Operant Subjectivity: The International Journal of Q Methodology
43 (2021): 1-13, DOI: 10.22488/okstate.21.100588

Operant Subjectivity
The International Journal of Q Methodology

Q-Sorting Dynamics – A Note on a Computer-Mediated Tool and its Added Value to Q Methodology

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Abstract: The analysis of the results of Q sorting mainly focuses on the final sort made by each individual. The only way to take into account the dynamics of sorting construction is through the post-sorting interview, which normally requires a face-to-face context. Recently, the analysis of this dynamic has raised the interest of psychometric researchers. Specifically, scholars of the subdomain of psychometrics known as the Cognitive Aspects of Survey Methodology have confirmed the value of collecting further data through digital tools. In this methodological note, we explore the contribution of information collected through digital traces measured during the sorting process. A purposely designed software allows us to capture all events generated by a respondent's computer mouse during the two main stages of Q sorting. We report on the identification of different sorting behaviours which allows the detection of both atypical statements and atypical respondents that may require closer attention. In addition, a complementary analysis based on weighted PCA is investigated in order to test how such additional information can be integrated into traditional Q-factor analysis. An example is provided using a previously validated subjective inquiry on the perception of augmented reality by the general public.

Keywords: computer-mediated Q sorting, sorting dynamics, weighted PCA

Introduction

Since the ground-breaking invention of Q methodology by W. Stephenson (1935, 1953), several contributions have flourished in order to assist Q methodologists with the generation and analysis of Q data. This is particularly true over the last decade.

The technical possibilities stemming from the online environment are abundant and yet some of them are still under-exploited. While acknowledging that in order to fully grasp the differences induced by online sorting as compared to paper sorting there remains a need for more theoretical thinking as well as empirical exploring. We seek to

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provide additional data to online Q data by using the possibility to capture the sorting dynamics. Our aim is hence to share our preliminary findings in capturing the process that underline Q sorting, and in analysing its impact on the final results.

Probably each Q researcher has experienced or observed that the sorting process is uneven, nor is it uniform between participants. We all know that different sorting behaviours exist: what does it say about the final sort and the participant's viewpoint? What is the meaning of it? Does time taken to sort matter? Can we learn more by capturing this process and by interviewing our participants with this additional information in mind?

Our hypothesis is that it is worth exploring such dynamics. So, we designed software able to capture the sorting process by measuring the respondent's actions on the mouse of his or her computer. In the remainder of this note, we will first present the main features of this software. Second, we will share our preliminary results together with our observations and finally discuss open questions with the hope of initiating a fruitful discussion within the Q community.

Tool Development: Rationale, Collected Data, and Software Features

The recent development of online data-collection tools for Q methodology, such as Ken-Q (Banasick, 2019), Vqmethod (Nazariadli, 2018), Html-Q (Aproxima, 2015), to name a few, demonstrates the undeniable interest of the Q community in this mode of data generation. Parallel to these developments, a specific literature in psychology, Cognitive Aspects of Survey Methodology (CASM) has explored the affordances offered by the administration of online questionnaires (Tourangeau, Conrad and Couper, 2013; Meade and Bartholomew, 2012). While this research tradition is clearly R-oriented, several findings are of interest and offer perspectives in online Q sorting.

CASM had originally focused on response times, their measurement and interpretation in terms of attitude formation and attitude accessibility (Tourangeau, 2003, and Tourangeau and Plewes, 2013), building upon the early work of Fazio, Chen, McDonel, and Sherman (1982) and Fazio (1990a & b). More recent work on mouse- and eye-tracking has provided additional data and potential insights to Q methodologists (Hehman, Stolier, and Freeman, 2015; Koop and Johnson, 2011). We build upon these reflections to define the different measures to be considered in tracking Q-sorting processes.

New Collected Data and Q sorting

The majority of Q methodologists recommend the collection of Q sorts using a two-stage approach with (i) an initial distribution-free sorting into three rough categories (unlike my viewpoint, neutral, like my viewpoint) before (ii) a forced-choice finer categorisation (see Brown, 1980, McKeown and Thomas, 1988, Watts and Stenner, 2012). Thus, our purposely defined software, named Q-Trace[1], complies with this two-stage design. One of the distinctive features of Q methodology stems from the holistic dimension of the sorting process: thus, an additional Stage 0 is implemented, in which respondents first have to read each statement on screen, before they can begin the sorting process.

The collected measures entail both time and space. Concretely, those measures are collected using the following events: mouse click, drag, drop, move, and waiting time in-between, for each sorting step. Those events are characterised by the spatial coordinates of the mouse pointer on screen, and their timestamps, measured in milliseconds starting from the beginning of each stage: the duration of each micro-movement is computed later.

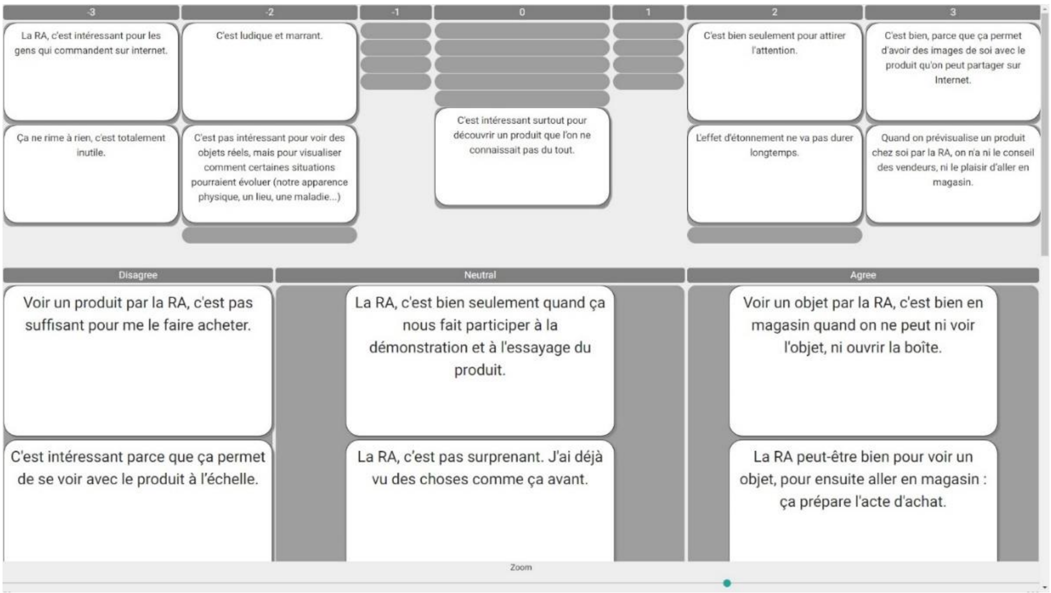
1 To date, the software is still a prototype for research only. A more user-friendly version, designed for Q researchers, is in-progress.

Q-trace Features

Figure 1 presents a screenshot of the interface as seen by the participant. The Q-trace software makes it possible to:

- present the study and the cards,
- use textual or multimedia cards (images, videos, sounds),
- present cards randomly for the sorting step,
- implement the three-stacks step,
- implement the final Q-sort step,
- add complimentary questions,
- record all Q-sorting dynamics.

Figure 1. The Q-Trace interface for Stage 2 of the Q sort



A Pilot Exploration

In order to illustrate how Q-Trace works and the insights it can provide, we use a Q sample (see appendix) that has been used in previous research aiming to grasp the vision of end-users pertaining to augmented reality (Gauttier, Gauzente, and Aikala 2016). The technology of augmented reality, consisting of adding a virtual layer to reality via devices such as computer, tablet, smartphone, is now easily available in everyday life. The original Q sample comprised 24 statements, generated following focus-group interviews; it is re-used here with a new P sample (n=13) composed of engineering students.

Our main objective is to analyse the collected data with two directions in mind: (i) the sorting process and strategies, (ii) inter-individual differences. Based on these findings, we can see that significant qualitative observations can be made. A secondary objective is to explore how information deduced from tracking data can be incorporated into Q calculations. This secondary line of analysis is at its very nascent stage.

Tracing the Q-Sorting Process

Findings in psychometry have pointed to the relationship between response latency and attitude formation. Response latency is defined as "*a general measure of the amount of information processing necessary to answer a question*" (Bassili and Scott, 1996, p. 392). Johnson (2004) points out that response latency is composed of four phases: interpretation latency, relevant information seeking, response elaboration and response selection. It is not possible to conduct such a fine-tuned analysis of collected traces, knowing that the Q-sort process is far more complex than the usual form of experiments in mouse-tracking (Hehman et al., 2015). We focus on the two dimensions that we suppose determine total latency, statement wording and respondent behaviour.

Sorting Dynamics and Statements' General Analysis

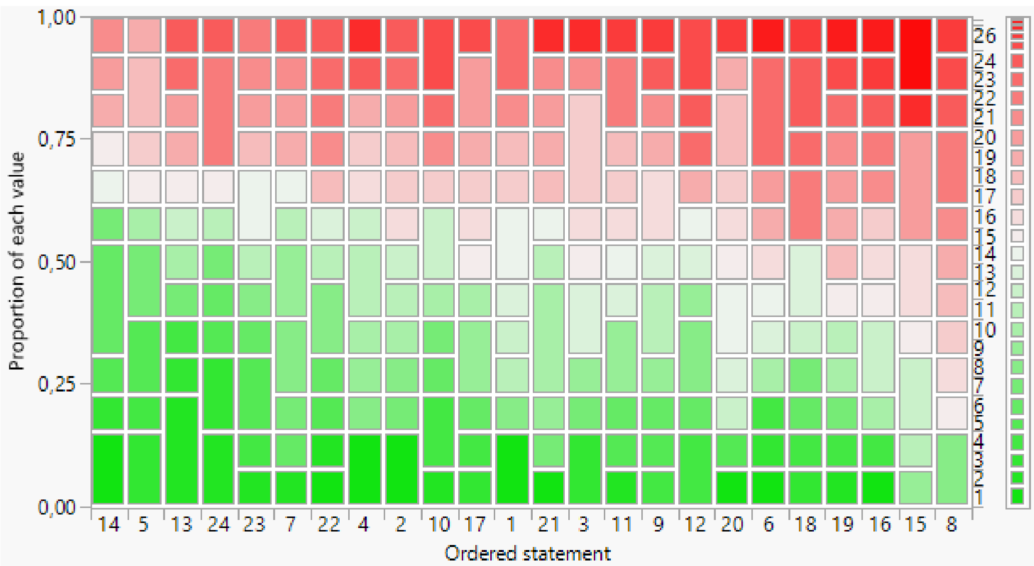
A first set of observations pertains to the two-stage sorting process. Tracking the whole process shows that sharp subjective orientations emerge at that stage and are then settled during the second phase. As shown in table 1, aside from marginal cases, most participants refine their three-piles sorting coherently from Stage 1 to Stage 2.

Table 1: Sorting consistency between Stage 1 and Stage 2 (number of statements)

		First move in Stage 2							
		−3	−2	−1	0	1	2	3	Total
First move in Stage 1	disagree	28	37	27	13	3	2	1	111
	neutral	0	1	23	58	23	1	0	106
	agree	0	1	0	10	23	35	26	95

A second set of observations relates to the identification of statements' singularities. The mosaic plot in Figure 2 shows the proportion of participants (left scale) that placed each statement during their first moves (green, see right scale) or last moves (red), the grey cells being in-between[2].

Figure 2: Statement placement ordering during Stage 1.



Considering this plot, where statements are ordered by decreasing median rank of placement, we notice that statements #8 and #15 were never placed during the earliest stages of the sorting process, as if they were more difficult to assess for the respondent. These statements therefore stand as good candidates for more specific attention.

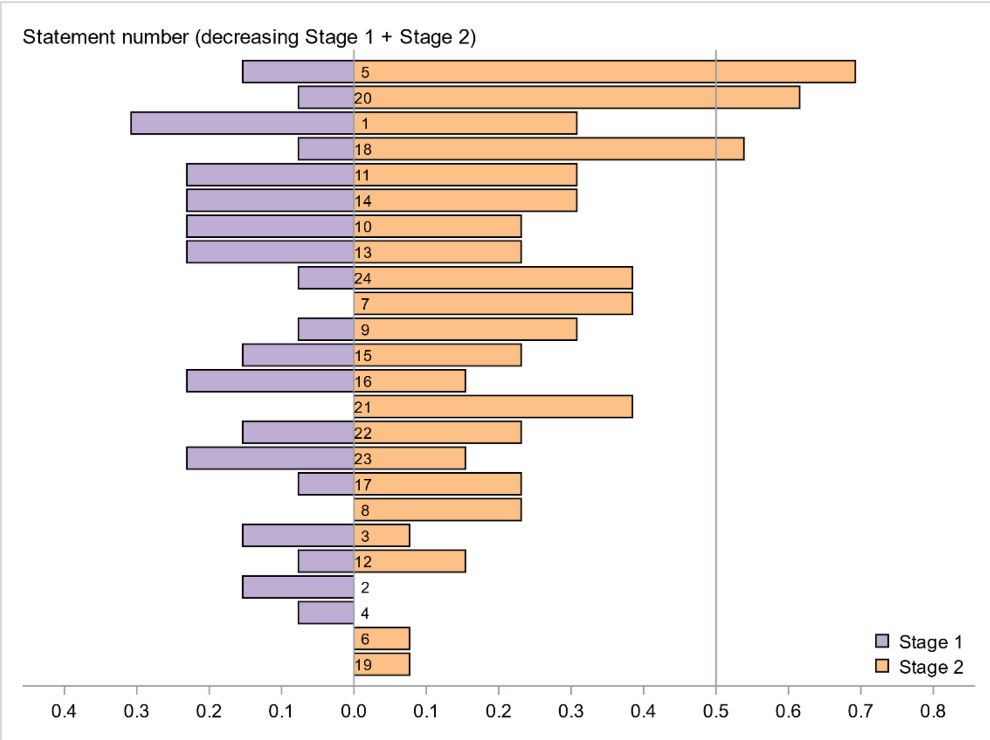
Figure 3 shows the average number of relocations of statements, i.e., the average number of moves for each stage minus one: the statements are sorted by decreasing total of movements for both stages. We can see that almost every statement is moved from one position to another at least once by at least one respondent, but that, however, the averages of the number of relocations are rather low: this suggests an overall stability of

2 Software credits are given at the end of the reference section.

judgement for the respondents. In detail, for the two statements detected earlier as "late evaluation":

- Statement 8 (*Augmented reality is not interesting for real objects, but for visualising how specific situations could evolve*) is relocated less than others, especially in Stage 1.
- Statement 15 *(When you visualise a product using AR, you do not interact with the vendor or have the pleasure of wandering in shops)* is relocated more often than Statement 8 (around 1 time for each 5 respondents) but still less than half of the other statements.

Figure 3: Average number of place changes per statement, Stage 1 and Stage 2



There are competing interpretations of this discrepancy between time spend on the first evaluation and placement of a statement, seen in figure 2, and the number of its relocations afterwards: this might need further experimentation. But what is common between statements #8 and #15 is the presence of two sub-sentences in each, which increases the complexity of building an attitude for the respondent: see for example the Q-list discussion about double-barrelled statements, at

http://www.cios.org/mailboxes/Q-method/01188211.128.

Another interesting insight provided by this figure distinguishing relocations between Stage 1 and Stage 2 is that we can observe the impact of Q-methodology instructions on the sorting process. In Stage 1, participants can place in each basket as many statements as they wish, and there are fewer relocations than in Stage 2, where they must comply with the forced distribution. Hence the time taken to sort each statement during Stage 1 does not necessarily have the same meaning as in Stage 2. In Stage 1 participants are not familiar with the statements and they have to discover the meaning of each of them: some will appear clear, non-ambiguous and easy to sort, and others will not. Difficulties sorting a statement at this stage, as reflected in response latency, can be interpreted in light of CASM studies (Tourangeau, Conrad, et al., 2013). Our own preliminary experiences lead us to suggest the following potential reasons for increase latency:

- statement length,
- difficulty in understanding the statement because of: (i) an ambiguous formulation, (ii) poor wording, (iii) double-barrelled statement, (iv) complex wording, such as inclusion of technical vocabulary,
- difficulty in accessing a pre-existing attitude, either because the participant does not have an attitude toward the statement due to a lack of knowledge/expertise, and/or experience, or because the participant is ambivalent toward the statement.

These are hypotheses that can or should be explored during the post-sort interview. In Stage 2, with the forced distribution, relocations might correspond to partly different reasons:

- attitude refinement, i.e., balancing one statement against another,
- practical refinement, i.e., having to find some room for a statement not yet placed.

Again, interviewing the participants at the end of the sorting process will be informative. The possibility offered by the Q-Trace software to identify volatile statements enables the use of fine-tuned exit interviews with special attention given to those statements in addition to the ones placed on the extreme categories.

Exploration of Inter-Individual Differences

There are two main causes of differences between respondents: cognitive differences, or misbehaviour. As stated in the presentation of our experiment, the P-sample of our example is very homogenous, in age as in educational level, and the first cause can thus be neglected. But misbehaviour is commonplace in investigations: on one hand, the respondent may be distracted by other thoughts, taking more time to complete the task. More frequently, he or she may engage in behaviour known as speeding (Zhang & Conrad, 2013): then, statements are sorted without real reflection, almost at random. Figure 4 represents boxplots of the distribution of latency for each respondent, i.e., the time spent before and during each statement move, sorted by decreasing total time spent on Stage 1 and Stage 2. It shows that, in our P-sample, both behaviours seem to exist. Respondent 6 is much slower than the others, while Respondent 5 is particularly rapid. The interpretation of these sorting behaviours is not straightforward, even if literature on CASM can serve as a basis. However, if the Q-Trace software is adopted and used in several research projects, it will be possible to develop mean expectancies that will help researchers to identify particularly rapid and particularly slow sorters, and then to conduct adapted exit interviews taking their peculiarities into account.

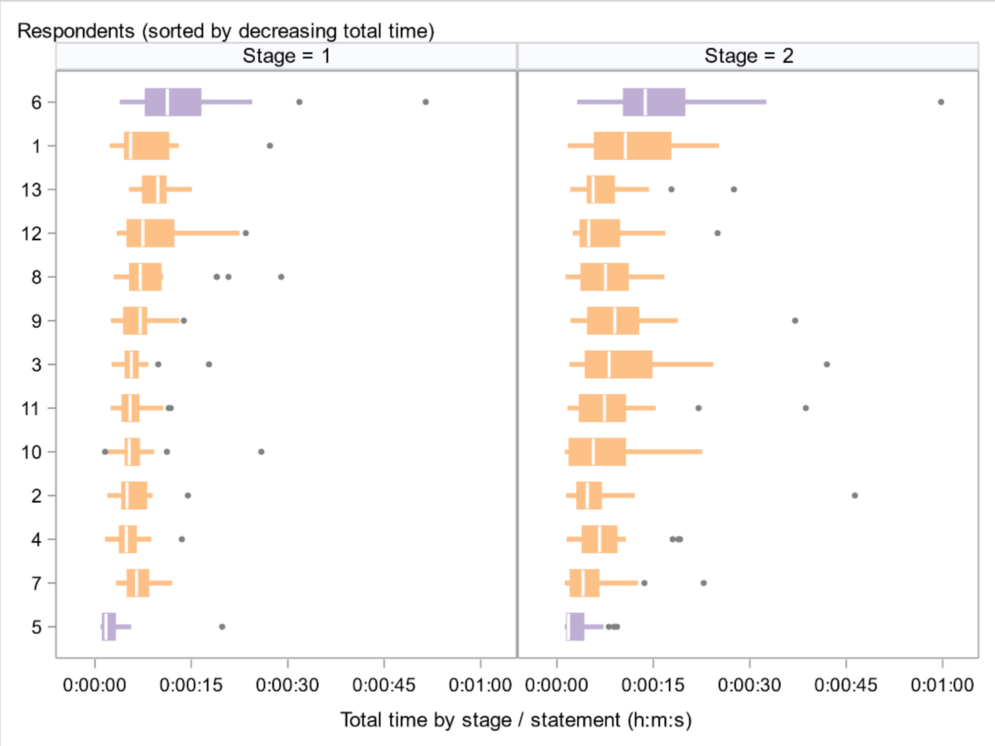
Trace-Informed Analysis

Previous observations can be incorporated into the analysis of Q sorts at different stages: in the statistical analysis and in the exit interviews and factor interpretation. Once the general examination of the sorts' dynamics is done and when specific sorting behaviours are identified, or when specific statements appear to require much less or much more efforts from the participants, it is possible to mitigate it in the data analysis. Clearly, such analytical choices should be conducted with care and with either theoretical or empirical justification or, as was discussed in Brown, Wolf and Rhoads (2017) as a complementary means to explore the data on an abductive basis.

Weighted Factor Analysis

Identified differences, pertaining either to Q sorts or to statements or both, can be included in the factorial analysis by weightings. Different integration of weights into principal components analysis (PCA) have been proposed in the literature (Härdle and Simar, 2007).

Figure 4: Distribution of total sorting time per respondent (Stage 1 and Stage 2)



Weighting variables, or Q sorts in our case, is nothing more than multiplying the values of the Q sort by a coefficient belonging to the]0,1] interval. To keep this correction, the eigenvalues and eigenvectors must be computed on the covariance matrix instead of the correlation matrix: this is very common in R methods when variables are measured on the same scale, a smaller variance indicating a variable of lesser interest for the participants. And this is precisely the goal of the weighting scheme proposed: to reduce the importance of the information given by the potentially misbehaving respondents.

Weighting rows, in this case statements, is also a common practice in surveys where sample adjustment is needed (Fuller, 2009). Weighting rows has also been used in an iterative way to compute robust covariance matrices (Rousseeuw and van Zomeren, 1990) in the presence of unknown outliers or leverage points. Such a technique cannot be used in this study for two main reasons: (i) because it relies on large samples (Yuan and Hayashi, 2010), and (ii) because the iterative part of the weighting scheme loses its interest as the potential outliers are not unknown: they have been already detected by looking at traces. The logic is then the same as for Q sorts: to reduce the amount of information provided by statements about which there is a doubt. As there is no formal rule for determining optimal weights, an alternative is to adopt judgemental weighing based on the qualitative analysis and interpretation of statements' profiles and participants' sorting behaviour provided by Q-Trace. The drawback is that the analysis cannot be performed with the usual packages devoted to Q Methodology, and we had to develop special procedures for this[3].

Application

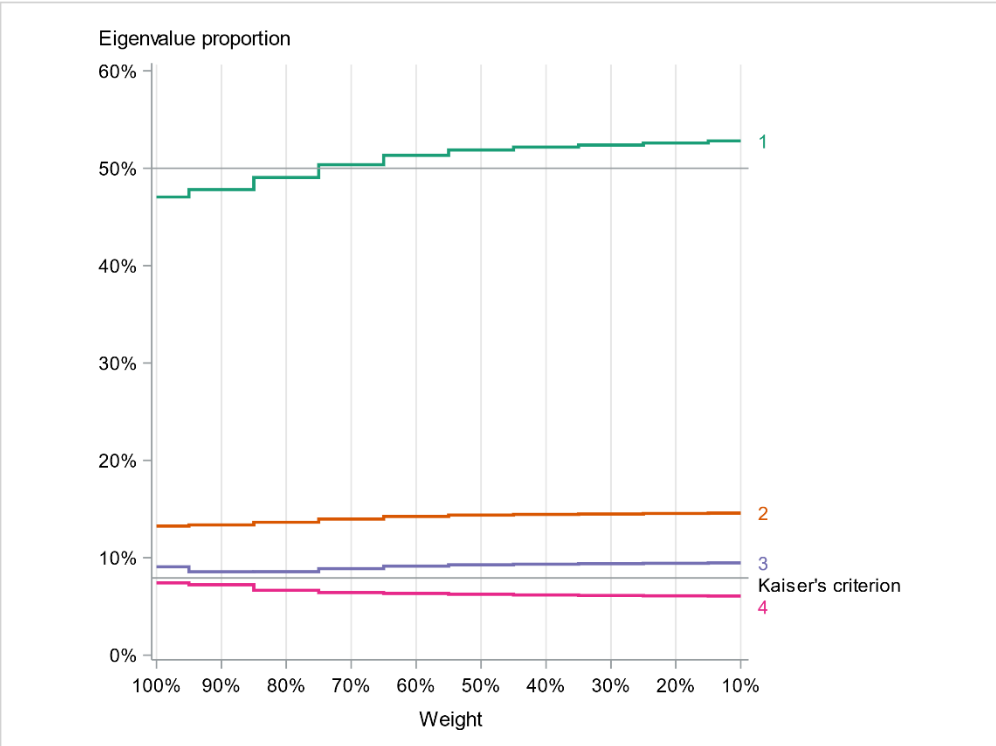
Based of tracking observations reported in previous sections, we have identified atypical individuals (#5 and #6) and statements (#15 and #8) that significantly differ from the others. We assume that the quality of information given by these statements and these respondents might not be as good as expected. And that there is a need to cope with this problem, and the underweighting of these elements is a way of coping. Obviously, many

3 See software credits at the end of the Refences section.

combinations are possible in terms of underweighting one sort or two sorts, one statement or two statements, etc. In the following we explore the impact of a simple weighting scheme: we underweight with the same coefficient both Q sorts #5 and #6 and statements #15 and #8. Then we evaluate the consequences of such a transformation of the data by varying the shared weight from 1 (no weight) to 0.1 (near-elimination) in steps of 0.1, and computing two indicators: (i) the distribution of the eigenvalues extracted from the PCA, which guides the selection of the number of significant factors in the analysis and (ii) the factors resulting from the rotated (varimax) PCA which are used to determine the impact of atypical items in the Q analysis. We present our exploratory results here.

Figure 5 compares the first four eigenvalues for different weights: from no weighting at all (w=1) to a strong underweighting (w=0.1). In the following, we retain the first three values that remain above Kaiser's criterion, whatever the weighting scheme. Unsurprisingly, the weighting effect is greater for the first eigenvalue. It increases up to 50% and then stabilizes. For the second eigenvalue the increase is much smaller, but the stabilization is similar. Mechanically, the two other eigenvalues decrease.

Figure 5: Distribution of eigenvalues of F1 to F4 with different weights for participants #5 and #6 and statements #8 and #15



In order to finely analyse weighting effects on factors composition, we observed the statement displacements in the resulting synthetic Q sorts for the different weights. Figure 6 shows the results for the two first factors: a colour gradient has been applied to the different values (dark red for −3 to dark green for +3), to highlight variations and their magnitude. A line which remains in the same colour corresponds to a statement which stays at the same place in the Q sort whatever the weight applied to both respondents #5 & #6 and statements #8 & #15.

Figure 6: Variation of statements' ordering in the synthetic Q sort resulting from Rotated PCA (varimax) with different weights (Factors 1 and 2)

	RFDistrib1										RFDistrib2									
statement	1	0,9	0,8	0,7	0,6	0,5	0,4	0,3	0,2	0,1	1	0,9	0,8	0,7	0,6	0,5	0,4	0,3	0,2	0,1
1	0	1	-2	-2	-2	-2	-2	-2	-2	-2	-1	-1	1	2	2	2	2	2	2	2
2	-3	-2	-3	-3	-3	-3	-3	-3	-3	-3	-1	-1	-2	-1	-1	-1	-1	-1	-1	-1
3	0	0	0	0	0	0	0	0	0	0	-2	-2	0	0	0	0	0	0	0	0
4	1	1	-1	-1	-1	-1	-1	-1	-1	-1	0	0	2	1	1	1	1	1	1	1
5	-3	-3	-1	-1	-2	-2	-2	-2	-2	-2	-2	-3	-3	-3	-3	-3	-3	-3	-3	-3
6	-2	-3	-1	-1	-1	-1	-1	-1	-1	-1	3	2	-3	-2	-2	-2	-2	-2	-2	-2
7	-1	-1	0	0	0	0	0	0	0	0	0	0	-1	-1	-1	-1	-1	-1	-1	-1
8	-1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	-2	-2	1	1	1	1	1	1	1	1	0	-1	-2	-3	-3	-3	-3	-3	-3	-3
10	-2	-2	-1	-1	-1	-1	-1	-1	-1	-1	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2
11	2	1	3	3	3	3	3	3	3	3	0	0	0	0	0	0	0	0	0	0
12	3	3	0	0	0	0	0	0	0	0	-3	-2	3	3	3	3	3	3	3	3
13	2	2	1	2	2	2	2	2	2	2	2	3	1	1	1	1	1	1	1	1
14	-1	0	-2	-2	-2	-2	-2	-2	-2	-2	1	1	1	1	1	1	1	1	1	1
15	0	0	0	0	0	0	0	0	0	0	1	1	-1	-1	-1	-1	-1	-1	-1	-1
16	-1	0	-3	-3	-3	-3	-3	-3	-3	-3	0	0	1	1	1	1	1	1	1	1
17	2	1	3	3	3	3	3	3	3	3	-1	-1	0	0	0	0	0	0	0	0
18	0	-1	1	1	1	1	1	1	1	1	2	2	-1	-1	-1	-1	-1	-1	-1	-1
19	1	2	0	0	0	0	0	0	0	0	-3	-3	2	2	2	2	2	2	2	2
20	0	0	2	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
21	3	3	2	2	2	2	2	2	2	2	-1	0	2	2	2	2	2	2	2	2
22	1	2	-2	-2	-1	-1	-1	-1	-1	-1	1	1	3	3	3	3	3	3	3	3
23	1	0	2	2	2	2	2	2	2	2	2	2	0	0	0	0	0	0	0	0
24	0	-1	1	1	1	1	1	1	1	1	3	3	-1	-2	-2	-2	-2	-2	-2	-2

The results confirm the stabilization of the weighting effect from 0.5 (resp. 0.8) for the first (resp. second) factor. Moreover, for the first factor, all statements are impacted by at least one of the weights and for some of them the effect is important, partly due to the rotation process. For instance, Statement 9 moves to −2 to +2 for, respectively, weights equal to 1 and 0.8. For the second factor, as expected by the eigenvalue distribution, order changes are much more limited but some variations can still be identified: e.g., Statement 12 moves to −3 to −1 for, respectively, weights equal to 1 and 0.8. All those changes have a significant impact in terms of factor interpretation.

Another visualisation, useful as a diagnostic tool, is provided by figures 7a and 7b, which are inspired by the work of Zabala (2014, p 170). They represent the rotated factor scores of each statement on the first 3 factors, with or without weighting: the statements are sorted by descending standard deviation, each marker is filled when the statement is distinguishing for the factor, empty otherwise, and the 95% and 99% confidence intervals are materialized by vertical dashed lines.

Overall, the two different scenarios of figure 7 show that factors' stability can be significantly impacted by reducing the information provided by potentially misbehaving respondents and imperfect statements, and that might help interpretation. For example, statement 8, rather complex, stays distinguishing for the first factor after the weighting procedure: it is clearly not a consensus statement. By contrast, statement 15, obviously double-barreled, becomes non distinguishing after the same procedure. Further interpretation will require more data and Monte-Carlo analysis, that are far beyond the scope of this research.

Figure 7a: Statements rotated factor scores and distinguishing property, unweighted results

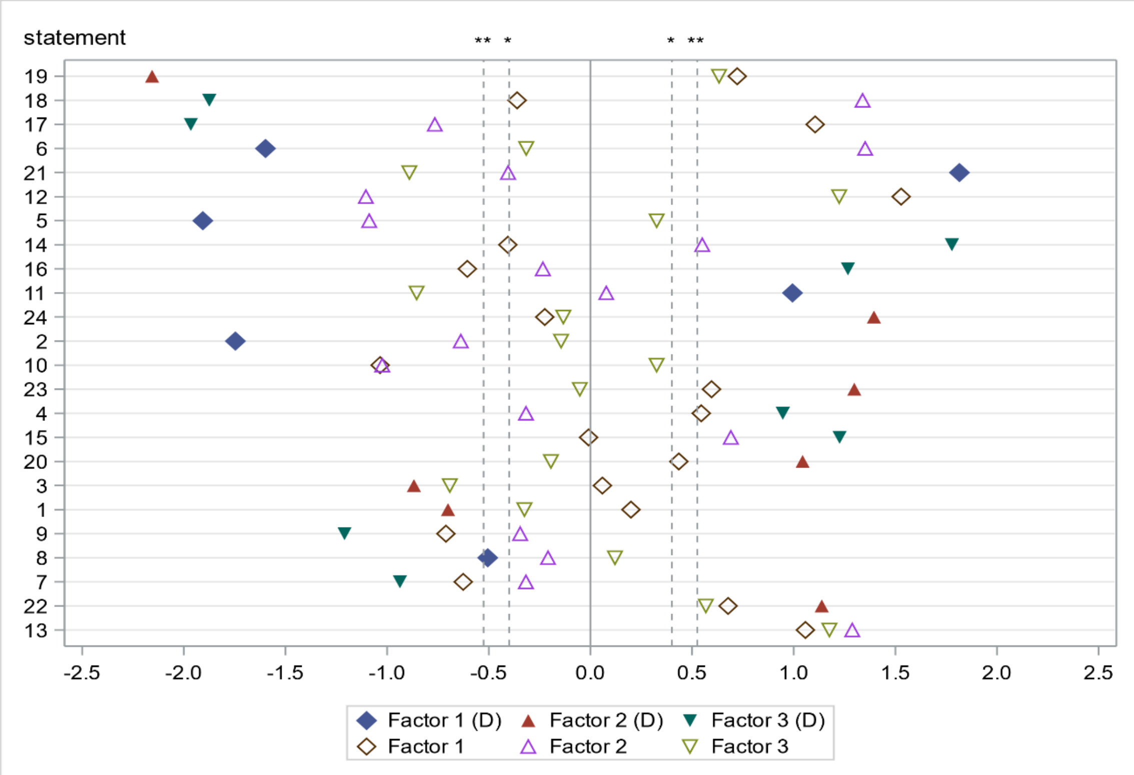
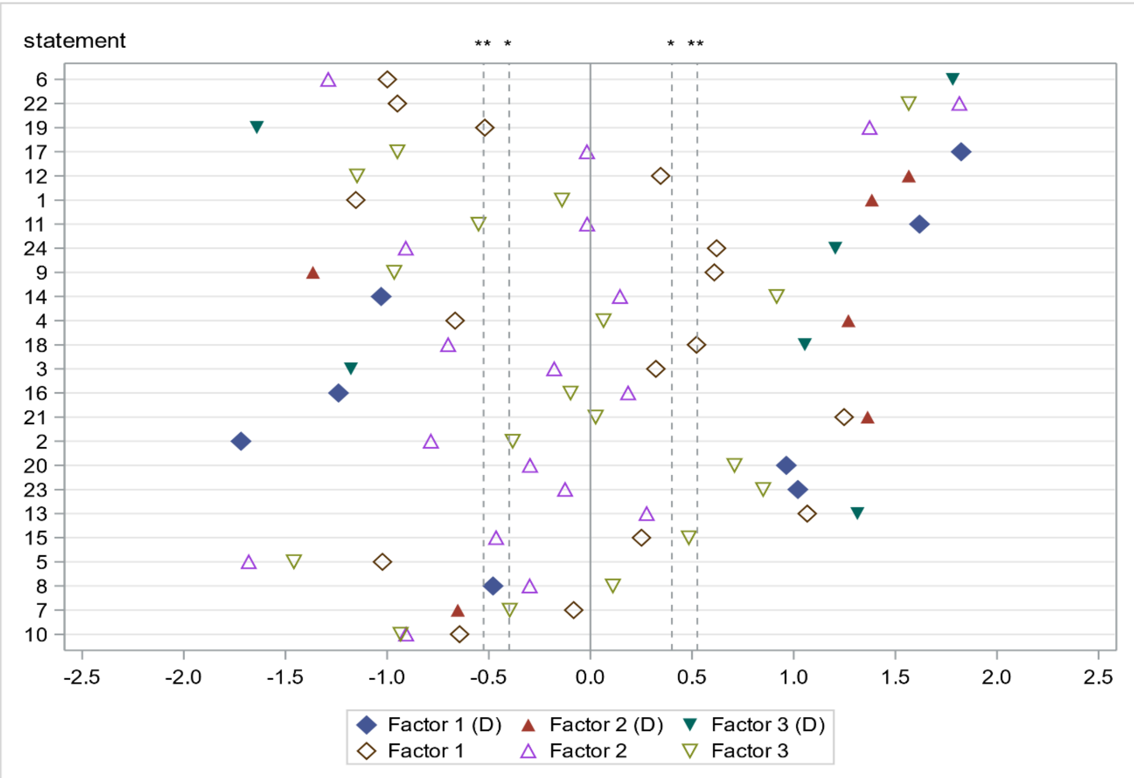


Figure 7b: Statements rotated factor scores and distinguishing property, weighted results, *w*=0.6



Discussion and Future Directions

This note is intended to share the first explorations and observations made possible by the capture of Q-sorting dynamics. Many questions are raised by our results, but it is not our objective here to exhaustively cover their range. We can, however, discuss three meaningful avenues.

Firstly, the capture of Q dynamics not only offers fruitful avenues for Q-factor analysis but also for the whole process of Q methodology. The post-sorting, or exit, interview is a crucial methodological phase, and the possibility of benefitting from tracing observations significantly expands the conduct of Q studies. The incorporation in the online tool of exit questions based on the real-time volatility of statements is possible. Two options are integrated: additional open questions about the statements that were moved most often, what we call high-change statements, and additional questions based on high-leap statements, exhibiting a great leap from one category to another. So as pertains to the interpretation of final Q factors, in addition to current recommendations in the Q literature (e.g., Watts and Stenner, 2012), two additional questions and subsequent comments are available to make sense of the data.

Secondly, the use of a computer-mediated tool to gather Q sorts allows the capture of the sorting dynamics, but there will be a need in the future to develop further knowledge of the differences between physical Q sorting and digital Q sorting. And it will be useful to analyse the Q-sorting dynamics associated with the different disposal of the statements on the screen. The combination of online and face-to-face exit interviews also needs to be tested in order to explore the added-value of the additional questions related to unstable/stable statements and their inputs in Q-factor interpretation.

Thirdly, as suggested in our calculations, the information drawn from Q-sorting traces might also be incorporated into the Q-factor analysis, thanks to judgemental-weighted factor analysis. Our first attempts show sharp differences when weights are considered. It is particularly interesting to see that some statements may switch from a negative rank to a positive one (as for Statement 9 in figure 6); or to observe the stability of some statements (as for statement #2 or #13). Clearly, the extent to which this procedure should or should not be used is linked to the theoretical as well as the empirical background of any specific research study. Brown (1978) pointed insightfully in his example about a hospital department that in addition to shared viewpoints with higher-than-one eigenvalues, other Q factors might -and should be- considered. In other words, if the viewpoint of the head of the department loads on a less-than-one eigenvalue factor, that viewpoint is still important and deserves as much attention as the others. So, the underweighting technique is not necessarily required in the end, but it can help in identifying more or lesser stable statements and in challenging interpretations. It indicates where *thin ice* is located for the interpretation process and may also serve as a probe in the exploration of meaning construction (Brown, Wolf and Rhoads, 2017).

At this stage, it is premature to recommend weighting strategies. It obviously offers many possibilities for data manipulation, just as judgmental rotations do, and it might not always be desirable. Given the significant impact on final Q factors, there will be a need to develop further research, and eventually employ meta-analyses. While our observations obviously need further experimentation with additional Q sets and P samples, we anticipate that the enrichment of Q methodology using computer-mediated artefacts represents a promising avenue.

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Software credits

Figure 1 was created using an alpha version of the Q-Trace software (Gauzente, Kuntz, Roy, and Milliat, 2018).

Figure 2 was generated using JMP Pro software, version 14.3 for Windows, © 2018, SAS Institute Inc.

All computations and all other figures and tables were generated using SAS/STAT software and SAS/IML Software, version 9.4 of the SAS System for Windows, © 2016, SAS Institute Inc.

Appendix

Q sample (initial instrument in French):

1. Using AR with a webcam is too complicated. With a phone, it is OK.
2. I do not understand how it works; it is too complicated. I do not want to try.
3. AR is not surprising. I have already seen things like this before.
4. The wow-effect will not last long.
5. It does not make sense; it is absolutely useless.
6. It is better to go into shops than to live behind your screen and try things with AR.
7. I would use AR only as an exception, if I had not a second to spare to go into a shop.
8. It is not interesting in order to see real objects, but to visualize how some situations could evolve (our physical appearance, a location, an illness …).
9. It is good only to draw attention
10. It is not for me, but for people who already know this technology very well.
11. Seeing an object through AR, it is good in a shop when you can neither see the object nor open the box.
12. Seeing products through AR saves time. It is quicker than searching for the products in a shop and trying them on.
13. It is playful and funny
14. One needs to be able to touch a product.
15. When pre-visualizing a product through AR at home, one lacks the pleasure of going into a shop as well as the advice of the salesperson.
16. Using AR to visualize a product is stupid, because one cannot be sure it will look like this in the real world.
17. AR is interesting for people who order on the Internet.
18. Seeing a product through AR is not enough to make me buy it.
19. It is good because it allows you to have pictures of yourself with the product you can share on the Internet.
20. It is interesting mainly to discover a product one did not know at all.
21. It is interesting because you can see yourself with the product on scale.
22. AR is good only when it actively involves us in the demonstration and the trying of the product.
23. AR can be good to first see a product and then go into a shop: it prepares the act of buying.
24. It is not necessary; I do not really need it.