Individual differences in aesthetic preferences for Interactive Objects: a Q-methodology study.

SORANZO, Alessandro <http://orcid.org/0000-0002-4445-1968> and GAO, Jie

Published version

SORANZO, Alessandro and GAO, Jie (2018). Individual differences in aesthetic preferences for Interactive Objects: a Q-methodology study. Art and Perception, 6 (4).

Individual differences in aesthetic preferences for Interactive Objects: a Q-methodology study

SORANZO, Alessandro <http://orcid.org/0000-0002-4445-1968> and GAO, Jie <http://orcid.org/0000-0002-4996-2556>

Published version

SORANZO, Alessandro and GAO, Jie (2018). Individual differences in aesthetic preferences for Interactive Objects: a Q-methodology study. In: Visual Science of Art Conference, 24 Aug 2018 - 26 Aug 2018.

Copyright and re-use policy

Individual differences in aesthetic preferences for Interactive Objects: a Q-methodology study

Alessandro Soranzo & Jie Gao – Sheffield Hallam University
a.soranzo@shu.a.cuk

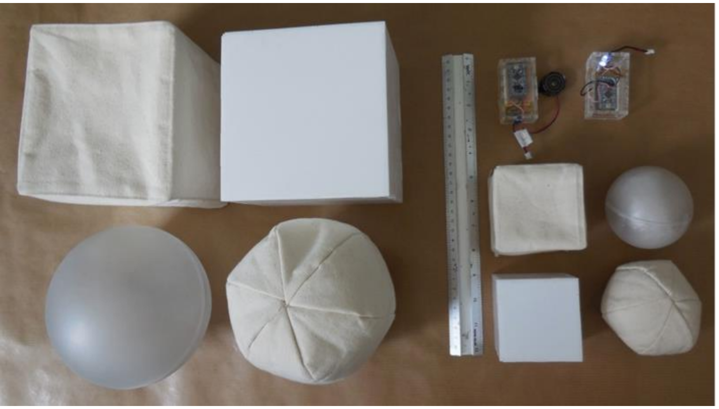
Aims:

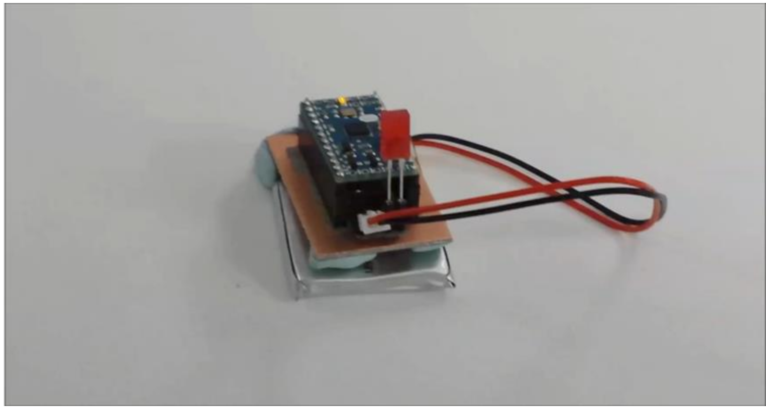
a) to explore how different senses contribute to the overall aesthetic experience (e.g. how vision and touch interact to affect aesthetic judgment)

b) to explore individual differences in this process

c) to expand the application of Q methodology to multidimensional structures

Interactive Objects are three-dimensional physical artefacts that exhibit autonomous behaviour when handled, such as lighting, sounding and vibrating (Soranzo et al, 2018).





Form			Behaviour
Size	*Surface texture*	*Contour*	
Small (7.5cm)	Smooth (plastic)	Round (sphere)	Emit a light
Large (15cm)	Rough (fabric)	Angular (cube)	Play a sound
			Vibrate
			Quiescent

Total number of IOs = 32

Developed by William Stephenson in the 1930s, Q methodology was designed to study subjectivity (e.g., attitudes, viewpoints, or perspectives). It is an ideal tool to investigate aesthetic preferences which are essentially subjective (e.g. Thorndike , 1917; Schloss, & Palmer, 2011, etc).

Q methodology has multiple methodological advantages:

- More interesting and engaged, less time-consuming
- Minimise the order effect
- More coherent and holistic result
- Objectively analyse subjective data
- Combine quantitative and qualitative methods

Experiment: Q-sorting procedure

Participants were 18 undergraduates (14 females and 4 males, 18-24 years). Each experiment session lasted about 30 mins.

Participants were firstly asked to play with the 32 IOs and subsequently to rank-order all the IOs into one single quasi-normal response grid which represents a continuum of preference ranging from 'the least preferred' (-5) to 'the most preferred' (+5).

After Q-sorting, participants were asked to elaborate on their aesthetic judgement.

Least preferred **Most preferred**

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5

Results:

- Principal component analysis with varimax rotation
- Three factors emerged from the data, which explained 70% of the variance:

	NO of participants	Eigenvalue	Explained Variance (%)
Factor 1	8	5.4	30%
Factor 2	6	4.1	23%
Factor 3	3	3.1	17%

Results: factor loadings of participants

	FACTOR 1	FACTOR 2	FACTOR 3
P01	0.28	0.70*	0.29
P02	0.24	0.74*	0.05
P03	-0.36	0.65*	-0.38
P04	0.58*	0.18	0.47
P05	0.47	0.61*	-0.04
P06	0.54	0.43	0.41
P07	0.16	0.80*	0.22
P08	0.82*	-0.16	0.13
P09	0.71*	0.16	0.16
P10	0.89*	0.27	-0.15
P11	0.02	-0.04	0.86*
P12	0.09	0.28	0.86*
P13	0.91*	0.16	0.02
P14	0.83*	0.26	0.05
P15	0.20	0.81*	0.37
P16	0.52*	0.28	0.10
P17	0.06	0.17	0.85*
P18	0.70*	0.62	0.12

* indicates significant loadings

- First Letter: **Size**
  Big/ **S**mall

- Second letter: **Surface texture**
  Smooth/ **R**ough

- Third Letter: **Contour**
  Round/ **A**ngular

- Forth letter: **Behaviours**
  Lighting/ **S**ounding/ **V**ibrating/ **Q**uiescent

	Factor 1	Factor 2	Factor 3
Obj_1	-2	0	-2
Obj_2	-2	1	2
Obj_3	-1	1	-1
Obj_4	-4	-2	0
Obj_5	-1	2	-3
Obj_6	0	4	4
Obj_7	-1	5	1
Obj_8	-4	-3	1
Obj_9	1	-2	-4
Obj_10	1	-1	2
Obj_11	4	0	2
Obj_12	-1	-4	-1
Obj_13	2	-1	-2
Obj_14	3	2	3
Obj_15	3	3	1
Obj_16	-3	-3	-1
Obj_17	0	0	-4
Obj_18	0	2	3
Obj_19	0	1	0
Obj_20	-5	-2	0
Obj_21	0	1	-3
Obj_22	0	3	5
Obj_23	1	4	0
Obj_24	-3	-3	0
Obj_25	3	-1	-5
Obj_26	2	0	3
Obj_27	5	0	1
Obj_28	-3	-4	-2
Obj_29	1	-1	-3
Obj_30	2	0	4
Obj_31	4	3	0
Obj_32	-2	-5	-1

Least preferred Most preferred

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
SRAS	BRAS	SRRS	SSRS	BSAS	BRRV	BSAQ	BSRQ	BSRV	BSAL	SSAL
	BRRS	BSRS	BRAV	BRAL	SRAQ	BSAV	SSAV	BSRL	SSRL	
		SSAS	BRAQ	BRRL	SRAV	SSRQ	SSRV	SSAQ		
				BRRQ	SRAL	SRRL				
					SRRQ					
					SRRV					

Least preferred Most preferred

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
SSRS	BSAS	BSRS	BRAS	BSAV	SRAQ	SRRQ	BRRQ	SRRV	BRRV	BRRL
	SSAS	BRRS	SRAS	BSRQ	BRAQ	BRAL	BSRV	BSRL	SRRL	
		SRRS	BSAQ	SSAQ	BSAL	SRAL	SRAV	SSRL		
				SSRQ	SSAL	BRAV				
					SSAV					
					SSRV					

Least preferred Most preferred

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
SSAQ	BSAQ	BRRQ	BRAQ	BRAL	SRRL	BRRL	BRAV	BSRV	BRRV	SRRV
	SRAQ	SRRQ	BSRQ	BSAS	SRAL	SSAL	BSAV	SRAV	SSRV	
		SSRQ	SSAS	BSRS	SSRL	BSRL	BSAL	SSAV		
				SSRS	BRAS	BRRS				
					SRRS					
					SRAS					

Which is the dominant dimension in a decision-making process?

$$I_d = \text{Max}\,(C(\sum_{i=1}^{i=n}(l_i) - \sum_{i=1}^{i=n} l_{\neq i}, 2))$$

(Eq 1)

The Importance of a dimension (I_d) is given by the maximum between the Combinations (C) of two of the differences between the sums of scores of each level (l) *i* in a dimension with *n* levels.

This is a measure of spread the items within one dimension are in the Q-sorting grid.

Equation 1, however, cannot be generalised to experimental designs in which dimensions have different number of levels (*n*). The lower the number of dimensions the higher the maximum difference between scores can be. For this reason, the I_d score has to be weighted for the maximum obtainable difference, which depends on *n*. Equation 2 shows how to obtain the weighted importance of each dimension *d* (WI_d).

$$WI_d = I_d / (\sum_{\frac{items}{n}}^{\max\ in\ grid} score\ in\ grid * 2)$$

(Eq 2)

Which is the dominant dimension in a decision-making process?

The maximum obtainable difference (the denominator of equation 2) is given by the sum of each of the score in the Q-sort grid (score in grid) from the maximum (max in grid) backwards to the number of all items (items) divided by the number of levels (n) times 2.

By multiplying now these weights for the average of the maximum possible across the N dimensions, we get the Comparable Score Difference for each dimension d (CSDd), that is the difference among the scores which is comparable across dimensions (equation 3).

$$\mathbf{CSDd = WId * \frac{\left(\sum_{\frac{items}{n}}^{max\ in\ grid} score\ in\ grid\right)*2}{N}}$$

(Eq 3)

It is also possible now to get the proportions of importance of each dimension (PId) relative to the others. This is simply done by dividing the weighted importance for each dimension (WId) from equation 2, by the sum of the weights of all N dimensions (equation 4).

$$\mathbf{PId = WId \ / \sum_{i=1}^{i=N} WI_d}$$

(Eq 4)

Three clusters of responders shared similar preferences:

- Cluster 1 preferred smooth surface texture to rough surface and disliked the behavior of making a sound.
- Cluster2 disliked the sounding behavior and liked rough round objects.
- Cluster 3 preferred vibrating IOs to lighting and sounding IOs.

Qmulti()
Dimensions' weights

	Factor 1	Factor 2	Factor 3
Size	0.093	0.038	0.049
Surface texture	0.410	0.248	0.024
Contour	0.037	0.210	0.146
Behaviour	0.459	0.504	0.780

By reading these weights, we can infer the dimensions which participants based their aesthetic judgement on:

- Factor 1: the surface texture and behaviour of IOs
- Factor 2: mainly the behaviour of IOs and subsequently the surface texture and contour
- Factor 3: mainly focused on the behaviour of IOs

References & R code:


ferred
P10