Image-based Emotion Feedback: How Does the Crowd Feel? And Why?

David A. Robb[1] **Stefano Padilla**[1] **Thomas S. Methven**[1] **Britta Kalkreuter**[2] **Mike J. Chantler**[1]
[1]School of Mathematical and Computer Sciences, [2]School of Textiles and Design,
Heriot-Watt University, Edinburgh, UK. EH14 4AS
{d.a.robb, s.padilla, t.methven, b.kalkreuter, m.j.chantler}@hw.ac.uk

ABSTRACT
In previous work we developed a method for interior designers to receive image-based feedback about a crowd's emotions when viewing their designs. Although the designers clearly desired a service which provided the new style of feedback, we wanted to find out if an internet crowd would enjoy, and become engaged in, giving emotion feedback this way. In this paper, through a mixed methods study, we expose whether and why internet users enjoy giving emotion feedback using images compared to responding with text. We measured the participants' cognitive styles and found that they correlate with the reported utility and engagement of using images. Those more visual than they are verbal were more engaged by using images to express emotion compared to text. Enlightening qualitative insights reveal, surprisingly, that half of our participants have an appetite for expressing emotions this way, value engagement over clarity, and would use images for emotion feedback in contexts other than design feedback.

Author Keywords
Cognitive styles; affective computing; creativity; design feedback; crowdsourcing; perceptual and emotional feedback; image summarization.

ACM Classification Keywords
H.5.3 [Information Interfaces and Presentation]: Group and Organization Interfaces.

INTRODUCTION
The image-based emotion feedback method (IEFM) was developed to provide fashion and interior designers with visual feedback on the perceived mood of their designs. It was found in an evaluation to be popular with the designers receiving the feedback [47]. Those providing the feedback choose images from perceptually organized image browsers instead of using text. The motivation for the method was to allow designers in these domains to build large followings and engage them in visual co-design conversations around prototype designs and finished products. Images, rather than emoji, were used as it was important that the output be visually inspiring for the designer consumers and not too formulaic. Image summarization is used to allow designers to access the "wisdom of the crowd" [56] within the image feedback in a visually inspiring way analogous to their use of mood boards[1]. These thought provoking summaries are condensed from the massed image feedback. The algorithm used for this was validated in another experiment showing that the summaries effectively represented the totality of the feedback [48].

Those two investigations showed that, from the point of view of designers consuming the feedback, the method was viable. However, for the IEFM to work for designer users, crowd users would need to be attracted to giving feedback. A brief evaluation of the experience of those who gave the feedback consumed during the designer study was reported along with a demonstration of the software components [46]. It was noted that a proportion of the group of undergraduate participants involved did prefer using sets of images to express their emotional reaction to a design whereas others preferred text. It was speculated that individual differences including cognitive style, rather than simply personal taste, were a factor in this. Due to the narrow nature of that group of feedback-givers, generalizing beyond them was not possible.

Following that work we were motivated to discover what a wider sample of internet users would think of giving emotion feedback using the image browsers developed for the IEFM and the reasons underlying any preferences they expressed. Knowing why some people prefer using text or images for emotion feedback and whether they prefer particular types of images would be useful in formulating future image banks for use with the IEFM. This might also help understand why some people wish to comment using images rather than text in contexts outside design feedback.

In this paper we demonstrate for the first time that crowdsourced image-based design feedback engages a particular section of internet users. We describe a mixed methods study in which a gender balanced sample of 50

[1] Mood boards are used to establish a perceptual and emotional theme when creating a design [16].

DIS 2017, June 10-14, 2017, Edinburgh, United Kingdom
ACM 978-1-4503-4922-2/17/06.
http://dx.doi.org/10.1145/3064663.3064665

internet users, spread across a wide age range, contrasted two formats of image-based feedback with text in the context of giving their emotional reaction to interior designs. We measured participants' cognitive styles and correlated these with their experience of the formats. We show that those users who are, by nature, more visual than verbal in cognitive style, are more engaged by using images in the IEFM for emotion feedback compared to text. We hope that by demonstrating this empirically we will motivate the HCI community to further develop image-based response modes for emotion feedback. We argue that this will encourage inclusion of feedback from those who might previously have remained silent due to lack of an image-based mode of expression suiting their nature. Our study shows that internet users think that the IEFM, a medium for readily summerizable image-based emotion feedback, is applicable outside the realm of interior design feedback.

The rest of this paper is structured as follows. We examine other work forming the background to this paper. We describe our study and report the results. Finally we discuss the implications of our findings and draw conclusions.

BACKGROUND AND RELATED WORK

In this section we first situate image-based emotion feedback within the field of crowdsourced design feedback. We briefly review computer mediated emotion expression and then discuss the significance of emotion in design along with the use of images in accessing emotions. We then review the development of the visual and verbal cognitive styles construct which has culminated in the current instruments for measuring that aspect of individual differences.

Design Feedback from Crowds

Blogging or involvement in communities such as *Dribbble* [12] has given designers access to feedback from crowds. However, participation in such communities is limited due to the levels of commitment required [8]. In addition, tools have been created for crowdsourcing feedback using non-expert, paid, remote workers to provide supported, objective, critiques [27,69]. The image-based emotion feedback method (IEFM) has been developed to complement such systems by encouraging the participation of volunteer crowds, perhaps engaged through social media [11,70], in giving subjective, impressionistic, emotion feedback.

Computer Mediated Emotion Expression

Much of the area of Affective Computing is concerned with the sensing of emotions within users and with the expression of emotion by computer systems such that the user and the computer are to some degree in empathy with each other [38]. Studies in this area on the emotions that can be perceived in various forms of stimuli presented to participants have used multiple modes including sound and thermal stimuli as well as visual stimuli including animated shapes and color [4, 36, 50, 51, 52, 67, 68].

Work on person to person emotion communication mediated by computer systems has included visual modes and physicality such as gestures and squeezing of specially built input devices: In the *eMoto* studies, gestures along with squeezing on a modified mobile device stylus and selecting a colored animation have been used to allow users to express their emotions to accompany SMS messages [55]. Shape and the physicality of distorting a flexible surface have also been investigated [54]. Physicality and color (colored squeezable balls) were also used to gather the mood of a building's occupants in an in-the-wild study [14].

Emoji (pictographs represented by Unicode characters) are an important method of emotion expression. They have grown in popularity especially since the introduction of the iOS and Android Emoji keyboards (in 2011 and 2013). Although Emoji also depict non-emotion concepts their chief use is adding tone and emotion to text communication which they do with varying success [10, 30]. We believe that images offer a richer medium both for those expressing their emotions and for the inspiration of fashion and interior designers receiving feedback. In the next subsection we examine aspects of images as a feedback medium.

Emotion, Images and Design

Emotions play an important role in making purchasing and other decisions [26,58]. The emotions of users or consumers are acknowledged as being important in design [31,32]. The influence of emotion and images in design domains such as fashion is recognized in the design practice of mood boards (the arrangement of images and other materials to establish a perceptual and emotional theme for a planned design or work). It is this connection between emotions, designing, and the success of designs that led to the development of the IEFM. To avoid specific figurative connections affecting an individual's perception of a mood board abstract images are often used [16]. However, deliberately figurative images can access emotions in a more specific way than abstract images and such emotion imagery can be categorized by the emotions it evokes [25, 29]. The fact that people rapidly interpret the emotion content of images [20] indicates that images should work well for emotion feedback in fashion and interior design and possibly in other domains.

Cognitive Styles and Their Measurement

Images as a medium do have appeal for many and it is not unusual to hear people describe themselves as "visual" or indeed, "verbal". The idea that there are individual differences in the tendency of people to conceptualize in the form of mental imagery or in language has been considered and written about since Galton in the 19th century [15]. More recently psychologists developed this idea as a bipolar visual-verbal dimension - part of a larger construct of *cognitive styles* explaining individuals' differing preferences in the mental processing of information [e.g. 42, 35]. Cognitive styles are not to be confused with learning styles (or strategies) which are the particular strengths that individuals have in ways of learning and are recognized as a separate construct [49]. Models encompassing both describe cognitive styles as feeding into learning styles along with other factors including working memory, intelligence, and personality [43].

Riding & Cheema [44] reviewed cognitive styles and distilled the various constructs and terminology into two bipolar dimensions: *verbal-imagery*, and "*wholist-analytic*". Various methods of measuring cognitive styles were devised. Instruments to measure the visual-verbal dimension include Richardson's 15-item Verbalizer-Visualizer Questionnaire (VVQ), a pen and paper self-report questionnaire [42], and Riding's Cognitive Styles Analysis (CSA), a behavioral test administered on computer. The CSA also measured the "wholist-analytic" dimension [45]. By the early 2000's several other studies confirmed this two-bipolar-dimensional view of cognitive styles [7, 21, 22, 28, 64].

More recently, the validity of the bipolar visual-verbal dimension of cognitive styles was questioned [2, 23, 41]. A new model of *visual cognitive style* was proposed, based on the inconsistencies in the previous model and on neurophysiology [24]. That research included work showing that areas of the parietal lobes of the brain activated when participants imagined faces and colors whereas areas of the temporal lobe were activated when imagining a route map. The new model had two monopolar visual cognitive style dimensions: *object imagery* and *spatial imagery* and a new instrument to measure them, the Object-Spatial Imagery Questionnaire (OSIQ) [6]. The object imagery scale measured preferences for the representing and processing of "*colorful, pictorial and high resolution images of individual objects*" while the spatial imagery scale measured that for "*schematic images, spatial relations amongst objects and spatial transformations*". This was followed up with the Object-Spatial-Verbal cognitive style model measured by a three-subscale questionnaire. The Object-Spatial Imagery and Verbal Questionnaire (OSIVQ) measures those three monopolar dimensions [5]. An alternative three-subscale cognitive styles questionnaire was developed by Thomas & McKay [57] for a study on the design of teaching materials. However, that instrument has not been otherwise validated. The OSIVQ [5] was rigorously validated in the study which introduced it and has been used in other recent studies for measuring cognitive styles [e.g. 3, 17, 33]. The OSIVQ was therefore chosen to measure cognitive styles for our study.

STUDY

In this section we describe the aims and methods of the study in which we evaluated the feedback-giver view of the image-based emotion feedback method (IEFM).

Aim

Our aim was to find out what potential crowd users (feedback-givers) of image-based emotion feedback think about it in contrast to text, including their preferences and reasons for these preferences. Although *engagement* was our main focus we decided it was also important to probe *utility*, i.e. whether users felt able to express their emotions using the formats. We formulated these research questions:

RQ1 Do feedback-givers find image feedback formats more engaging or less engaging than text?

RQ2 Do feedback-givers feel able to express their emotions using image feedback formats?

RQ3 Are cognitive styles a factor in feedback-givers' experience of different feedback formats?

RQ4 Do feedback-givers prefer using images or text when describing their emotions and what is their reasoning for this?

Method

RQ1 and RQ2 were investigated in a repeated measures experiment. Participants rated the *engagement* and *utility* of two image-based feedback formats and text. RQ3 was addressed by measuring participants' cognitive styles and carrying out a correlation analysis against their *engagement* and *utility* ratings. RQ4 was probed in a questionnaire. The participants in our study did the following:

1) Completed a cognitive styles questionnaire.
2) Did a feedback task.
3) Completed a post-task questionnaire.

In the subsections below we describe a) the formation of our participant group, b) the measurement of their cognitive styles, c) the construction of the two image browsers which, together with text, would constitute three feedback formats for the task, d) the feedback task itself and finally, e) the post-task questionnaire.

Participants

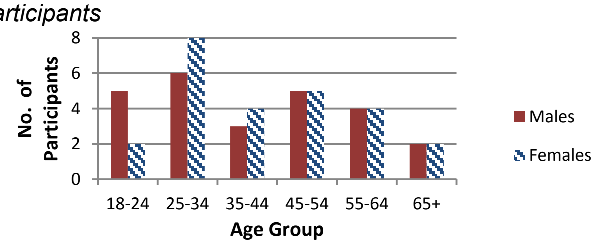

Figure 1. Participant gender and age group composition.

Participants were recruited by a combination of social media, email publicity, convenience and snowball sampling [66]. The target age profile was intended to reflect internet users in the UK [61, 62]. To achieve a gender balance and the desired age profile, purposeful sampling based on age and gender was used [37, 66]. We did not reach as many in the 35-44yrs and over-64s age groups as hoped and the sample had slightly more 25-34yrs and fewer over-64s than would be representative. The oldest was 77 and the youngest 19. (Figure 1). The final sample was 50 (25 male, 25 female). (A power analysis had indicated that this should be enough for the study's repeated measures experiment to expose a medium effect.)

Participants completed an online consent and demographics form. They were asked to report education level (Figure 2) and occupation. Occupations varied from electrician through admin assistant, police officer, occupational therapist, part-time event organizer, teacher, lawyer, stay-at-home mother and artist, and retired electrical engineer. They also included nine students (eight full-time and one part-time). The demographic data show that, while we made efforts to make our sample representative by age and gender, unskilled workers were under-represented and those more highly educated were over-represented. Eight (16%) were ethnic minorities (within 2% of UK average [60]). As a minimum, participants had to have English as a foreign language. They were required to have access to a computer or iPad with an internet connection as they would take part remotely. (It has been shown that reliable quality usability data can be gathered away from the lab [1, 59].) After it was established that they fit a gap in the age and gender profile for our sample, participants had a short screening interview by phone to ensure they understood their tasks. Participants were rewarded with a $20 shopping voucher.

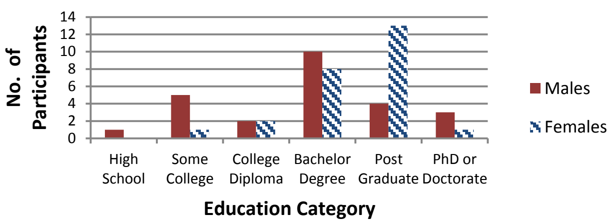

Figure 2. Education attainment level of the participants.

Cognitive Styles Measurement (OSIVQ)

The OSIVQ [5] was used. Each OSIVQ item is a 5 point Likert scale item. 45 items form three subscales. Participants completed the OSIVQ following its standard instructions and their responses were collated into three subscale scores (object, spatial and verbal). These are ratio data ranging between 1 and 5.

The Image Browsers for the Feedback Task

Figure 3. Screenshots from the abstract image browser. Right: the full array of stacks. Left: a stack from the array is shown opened. Each image occurs only once in the browser.

Two image browsers based on human perceptual data were built to provide intuitive browsing and two different styles of image for responses. One contains 500 abstract images in a self-organizing map (SOM) browser [63] based on similarity data from 20 lab-based and 200 paid crowdsourced participants. Its construction is described by Padilla et al. [34] and it provides a broad pallet of visually diverse images (Figure 3).

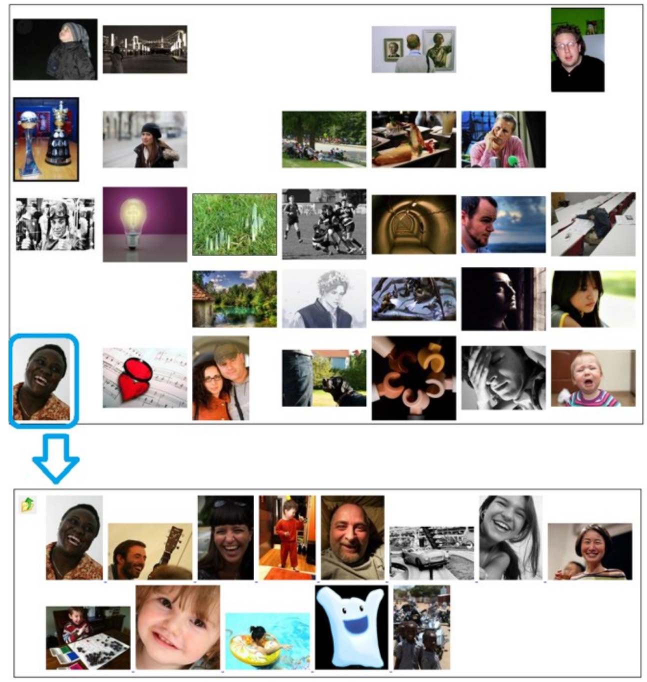

Figure 4. Screenshots from the emotion image browser. Top: the full array of stacks. Bottom: an opened stack.

To allow more specific emotion communication, a second browser was assembled (Figure 4). 2000 Creative Commons images were categorized by having 900 paid crowdsourced participants tag them with terms from the Plutchik emotion circumplex model [39]. As a result, each image has an emotion tag frequency profile representing the judgments of 20 different tagging participants (Figure 5).

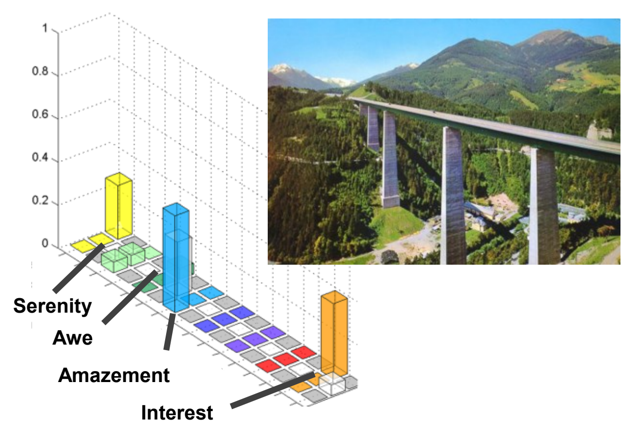

Figure 5. An image from the emotion image browser with its emotion profile. Labelled peaks correspond to popular tags for the image. The histogram shows the normalized tag frequencies laid out on the Plutchik emotion model [39]. Coloured and white spaces represent the model's 32 emotions. (Grey spaces are padding for chart layout purposes).

A subset of emotions was defined following a survey of 18 staff and students at a design institution in which respondents rated emotions for meaningfulness to design feedback. Based on this 19 out of the 32 emotions in the model were included in the browser. E.g. joy and sadness were included but ecstasy and grief were not. We aimed for a balanced coverage of the 19 emotions. The 2000 available tagged images were filtered to include 10 or 11 images with profiles best fitting each of the 19 emotions. The filtering algorithm took account of an image's highest emotion tag peak and the contrast between that and peaks for other emotions. For some of the emotions, there were no more than 10 images with clear profiles for those emotions and this limitation meant that the emotion image browser contained fewer images (204) than the abstract image browser (500). The images were arranged in a SOM browser defined by their emotion profiles (tag frequency vectors).

What makes a SOM browser intuitive to use is the organization of images in stacks. Tapping or clicking the top image of a stack reveals the full stack. Adjacent stacks contain similar images. Stacks far apart contain dissimilar images as defined by the human perceptual data. Tapping or clicking a thumbnail in an open stack displays the individual image at full size. 7 stacks by 5 was chosen as the size of the top-level grid for the SOM. This would allow it to be viewed on an iPad or small laptop screen and so place fewer limitations on the participant pool.

The Feedback Task

In itself the feedback task constituted a repeated measures experiment with three conditions. The measures were *Engagement* and *Utility*. The conditions were the three response formats: abstract images (AI), emotion images (EI), and text. Our participants were informed that they would a) see a series of designs by interior design students, b) for each design, be asked the question "How did the design make you feel?" and c) respond three times using three formats: two types of images and text. They were told that the student designers would each get three feedback summaries; one for each format used by all the anonymous participants when responding. Actually, as the focus of the study was on the feedback-givers themselves, it was not planned to show the feedback to the designers but it was necessary that participants believe their responses would go to the designers to ensure they approached the feedback task as a live exercise. In accordance with ethical guidelines the participants were debriefed about the true focus of the study later, after all data was collected.

Participants viewed a random selection of five interior designs from a pool of 12. For each they were asked "How did the design make you feel?", and they responded using the three formats: AI, EI and text. For each participant the format order was randomized. An image response consisted of three images chosen from the required browser. This was in case a combination of emotions was evoked by a design. A text response consisted of entering text into a text box. After each response to a design, participants were asked to rate that response format using visual analogue scale (VAS) items shown in Figure 6. VAS items were used as they yield high resolution interval data which is linear [18, 40] and ideal for correlating against the ratio data from participants' OSIVQ scores. The Engagement item was developed from an item used in Robb et al [46] which was based on items in a questionnaire by Webster & Ho [65]. The Utility item was that used in Robb et al [46]. Each raw VAS item rating ranged from zero to the length of the scale in pixels [40]. To aid understanding the ratings were normalized 0 to 100 by dividing by the pixel length of the scale and multiplying by 100. These were analyzed as follows. Each participant viewed five designs. For each design they provided two VAS ratings (Engagement and Utility) for each of the three answer formats: AI, EI and text. During the first design participants were familiarized with the experiment application, including the rating items, in relation to all three response formats. These ratings while responding to the first design were discarded and were not analyzed. Thus, for example, for text-Utility a participant would have four VAS ratings in total to be analyzed. The median of those four was taken to represent that participant's overall VAS rating for text-Utility; likewise for the other two formats and similarly for the Engagement item.

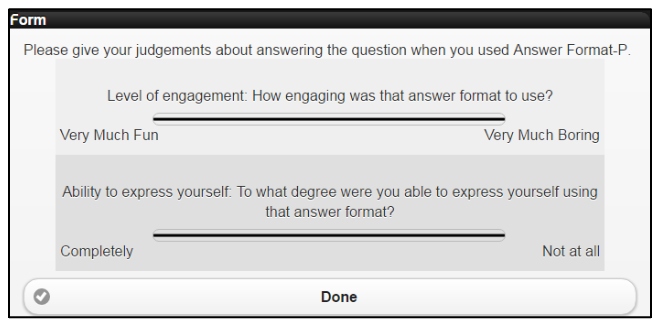

Figure 6. The rating items. On first click a 'draggable' cross appeared on the item scale. The answer formats were referred to by randomly chosen letters to avoid introducing preconceptions to the participants (e.g. *emotion images* were not called that during the task).

Post-Task Questionnaire

After finishing the feedback task the participants completed a questionnaire in which they were asked to rank the three answer formats (AI, EI and text) by overall preference. They were asked open questions as follows: *1) Please describe the reasons for the rankings you gave to the formats. 2) What do you think about using text to describe how the designs made you feel? 3) What do you think about using abstract images to describe how the designs made you feel? 4) What do you think about using emotion images to describe how the designs made you feel? 5) Please tell us anything else you feel is relevant about the idea of describing your emotions using images versus text. 6) Did you hold back (or consider holding back) from criticizing any designs in your responses to prevent hurting the designer's feelings? Whether or not you did, please comment about this stating which response format(s) you* *have in mind.* There was one closed question asking, "*For what other purposes do you think you would like to see image-based feedback as an option available for you to use?*" and giving a list of options including a negative option (detailed in Results). The questionnaire concluded with an open opportunity to comment. The open question responses were analyzed using a grounded theory approach with open, followed by axial coding [9, 53]. The open coding produced 73 codes in 22 categories during the first pass of the data. Overarching themes and subthemes were developed from this and, in a second pass, data was coded to these. There was a single coder (the lead author).

RESULTS FROM FEEDBACK TASK AND OSIVQ

In this section we report the results from the visual analogue scale (VAS) item ratings of the formats during the task and then correlations of those with the OSIVQ scores.

Utility and Engagement for the 50 Participants

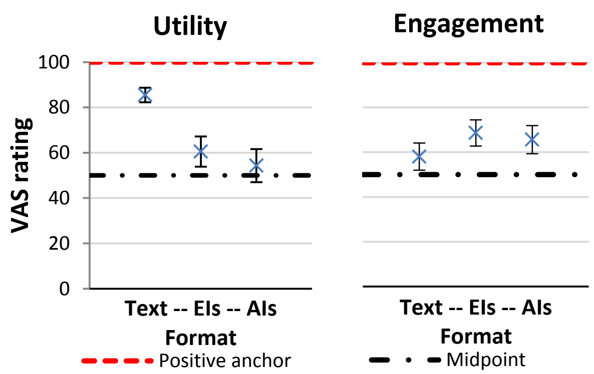

Figure 7. Mean VAS ratings for Utility and Engagement N=50. 0 marks the negative anchor. Error bars show 95% confidence intervals.

Figure 7 shows the mean *Utility* and *Engagement* VAS ratings for the 50 participants. It was clear from the chart for *Utility* that text was rated highest. For *Engagement,* emotion images (EI) appeared higher than text. VAS ratings are interval data, linear, and amenable to parametric tests [18]. A one-way repeated measures ANOVA was carried out on the *Engagement* scores. Greenhouse Geisser correction was used as sphericity was violated. *Engagement* was significantly affected by answer format, $F(1.54, 75.32) = 3.65$ $p<0.05$. However, post hoc tests using Bonferroni correction showed that, despite there being a statistical main effect of format on *Engagement* for the 3 formats (text, EI, and AI, M=58.0, M=68.6, and M=65.6 respectively), it was not possible to state which was statistically significantly greater than another at the 95% confidence level. However a difference was found when age was taken into account (see Age sub-section below).

Age

We split the participants into two groups at a point where there was a clear break in the ages and examined their ratings for *Engagement*. We took age groups 18 to 44 as the "Younger" group (N=28) and over-44s as the "Older" group (N=22). See Figure 8. (It happened that none were aged 40-44 so that is where we divided them giving two comparable sized groups and this was less arbitrary than splitting down the middle. We analyzed no other split.). It was clear from the chart that there was no difference between *Engagement* of the formats in the older group. A one way repeated measures ANOVA showed that *Engagement* in the younger group was significantly affected by the answer format, $F(2, 54) = 7.18$, $p<0.05$. Post hoc tests using Bonferroni correction showed that, while there was no significant difference between *Engagement* for AI (M=67.3) and either EI (M=73.5) or text (M=53.2), *Engagement* for EI was significantly greater than for text in the younger group.

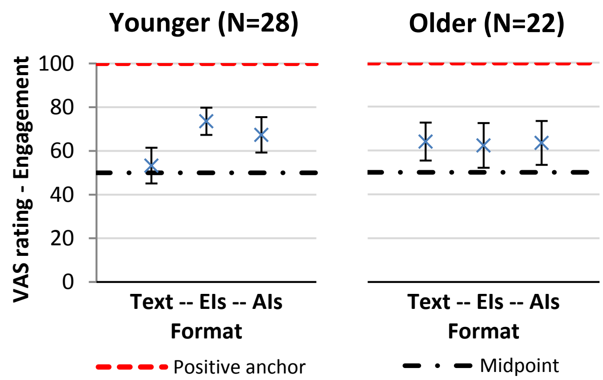

Figure 8. Mean VAS ratings for *Engagement* in younger and older groups. 0 marks the negative anchor. Error bars show 95% confidence intervals.

Correlation Analysis of Ratings with Cognitive Styles

It is a fundamental aspect of the monopolar dimensional model of visual and verbal cognitive styles that a person can be, for example, high on the verbal subscale and also high on the object imagery subscale. To gauge the degree to which a participant is more object visual than verbal we subtracted their verbal score (Vrb) from their object score (Obj) giving us the difference between their object and verbal scores (ObjVrbDif). We did the same with their spatial (Spt) and verbal scores obtaining their SptVrbDif. For these differences a low value indicated a participant more verbal than visual while a high value indicated one more visual than verbal. Paralleling this in the VAS ratings, we subtracted each participant's rating of *Engagement* for text from their rating of *Engagement* for EI (and similarly for AI) to gauge the degree to which they found EI (or AI) more engaging than text. The same was done with the *Utility* ratings. As we had earlier found a difference between ratings for *Engagement* between two age groups (Figure 8) we looked for a correlation between participants' age and ObjVrbDif. There was a significant negative correlation, $r = -.38$, $p < .01$(two tailed), meaning that, in our sample, the older the participant, the less object visual and more verbal they were likely to be. (There was no significant correlation between age and SptVrbDif.) In view of this when calculating correlations involving ObjVrbDif we controlled for age by using partial correlation [13]. Table 1 sets out these correlations. What

Table 1 shows is that when both *Engagement* and *Utility* VAS ratings for text were subtracted from those for the emotion images (EI) significant positive correlations existed with participants' ObjVrbDif (controlling for age). This means that the greater the degree to which a participant was more object visual than verbal in cognitive style the more likely it would be that the difference between their ratings of emotion images and text (for both *Engagement* and *Utility*) would be larger. We did the same for SptVrbDif (without the need to control for age) and found this only correlated significantly with *Engagement*.

VAS Rating Differences	**Partial Correlation v.s. ObjVrbDif (Controlling for Age)**	
	r	***p*** (two-tailed)
Engagement EI –Text	**.34**	**< .01**
Engagement AI –Text	.23	-
Utility EI –Text	**.31**	**< .05**
Utility AI –Text	.02	-
VAS Rating Differences	**Bivariate Correlation v.s. SptVrbDif**	
	r	***p*** (two-tailed)
Engagement EI –Text	**.31**	**< .05**
Engagement AI –Text	.20	-
Utility EI –Text	.24	-
Utility AI –Text	.10	-

Table 1. Participant VAS ratings for text subtracted from those for image formats correlated v.s. their OSIVQ verbal subtracted from OSIVQ object scores (ObjVrbDif) and spatial scores (SptVrbDif). Significant correlations are in bold.

RESULTS FROM POST-TASK QUESTIONNAIRE

Below we report quantitative and qualitative findings from the post-task questionnaire.

Format Preference Rankings

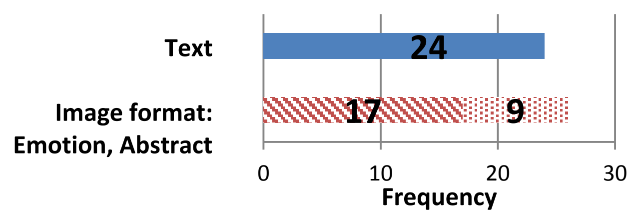

Figure 9. The frequency with which participants ranked each of the three formats top for overall preference.

Figure 9 shows the numbers of participants ranking a given format first for overall preference. Numbers preferring images (26 in total: 17, EI and 9, AI) and text (24) were roughly similar. While this is interesting, the reasons given by participants for the way they ranked the formats contribute enlightening insights in the themes below.

Themes from the Open Questions

Two overarching themes, *Engagement* and *Expression* arose from analysis of responses to the open questions and are described below.

Theme - Engagement

The abstract images engaged seven participants e.g. *"I have felt excited and interested in doing the evaluation this way"* [P3], *"…they were far more interesting to interact with. I also think some people will find it gamifies response and so might engage more deeply with it than words."* [P13]. For two their enjoyment of the abstract images was linked to the ability to express their feelings, e.g. *"I really enjoyed this. It was fun to see how much I was drawn to some over others and how satisfying it was to find one that fit how I felt. I might explore more abstract art now."* [P43]

The emotion image set was engaging for 15 e.g. *"Surprisingly easy and fun. [A] very interesting way to describe feelings"* [P32], "*It was fun to select emotion images, as many of them used facial expressions"* [P16], "*Fun and creative.*" [P38]. As with abstract images enjoyment was also linked to expression e.g. *"more exciting than just descriptions... and I liked exploring the images to find the right ones to use."* [P17].

Notably, no participant described text as being engaging or enjoyable despite equal opportunity to comment about text specifically. However, text was referred to negatively in terms of engagement by seven participants usually while linking this with expression e.g. "*Text box answers are boring and can become time consuming trying to describe how I felt*" [P15], and here although stating text was easy for expression it was still viewed negatively for engagement: *"[Text is] an, to me, easy way to express myself, though also boring."* [P19], *"Although I find the text option the least appealing, I do think I could describe how I felt about a design more accurately with the text option."* [P29].

These qualitative responses showed that many participants found the image formats enjoyable and for several their enjoyment was closely linked with the satisfaction of being able to express their emotions this way. No participants viewed text as engaging and some commented negatively about the engagement of text.

Theme – Expression

This theme was divided into a number of sub-themes.

Sub-Theme – Ease of Expression

23 participants expressed the view that text was an easy way to express how they felt, e.g. *"Text seemed much easier and quicker than trying to relate to an image to express an opinion."* [P45], *"… text is my comfort zone"* [P39], and *"I was able to immediately and easily find words to describe my feelings about the designs, but often struggled to find images which reflected my feelings about them"* [P37].

15 participants found the emotion images easy to use, e.g. *"I found this the easiest to do."* [P26], "*I enjoyed it - the images were nicely varied, and helped convey feeling and emotion well*" [P36], "*It was fun, and summarized the feelings more quickly than a text description would."* [P43],

and "*I liked this because for me I find it easy to look at someone and think yeah you look exactly how I feel*" [P50]. Some did wish for more choice in the emotion images e.g. *"it was sometimes difficult to find a face/scene that conveyed my exact response, so I would have to settle for one that was closest"* [P20].

The abstract images were found to be problematic by 16 e.g. *"[These were] really hard, I couldn't 'match' the images to my feelings very well"* [P32], and *"[I was] frustrated. Some feelings [were] not in abstracts."* [P47].

Sub-Theme – Clarity of Text

Text was pointed out as allowing clarity and precision by 17, e.g. *"[With text] Mostly, I felt I could pinpoint exactly what I thought and how I felt."* [P46], *"Text allows a more accurate and succinct method of conveying feedback."* [P45]. It was also pointed out, however, that vocabulary can be limiting e.g. *"Expressing emotions through text needs good vocabulary and a shared understanding of what that vocabulary actually means*" [P13].

Sub-Theme – Ambiguity of Images

The ambiguity of images was expressed as both a positive and a negative. Participants who appreciated the clarity of text thought the vagueness of images was a disadvantage e.g. *"You could pick images that expressed your own emotions but this still lacked the precision of language."* [P10]. Conversely ambiguity was also seen as useful e.g. *"I felt that the Emotion images were a really good way of encapsulating how I felt about the designs, because much of the ambiguity in my response could be captured, in a way that can be missing when words are stripped of tone and context."* [P41].

Sub-Theme – Images Worked Well for Emotions

18 participants expressed this theme in relation to the emotion images. e.g. *"[I] found it easier to ascribe my feelings to the emotion images especially those with faces or natural views"* [P1], and *"The emotion images felt like a truly efficient way of expressing how I felt about the design. I really enjoyed selecting a facial expression to match my emotion which I felt further helped me think of why I felt that way about the design."* [P2]. Three stated abstract images were better for emotion expression, e.g. *"I preferred the abstract [images] the most, as it was easier to summarize an overall feeling"* [P43].

Sub-Theme – Freedom of Images

10 participants felt that images liberated them from language: *"Text is limited by my language and experience. Images give more freedom but I felt I needed familiar parameters so faces were easier than totally abstract."* [P4] and about abstract images in particular: *"I think it allows you to have some freedom of thought, the abstract images can mean different things for different people and lets freedom of expression come through"* [P44]. In addition (for 6 participants) images, particularly the abstract images, were seen as requiring less consideration of the designers' feelings than text when offering criticism, e.g. *"[I] considered it, especially with the text format, but tried to be honest without being mean."* [P47].

Sub-Theme – Communicating With Another Person

Four participants were explicit about considering how someone would understand what they were trying to communicate. e.g. *"The emotion images were by far the best way of expressing my emotional response to the designs. This wasn't because they were all a literal representation of my response but because I felt that the pictures had a shared understanding between myself and those looking at the results. I felt it more likely that my intention would be understood."* [P38], and "*The abstract images could be interpreted in many different ways, and so I found it much more difficult to choose images that accurately reflected how I felt, and I worried that my answers would be likely to be misinterpreted*" [P41].

The *expression* theme showed that for many text offered clarity and was seen as an easy format to use. Finding images (particularly abstract images) to match emotions was problematic for some. For those who appreciated the precision of text, the ambiguity of images led to concern about misinterpretation. On the other hand images, particularly those from the emotion image browser, were seen as easy to use. Ascribing emotions to selections from the faces, people, and landscapes from that browser was often found to work well. Ambiguity in images was seen by some as a useful aspect of their responses. Some also appreciated the freedom from language that is afforded by images.

Use Beyond Interior Design Feedback

Participants were asked "For what other purposes do you think you would like to see image-based feedback as an option available for you to use?" and given a list of options. 15 participants chose the option, "I do not think image-based feedback should be an option for any other purpose". 35 chose at least one additional suggested purpose or specified another purpose of their own including: "*Product reviews, such as books, films*" [P19], and "*in response to TV or paper based advertising*" [P40]. Figure 10 shows the frequency with which options suggested in the question were chosen. The implications of this are examined in Discussion.

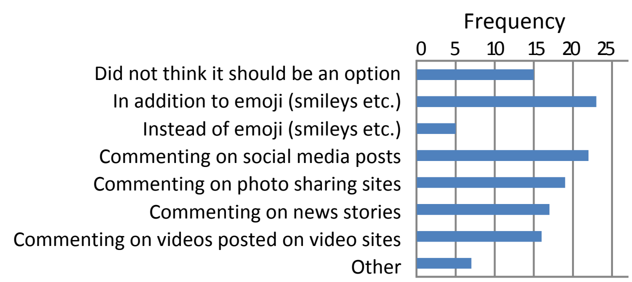

Figure 10. Suggested uses of image-based feedback. The bar chart shows the frequency with which participants chose the negative option or the additional suggested purposes.

DISCUSSION

Below we revisit the research questions posed in the study aims before widening the discussion. First we address RQs 1 and 3 and discuss cross cutting findings. Then we summarize findings for RQ2 and RQ4 before opening out our discussion to integrate the findings into the implications for the future of the IEFM and use of images for emotion feedback more generally.

RQ1 and RQ3

First we summarize the findings on the two questions and then we discuss the connection between them in our results.

RQ1 - Do feedback-givers find image feedback formats more engaging or less engaging than text?

In our sample, younger users (18-44yrs) found the emotion images significantly more engaging than text, whereas older users (over 44s) reported no significant difference in engagement. (Figure 8). See also RQ3.

RQ3 - Are cognitive styles a factor in feedback-givers' experience of different feedback formats?

Yes. a) For both engagement and utility the difference between participants' *object* and *verbal* style scores correlates significantly with the difference between their ratings for emotion images and text. b) Only for engagement (and not utility) did the difference between participants' *spatial* and verbal styles correlate significantly with the difference between their ratings of emotion images and text. (Table 1).

Age, Cognitive Styles and Generalizing Beyond Our Sample

Observing a correlation between age and OSIVQ object score in our sample raises a question over its representativeness. Riding [43] states that no significant correlation between age and cognitive style was observed. It is possible that the older participants in our sample could have non-typical OSIVQ scores and this might be contributing to our finding that younger participants are more likely to find images more engaging than older participants. i.e. the effects on engagement we observed due to age and cognitive style may just be down to the cognitive styles effect. To establish this definitively, a study with a larger sample, constructed using purposeful sampling beyond age and gender to include other demographic characteristics would be needed. Having said that, the partial correlations controlling for age did show that *even after taking age into account, cognitive styles were still a factor in the engagement ratings of image-based feedback compared to text.* (Table 1). This gives us confidence that it is safe to generalize about that finding beyond our sample.

RQ2 and RQ4

The findings directly relating to these two questions are briefly summarized here.

RQ2 - Do feedback-givers feel able to express their emotions using the image feedback formats?

On the whole participants reported while giving the feedback, that they were better able to express themselves using text. However, views in the questionnaire revealed this issue was more nuanced as described below.

RQ4 - Do feedback-givers prefer using images or text when describing their emotions and what is their reasoning for this?

In our sample approximately half (26/50) preferred images for this while the remainder preferred text.

The reasons participants gave for the preferences, set out in the themes from the questionnaire, were varied. In the sub-sections below, the different views expressed are integrated along with the other results into the discussion of the main implications arising out of the study.

Implications

Feedback-givers Valuing Engagement Over Clarity

Despite the reported superiority of text for clarity of expression, about half our sample still preferred image-based feedback over text. We interpret this as participants often valuing engagement over clarity. Does this mean that the IEFM might attract more but meaningless feedback for designers? We think that three issues come forward here. Firstly, the inspirational value of the visual feedback to designers will not depend on the exact communication of a specific message. According to Jakobsen's model of communication [19] a message can have its own inherent artistic quality. The fact that designers shown image-based feedback by Robb et al. [47] were inspired to make changes but were not so inspired by text feedback bears this out. Secondly, if designers can build a following by engaging people in feedback, the content of each message in the conversation need not be crucial. Again this reflects another aspect of the Jakobsen model i.e. the simple act of continuing the conversation in itself has value. In short, "it's good to talk". Thirdly, the idea that using images gives rise to inherently inaccurate feedback is countered by the popular sub-theme from the study that the emotion images were, in fact, good for expressing emotions. This included that ambiguity could be a desirable part of the feedback. The different qualities of the image feedback in regard to softening negative criticism compared to text were exposed particularly with regard to the abstract images. With the abstract image feedback, designers would have the opportunity of taking inspiration from feedback while avoiding the downsides of harsh criticism. Interestingly Emoji are also prone to ambiguity due to varying interpretations by users but also by variations in graphical rendering of Emoji characters [10, 30]. Emoji users, it seems, tolerate ambiguity; or at least those who are aware of it do. Perhaps some peoples' desire to express their emotions is greater than their desire to be fully understood?

Individual Differences

It is clear that a substantial proportion of internet users would prefer to use images rather than text when asked to express their emotional reactions. Equally, some prefer using text to express emotions but of course those users are already well catered for, and techniques such as text mining and topic modelling do exist for summarizing text. We have shown that important factors behind these preferences are individual differences including cognitive styles. The individuals expressing the preferences, although able to describe why they think they hold a given preference, also are behaving, in part at least, in line with deep individual characteristics. These may even go as deep as aspects of their neural anatomy and development [6]. The humble textbox in comment forums offers free rein to those who are more verbal than visual. The IEFM offers an alternative format, engaging, empowering, and embracing the strengths of users who are more visual than they are verbal.

A Summarizable Channel for Those More Visual than Verbal

Given that people's emotional reaction to potential products, services, or ideas is valuable information for their originators [26, 58], a channel encouraging the inclusion of input from people who are more visual than verbal in cognitive style is likely to be a benefit. The summarizable image-based emotion feedback method can fulfill this role. Its deployment alongside text-based feedback methods can serve to increase the overall amount of feedback available to designers by adding this new image-based strand.

Application Beyond Design Feedback

The 15 participants who did not wish image-based feedback as an option represent those users to whom using images this way clearly does not appeal. However, a majority of the participants could see that image-based emotion feedback would be useful outside design feedback and indeed would like to see that as an option. 23 wished to see it offered in addition to emoji, while five indicated they thought image-based feedback could be used instead of emoji. This implies that those participants see image-based feedback using browsers such as those in this study as possibly becoming a mainstream response option. The two participants who suggested it could be used for product reviews were indicating just the type of use that would exploit the capability of image selections from the IEFM browsers to be summarized. Large amounts of buyer feedback could be presented as a concise at-a-glance montage of images summarizing what users felt about a product. One notable aspect of the image banks for the IEFM is that they are controlled, unlike the user-sourced images in some comment forums which can require moderation when users post inappropriate content. The IEFM image banks might be useful as a comment medium outside design feedback resulting in a reduction in the moderation effort normally associated with allowing images in comments.

CONCLUSION

In order to find out whether and why image-based emotion feedback would be engaging for feedback givers we carried out a mixed methods study with 50 internet users from 19 to 77 years of age. Participants rated three feedback formats (abstract images, emotion images and text) for *engagement* and *utility*. We measured participants' cognitive styles. This allowed us to establish the degree to which each participant was more *object-visual* and *spatial-visual* than *verbal*. Significant correlations revealed participants more visual (both *object* and *spatial*) than they are verbal gave higher *engagement* ratings for emotion images relative to text. Those more verbal than they are visual gave lower ratings relative to text. Participants more *object-visual* than verbal also gave higher *utility* ratings for emotion images relative to text (and those more verbal than *object-visual* gave lower utility ratings relative to text). Overall text was rated best for utility (the clarity with which participants reported they were able to express their emotions). Additionally, we found that under-45s reported emotion images as being significantly more engaging than text but we remain cautious about generalizing beyond our sample about this particular age finding without further work.

Qualitative insights gathered from the participants showed that a substantial proportion (half in our sample) preferred one of the image formats over using text for expressing their emotions. It was common for engagement to be valued over clarity of expression. These expressed preferences, influenced by individual differences in cognitive styles, were accompanied by often cogent and revealing opinions of why images on the one hand, or text on the other, were good for expressing emotions. In cases where images were preferred reasons given included seeing ambiguity as an advantage (in that it can aid an ambiguous response) and seeing the selecting of images to represent feelings as being easier than trying to put their feelings into words.

As to which type of images (*abstract* or *emotion*) were preferred overall, considering all the evidence together, we conclude that while the *abstract* images do hold appeal for those who are particularly object-visual, it is the *emotion* images (faces, people in situations, and natural views) that resonate more with internet users the more visual they are than verbal (both object- and spatial-visual).

The qualitative data also showed that people (35/50 in our sample) wish to see image-based emotion feedback available as an option, for example, in comment forums for product reviews or for video posting sites. It was also seen as a useful addition alongside emoji and emoticons.

This style of image-based emotion feedback is designed to be summarized into a single montage of representative images making it useful for gathering and visualizing large volumes of impressionistic user feedback without the burden of content moderation. Our study shows that users who are more visual than verbal, giving feedback using this method, enjoy it and think it would be useful beyond interior design feedback.

ACKNOWLEDGMENTS

This work was assisted by Heriot-Watt University's CDI theme and EPSRC grant EP/L012626/1. Research data available in HWU repository (CC-BY). We gratefully thank Profs. Pat Thomas and Larry Katz for their correspondence on cognitive styles instruments. Creative Commons browser images are acknowledged here: bit.ly/tlab-ack.

REFERENCES

1. Chris Andrzejczak and Dahai Liu. 2010. The effect of testing location on usability testing performance, participant stress levels, and subjective testing experience. *Journal of Systems and Software*, 83(7), 1258-1266.
2. Alessandro Antonietti and Marisa Giorgetti. 1998. The verbalizer-visualizer questionnaire: A review. *Perceptual and Motor Skills*, 86(1), 227-239.
3. Ann Austin and Jose Abdelnour Nocera. 2015. So, Who Exactly IS The HCI Professional? In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems* (CHI'15), 1037-1042. http://dx.doi.org/10.1145/2702613.2732906
4. Pascal Belin, Sarah Fillion-Bilodeau and Frédéric Gosselin. 2008. The Montreal Affective Voices: A validated set of nonverbal affect bursts for research on auditory affective processing. *Behavior Research Methods*, 40(2), 531-539. http://dx.doi.org/10.3758/BRM.40.2.531
5. Olesya Blazhenkova and Maria Kozhevnikov. 2009. The new object-spatial-verbal cognitive style model: Theory and measurement. *Applied Cognitive Psychology*, 23(5), 638-663.
6. Olesya Blazhenkova, Maria Kozhevnikov and Michael A. Motes, 2006. Object-spatial imagery: a new self-report imagery questionnaire. *Applied Cognitive Psychology*, 20(2), 239-263.
7. Terry L. Childers, Michael J. Houston and Susan E. Heckler. 1985. Measurement of individual differences in visual versus verbal information processing. *Journal of Consumer Research*, 125-134.
8. Eric Cook, Stephanie D. Teasley, and Mark S. Ackerman. 2009. Contribution, commercialization & audience: *understanding* participation in an online creative community. In *Proceedings of the ACM Conference on Supporting Group Work (Group'09)*, 41-50. http://dx.doi.org/10.1145/1531674.1531681
9. Juliet Corbin and Anselm Strauss. 2008. *Basics of qualitative research: Techniques and procedures for developing grounded theory*, Sage.
10. Henriette Cramer, Paloma de Juan, Joel Tetreault. 2016. Sender-intended Functions of Emojis in US Messaging. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI'16),* 504-509. http://dx.doi.org/10.1145/2935334.2935370
11. Steven Dow, Elizabeth Gerber, and Audris Wong. 2013. A pilot study of using crowds in the classroom. In *Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI'13)*, 227-236. http://dx.doi.org/10.1145/2470654.2470686
12. Dribbble https://dribbble.com/ (Last accessed 16/1/2017)
13. Andy Field. 2009. *Discovering Statistics Using SPSS (3rd ed.)*. Sage.
14. Sarah Gallacher, Jenny O'Connor, Jon Bird, Yvonne Rogers, Licia Capra, Daniel Harrison, and Paul Marshall. 2015. Mood Squeezer: Lightening up the Workplace through Playful and Lightweight Interactions. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW'15),* 891-902, http://dx.doi.org/10.1145/2675133.2675170
15. Francis Galton. 1883. *Inquiries into the human faculty & its development.* JM Dent and Company.
16. Steve Garner and Deana McDonagh-Philp. 2001. Problem interpretation and resolution via visual stimuli: the use of 'mood boards' in design education. *J Art Design Educ*, 20(1), Blackwell, 57-64
17. Erhan S. Haciomeroglu 2016. Object-spatial Visualization and Verbal Cognitive Styles, and Their Relation to Cognitive Abilities and Mathematical Performance. *Educational Sciences: Theory & Practice*, 16(3), 987-1003.
18. Joeri Hofmans and Peter Theuns. 2008. On the linearity of predefined and self-anchoring Visual Analogue Scales. *Br J Math Stat Psychol*., 61(Pt 2).
19. Roman Jakobson. 1960. Closing statement: Linguistics and poetics. *Style in language*, 350, 377.
20. Markus Junghöfer, Margaret M. Bradley, Thomas R. Elbert, and Peter J. Lang 2001. Fleeting images: A new look at early emotion discrimination. *Psychophysiology*, 38(2), Cambridge Univ Press, 175-178.
21. Nancy H. Kerr, David Foulkes and Marcella Schmidt. 1982. The structure of laboratory dream reports in blind and sighted subjects. *The Journal of nervous and mental disease*, 170(5), 286-294.
22. John R. Kirby, Phillip J. Moore and Neville J. Schofield. 1988. Verbal and visual learning styles. *Contemporary educational psychology*, 13(2), 169-184.
23. Maria Kozhevnikov, Mary Hegarty and Richard E. Mayer. 2002. Revising the visualizer-verbalizer dimension: Evidence for two types of visualizers. *Cognition and Instruction*, 20(1), 47-77.
24. Maria Kozhevnikov, Stephen Kosslyn and Jennifer Shephard. 2005. Spatial versus object visualizers: A new characterization of visual cognitive style. *Memory & cognition*, 33(4), 710-726.
25. Peter J. Lang, and Margaret M. Bradley. 2007. The International Affective Picture System (IAPS) in the study of emotion and attention. *Handbook of emotion elicitation and assessment*, 29.

26. Jennifer S. Lerner, Deborah A. Small, and George Loewenstein. 2004. Research Report Heart Strings and Purse Strings Carryover Effects of Emotions on Economic Decisions. *Psychological Science*, 15(5), APS, 337-341

27. Kurt Luther, Amy Pavel, Wei Wu, Jari-lee Tolentino, Maneesh Agrawala, Björn Hartmann, and Steven P Dow. 2014. CrowdCrit: crowdsourcing and aggregating visual design critique. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW'14)*, 21-24. http://dx.doi.org/10.1145/2556420.2556788

28. Andrew L. Mendelson and Esther Thorso. 2004. How verbalizers and visualizers process the newspaper environment. *Journal of Communication*, 54(3), 474-491.

29. Joseph A. Mikels, Barbara L. Fredrickson, Gregory R Larkin, Casey M Lindberg, Sam J Maglio, and Patricia A Reuter-Lorenz. 2005. Emotional category data on images from the International Affective Picture System. *Behav Res Methods*, 37(4), 626-630.

30. Hannah Miller, Jacob Thebault-Spieker, Shuo Chang, Isaac Johnson, Loren Terveen, and Brent Hecht. 2016. "Blissfully Happy" or "Ready to Fight": Varying Interpretations of Emoji. In *Proceedings of the 10th International Conference on Web and Social Media, (ICWSM '16).*

31. Don Norman. 2002. Emotion & Design: Attractive Things Work Better. *Interactions*, 9(4), 36-42. http://dx.doi.org/10.1145/543434.543435

32. Donald A. Norman. 2005. *Emotional Design: Why We Love (or Hate) Everyday Things*: Basic books.

33. Valeria Occelli, Jonathan B. Lin, Simon Lacey and K. Sathian. 2013 Spatial imagery and cognitive style in blind individuals. *Multisensory Research*, 26(0), 186-186.

34. Stefano Padilla, Fraser Halley, David A. Robb, and Mike J. Chantler. 2013. Intuitive Large Image Database Browsing using Perceptual Similarity Enriched by Crowds. In *Proceedings of the 15th International Conference on Computer Analysis of Images and Patterns (CAIP'13)*, Springer, 169–176.

35. Allan Paivio and Richard Harshman. 1983. Factor analysis of a questionnaire on imagery and verbal habits and skills. *Canadian Journal of Psychology.* 37(4), 461.

36. Sébastien Paquette, Isabelle Peretz, Pascal Belin. 2013. The "Musical Emotional Bursts": a validated set of musical affect bursts to investigate auditory affective processing. *Frontiers in Psychology*, 4(509). http://dx.doi.org/10.3389/fpsyg.2013.00509

37. Michael Q. Patton. (1990). *Qualitative evaluation and research methods*. Sage.

38. Rosalind W. Picard. 1997. *Affective Computing*, MIT press Cambridge, Mass., USA.

39. Robert Plutchik. 2003. *Emotions and life : perspectives from psychology, biology, and evolution*, APA.

40. Ulf-Dietrich Reips, and Frederik Funke 2008. Interval-level measurement with visual analogue scales in Internet-based research: VAS Generator. *Behav Res Methods*, 40(3), 699-704.

41. Ali Reza Rezaei and Larry Katz. 2004. Evaluation of the reliability and validity of the cognitive styles analysis. *Personality and Individual Differences*, 36(6), 1317-1327. http://dx.doi.org/10.1016/S0191-8869(03)00219-8

42. Alan Richardson. 1977. Verbalizer-visualizer: A cognitive style dimension. *Journal of mental imagery.* 1(1), 109-125.

43. Richard J. Riding. 1997. On the nature of cognitive style. *Educational Psychology*, 17(1-2), 29-49.

44. Richard J. Riding and Indra Cheema. 1991. Cognitive Styles - an overview and integration. *Educational Psychology*, 11(3-4), Routledge, 193-215.

45. Richard Riding and Eugene Sadler-Smith. 1992. Type of instructional material, cognitive style and learning performance. *Educational Studies*, 18(3), 323-340.

46. David A. Robb, Stefano Padilla, Britta Kalkreuter, and Mike J. Chantler. 2015. Moodsource: Enabling Perceptual and Emotional Feedback from Crowds. In *Proceedings of the ACM Conference* Companion *on Computer Supported Cooperative Work & Social Computing (CSCW'15)*, 21-24. http://dx.doi.org/10.1145/2685553.2702676

47. David A. Robb, Stefano Padilla, Britta Kalkreuter, and Mike J. Chantler. 2015. Crowdsourced Feedback With Imagery Rather Than Text: Would Designers Use It? In *Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI'15),* 1355-1364. http://dx.doi.org/10.1145/2702123.2702470

48. David A. Robb, Stefano Padilla, Thomas S. Methven, Britta Kalkreuter, and Mike J. Chantler. 2016. A Picture Paints a Thousand Words but Can it Paint Just One? In *Proceedings of the ACM Conference on Designing Interactive Systems (DIS'16),* 959-970. http://dx.doi.org/10.1145/2901790.2901791

49. Eugene Sadler-Smith. 2001. The relationship between learning style and cognitive style. *Personality and individual differences*, 30(4), 609-616.

50. Katri Salminen, Veikko Surakka, Jukka Raisamo, Jani,Lylykangas, Johannes Pystynen, Roope Raisamo, Teemu Ahmaniemi. 2011. Emotional responses to thermal stimuli. In *Proceedings of the 13th ACM International Conference on Multimodal Interfaces (ICMI'11)*, 193-196. http://dx.doi.org/10.1145/2070481.2070513

51. Katri Salminen, Veikko Surakka, Jukka Raisamo, Jani,Lylykangas, Roope Raisamo, Kalle Mäkelä and Teemu Ahmaniemi. 2013. Cold or Hot? How Thermal Stimuli Are Related to Human Emotional System? In I. Oakley & S. Brewster (Eds.), *Haptic and Audio Interaction Design: 8th International Workshop*, *(HAID'13)*, Springer, 20-29.
52. Marc Schröder. 2003. Experimental study of affect bursts. *Speech Communication*, 40(1–2), 99-116. http://dx.doi.org/10.1016/S0167-6393(02)00078-X
53. Anselm L. Strauss. 1987. *Qualitative analysis for social scientist,* Cambridge University Press.
54. Paul Strohmeier, Juan Pablo Carrascal, Bernard Cheng, Margaret Meban and Roel Vertegaal. 2016. An Evaluation of Shape Changes for Conveying Emotions. In *Proceedings of the ACM CHI Conference on Human Factors in Computing Systems (CHI'16),* 3781-3792. http://dx.doi.org/10.1145/2858036.2858537
55. Petra Sundstrom, Anna Stahl and Kristina Hook. 2005. eMoto: Affectively Involving Both Body and Mind. In *Extended Abstracts on Human Factors in Computing Systems (CHI '05)*, 2005-2008, http://dx.doi.org/10.1145/1056808.1057078
56. James Surowiecki. 2004. *The wisdom of crowds: why the many are smarter than the few and how collective wisdom shapes business, Economies, Societies and Nations.* Anchor.
57. Patrick R.Thomas, and Jacinta B. McKay. 2010. Cognitive styles and instructional design in university learning. *Learning and Individual Differences*, 20(3), 197-202.
58. Larissa Z. Tiedens, and Susan Linton. 2001. Judgment under emotional certainty and uncertainty: the effects of specific emotions on information processing. *Journal of Personality and Social Psychology*, 81(6), APA, 973.
59. Tom Tullis, Stan Fleischman, Michelle McNulty, Carrie Cianchette and Margaret Bergel. 2002. An empirical comparison of lab and remote usability testing of web sites. Paper presented at the *Usability Professionals Association Conference (UXPA2002)*.
60. UK Government. 2012. *Ethnicity and National Identity in England and Wales 2011.* Office for National Statistics.
61. UK Government. 2016. *Internet users in the UK: 2016, Statistical bulletin 20 May 2016*. Office for National Statistics.
62. UK Government. 2016. *Overview of the UK population: February 2016*. Office for National Statistics.
63. Johan H. J. Vesanto, Esa Alhoniemi and Juha Parhankangas. 1999. Self-organizing map in Matlab: the SOM toolbox. *Procedings of the Matlab DSP Conference*, 35–40.
64. Rick S. Warren and Glenn Good. 1979. The verbalizer-visualizer questionnaire: Further normative data. *Perceptual and Motor Skills*, 48(2), 372-372.
65. Jane Webster and Hayes Ho. 1997. Audience engagement in multimedia presentations. *SIGMIS Database: the DATABASE for Advances in Information Systems*, 28(2), ACM, 63-77. http://dx.doi.org/10.1145/264701.264706
66. Tom Wengraf. 2001. Qualitative research interviewing: *Biographic narrative and semi-structured methods,* Sage.
67. Graham Wilson, Dobromir Dobrev and Stephen A. Brewster, 2016. Hot Under the Collar: Mapping Thermal Feedback to Dimensional Models of Emotion. In *Proceedings of the ACM CHI Conference on Human Factors in Computing Systems (CHI'16),* 4838-4849. http://dx.doi.org/10.1145/2858036.2858205
68. Graham Wilson, Pietro Romeo, and Stephen A. Brewster. 2016. Mapping Abstract Visual Feedback to a Dimensional Model of Emotion. In *Proceedings of the ACM CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA'16)*, 1779-1787. http://dx.doi.org/10.1145/2851581.2892320
69. Anbang Xu, Shih-Wen Huang, and Brian P Bailey. 2014. Voyant: Generating Structured Feedback on Visual Designs Using a Crowd of Non-Experts. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW'14)*, 37-40. http://dx.doi.org/10.1145/2531602.2531604
70. Anbang Xu, Huaming Rao, Steven Dow, and Brian P. Bailey. 2015. A Classroom Study of Using Crowd Feedback in the Iterative Design Process. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW'15),* 1637-1648. http://dx.doi.org/10.1145/2675133.2675140