. (QoMeX)*, Erfurt, Germany, 2017, pp. 224–229, doi: 10.1109/QoMEX.2017.7965654.

[41] J. Kennedy and R. Eberhart "Particle swarm optimization," in *Proc. IEEE Int. Conf. Neural Netw.*, Perth, WA, Australia, 1995, pp. 1942–1948.

[42] O. A. Ademoye and G. Ghinea, "Synchronization of olfaction-enhanced multimedia," *IEEE Trans. Multimedia*, vol. 11, no. 3, pp. 561–565, Apr. 2009.

[43] G. Ghinea and O. A. Ademoye "Perceived synchronization of olfactory multimedia," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 40, no. 4, pp. 657–663, Jul. 2010.

[44] G. Ghinea and O. A. Ademoye "The sweet smell of success: Enhancing multimedia applications with olfaction," *ACM Trans. Multimedia Comput. Commun. Appl.*, vol. 8, no. 1, 2012, Art. no. 2.

[45] G. Ghinea and O. A. Ademoye, "Olfaction-enhanced multimedia: Bad for information recall?" in *Proc. Int. Conf. Multimedia Expo (ICME)*, New York, NY, USA, 2009, pp. 970–973.

[46] G. Ghinea and O. A. Ademoye "User perception of media content association in olfaction-enhanced multimedia," *ACM Trans. Multimedia Comput. Commun. Appl.*, vol. 8, no. 4, 2012, Art. no. 52.

[47] G. Wilkstrand, "Improving user comprehension and entertainment in wireless streaming media: Introducing cognitive quality of service," M.S. thesis, Dept. Comput. Sci., Umeå Univ., Umeå, Sweden, 2003.

[48] O. A. Ademoye and G. Ghinea, "Information recall task impact in olfaction-enhanced multimedia," *ACM Trans. Multimedia Comput. Commun. Appl.*, vol. 9, no. 3, 2013, Art. no. 17.

[49] N. Murray, Y. Qiao, B. Lee, A. K. Karunakar, and G.-M. Muntean, "Subjective evaluation of olfactory and visual media synchronization," in *Proc. ACM Multimedia Syst. Conf.*, Oslo, Norway, Feb./Mar. 2013, pp. 162–171.

[50] N. Murray, B. Lee, Y. Qiao, and G.-M. Muntean, "Multiple-scent enhanced multimedia synchronization," *ACM Trans. Multimedia Comput. Commun. Appl.*, vol. 11, no. 1s, Sep. 2014, Art. no. 12, doi: 10.1145/2637293.

[51] N. Murray, Y. Qiao, B. Lee, G.-M. Muntean, and A. K. Karunakar, "Age and gender influence on perceived olfactory and visual media synchronization," in *Proc. IEEE Int. Conf. Multimedia Expo (ICME)*, 2013, San Jose, CA, USA, pp. 1–6.

[52] O. A. Ademoye, N. Murray, G.-M. Muntean, and G. Ghinea, "Audio masking effect on inter-component skews in olfaction-enhanced multimedia presentations," *ACM Trans. Multimedia Comput. Commun. Appl.*, vol. 12, no. 4, 2016, Art. no. 51, doi: 10.1145/2957753.

[53] D. S. Hands, "A basic multimedia quality model," *IEEE Trans. Multimedia*, vol. 6, no. 6, pp. 806–816, Dec. 2004.

[54] *Exhalia*. Accessed: Sep. 13, 2016. [Online]. Available: www.exhalia.com

[55] N. Kaye, “Symbolic olfactory display,” M.S. thesis, Dept. Archit., Massachusetts Inst. Technol., Cambridge, MA, USA, 2001.

[56] M. Chastrette, “Classification of odors and structure—Odor relationships,” in *Olfaction, Taste, and Cognition*. New York, NY, USA: Cambridge Univ. Press, 2002, pp. 100–116.

[57] “Subjective video quality assessment methods for multimedia applications,” Int. Telecommun. Union, Geneva, Switzerland, ITU-T-Recommendation P.910, 2008.

[58] Z. Huang, A. Arefin, P. Agarwal, K. Nahrstedt, and W. Wu, “Towards the understanding of human perceptual quality in tele-immersive shared activity,” in *Proc. ACM Multimedia Syst. Conf. (MMSYS)*, Feb. 2012, pp. 29–34.

[59] “Methodology for the subjective assessment of the quality of television pictures,” Int. Telecommun. Union, Geneva, Switzerland, ITU-T Recommendation BT.500, 2002, accessed: Sep. 13, 2016. [Online]. Available: www.originlab.com

[60] N. Murray *et al.*, “Olfactory-enhanced multimedia video clips datasets,” in *Proc. IEEE 9th Int. Conf. Qual. Multimedia Exp. (QoMEX)*, Erfurt, Germany, May 2017, pp. 1–5.

[61] A. N. Spiess and N. Neumeyer, “An evaluation of R2 as an inadequate measure for nonlinear models in pharmacological and biochemical research: A Monte Carlo approach,” *BMC Pharmacol*, vol. 10, Jun. 2010, Art. no. 6.

[62] Z. Yuan, T. Bi, G.-M. Muntean, and G. Ghinea, “Perceived synchronization of mulsemedia services,” *IEEE Trans. Multimedia*, vol. 17, no. 7, pp. 957–966, Jul. 2015.

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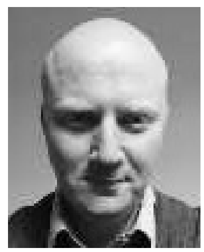

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