MULLEN, R.F., FLEMING, A., MCMILLAN, L. and KYDD, A. 2022. *Q methodology: quantitative aspects of data analysis in a study of student nurse perceptions of dignity in care*. [Case study]. London: SAGE [online]. Available from: https://doi.org/10.4135/9781529799705

Q methodology: quantitative aspects of data analysis in a study of student nurse perceptions of dignity in care.

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2022

Q Methodology: Quantitative Aspects of Data Analysis in a Study of Student Nurse Perceptions of Dignity in Care

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Pub. Date: 2022
Product: SAGE Research Methods Cases
Methods: Q methodology, Principal components analysis, Factor analysis
Disciplines: Health
Access Date: April 6, 2022
Academic Level: Postgraduate
Publishing Company: SAGE Publications, Ltd.
City: London
Online ISBN: 9781529799705
DOI: https://dx.doi.org/10.4135/9781529799705

Abstract

The purpose of this case is to introduce you to quantitative aspects of analyzing Q methodology data, a process I found complex and challenging as a novice Q-researcher. The case is illustrated by reference to a Q methodology doctoral study exploring student nurses' perceptions of preserving dignity in care. I benefitted greatly from the generosity of those in the Q methodology community who shared the practical lessons they had learned from analyzing their own data. This case is intended in that same spirit of generosity for those at the beginning of their own journey into Q methodology data analysis. This article focuses on the analysis of the data derived from the Q-sorts of its 21 participants rather than the research design and findings.

Learning Outcomes

By the end of this case, you should be able to:

- Define a range of key terms in Q methodology
- Outline three key transitions in moving from Q-sorts to factor interpretation
- Appraise these key transitions in the context of the case.
- Apply your learning to your own Q methodology research

Project Overview and Context

Rationale for Methodology

The case is drawn from my own experience of conducting a two-strand doctoral study in which I used Q methodology to explore nursing students' perspectives on preserving dignity in care (Mullen, 2019). This case is focused on Strand 2 and the quantitative aspects of data analysis in Q methodology.

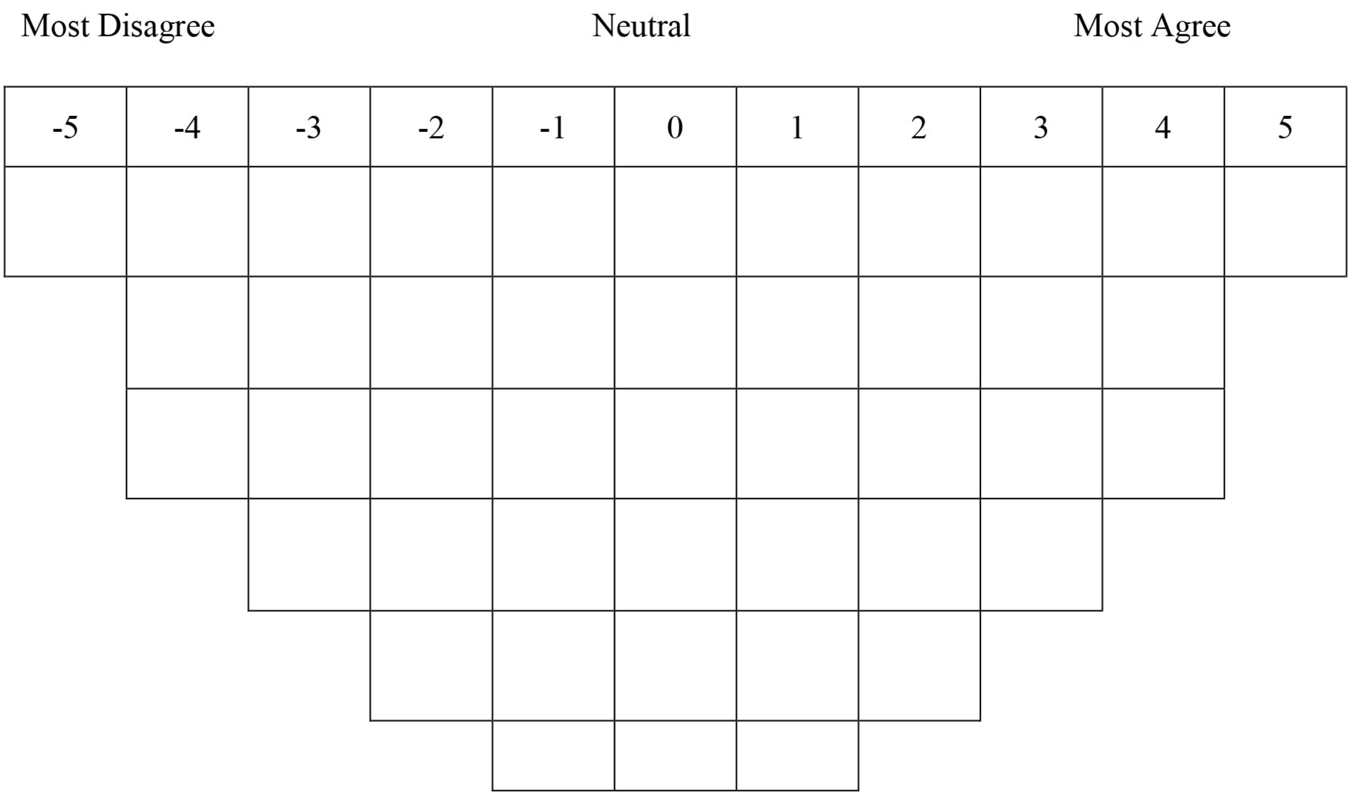
An Introduction to Q Methodology

Q methodology is well described in the literature, and my intention here is to provide a brief overview only. For more detail, I recommend readers to the "Further Reading," "Web Resources," and "References" sections at the end of this case and to the work of Watts and Stenner (2012), in particular.

Q methodology was first developed by physicist and psychologist William Stephenson in the 1930s (Watts & Stenner, 2012). Stephenson (1993) rejected the idea that subjectivity defies objective analysis. Instead, Steven Brown asserts Q methodology reflects Stephenson's belief that subjective, first-person viewpoints were just as amenable to the application of the scientific method as overt behavior (Brown, 1996). The opportunity afforded by Q methodology for the objective analysis of subjective viewpoints made it ideal for my study.

In Q methodology, participants—known as the *P-set* in Q methodology—construct accounts of their viewpoints through a process known as *Q-sorting*. Q-sorting involves rank-ordering statements, typically using a *sorting grid* resembling the one I used and shown in Figure 1.

Figure 1. Typical sorting grid.



The statements that are rank-ordered by the participants comprise the *Q-set* (sometimes referred to as the *Q-sample*). The Q-set is sampled from a larger collection of statements known as the *concourse*; "a universe of statements" about the subject (Stephenson, 1986, p. 37).

Q methodology data analysis is based on factor analysis; a means of data reduction that seeks to explain as much of the study variance as possible. It does so by identifying "sizeable portions" of common variance or shared meaning explaining the relationship between each participant's Q-sorts (Watts & Stenner, 2012). Factor analysis in Q methodology is, therefore, described as being "by-person" rather than "by-trait" as in conventional factor analysis. Dedicated statistical software packages—such as Peter Schmolck's PQMethod (Schmolck, 2012) and Shawn Banasick's "KenQ" (Banasick, 2017)—are then used to perform a by-person factor analysis of the Q-sorts to group together participants who share similar perceptions.

Once the Q-sorting process is complete, the researcher may conduct a post-sort interview to gain insight into participants' thoughts about items they most strongly agreed or disagreed with, any items they found difficult to rank, and whether they thought there was anything missing from the Q-set. The results of these interviews, together with any field notes made while observing participants during Q-sorting, can be used to inform subsequent factor interpretation as discussed in the section "Transition 3: Factor arrays to factor interpretation.” Accordingly, effective data analysis in Q methodology requires both quantitative and qualitative procedures.

Section Summary

- Q methodology provides an opportunity for the objective analysis of such subjective perspectives.
- Factor analysis in Q methodology is “by-person” rather than “by-trait”.
- Dedicated Q methodology programs are available online for data analysis and are free to download.
- Effective data analysis in Q methodology involves both qualitative and quantitative techniques.

Research Practicalities

Context

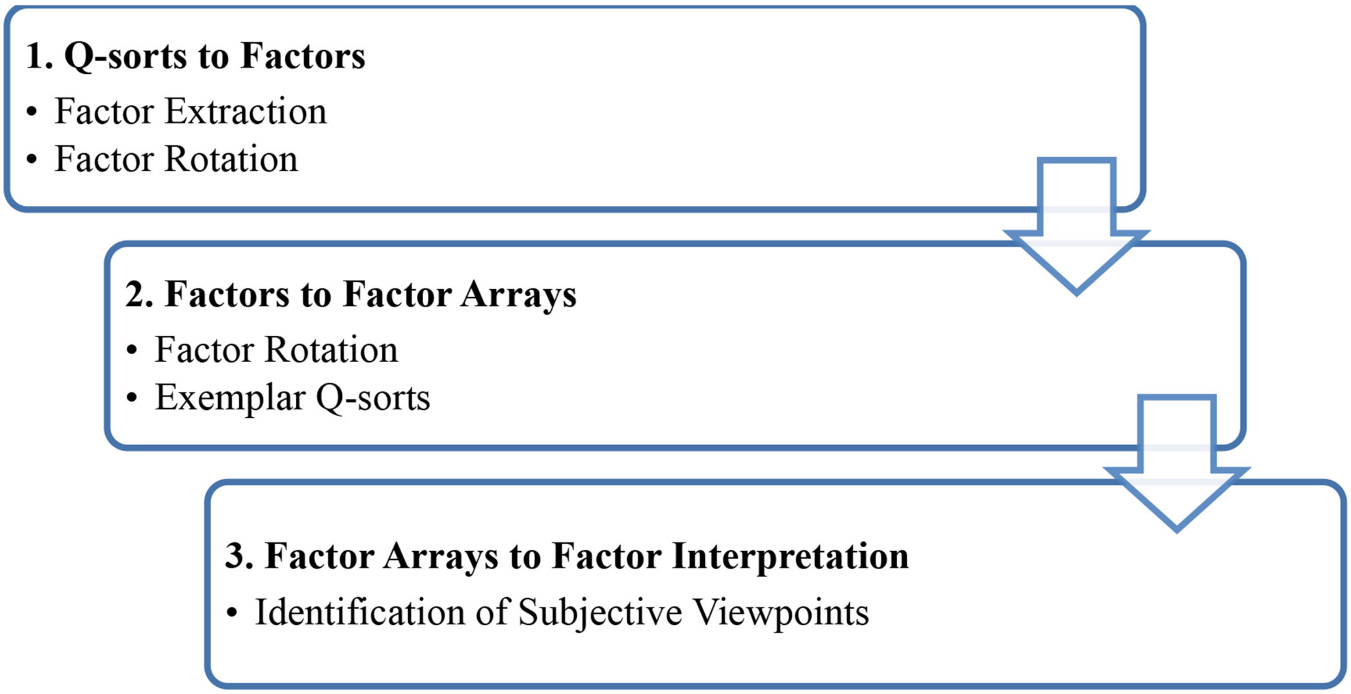
Following ethical approval, participants in the study from which this case is drawn were recruited from a 3-year undergraduate preregistration adult nursing program in Scotland (Mullen, 2019). A total of 31 nursing students participated in Strand 1 and a total of 21 nursing students in Strand 2. The concourse and Q-set were developed in Strand 1 using Nominal Group Technique and content analysis (Mullen et al., 2021, Mullen et al., 2015). The resulting concourse consisted of 141 statements from which the 44 statements comprising the Q-set were sampled.

Each participant completed their Q-sort with me in-person on an individual basis. While each participant completed their Q-sort, I made brief field notes. Immediately after each Q-sort, I conducted a post-sort interview with participants (Mullen et al., 2017). Following each Q-sort, I inputted the data into PQMethod (Schmolck, 2012). Doing so after each Q-sort helped me to manage the data and gain familiarity with the process. Later, I also used KenQ (Banasick, 2017) because I preferred the way in which it presented the results of the analysis.

Key Principles of Data Analysis

Simon Watts and Paul Stenner describe data analysis in Q methodology as a series of three key transitions; *Q-sorts to factors* followed by *factors to factor arrays* and then from *factor arrays to factor interpretation* (Watts & Stenner, 2012). The process is summarized in Figure 2.

Figure 2. Q-sorts to factors.



Key Terminology

One of the first barriers I encountered as a novice Q-researcher was the language of Q methodology, so I have provided a glossary in Table 1.

Table 1. Key terms in Q methodology

Term	Definition
By-person factor analysis	Participants are correlated with each other based on the similarities and differences in how they configure their Q-sorts (Valenta & Wigger, 1997)
Concourse	The sum of all statements made or thought by people about the subject (Simons, 2013)
Factor	A representation of shared meaning (Watts & Stenner, 2012)
P-set	The participants (Simons, 2013)
Q-set	A representative subset of statements drawn from the concourse (Brown, 1993; Paige & Morin, 2016)
Q-sort	An individual's rank-ordered arrangement of the Q-set (Paige & Morin, 2016)
Q-sorting	The process of administering or performing a Q-sort (Watts & Stenner, 2012)
Factor array	A Q-sort representing a given factor which can be presented in a sorting grid (Paige, 2015)

Term	Definition
Factor analysis	A statistical process aimed at identifying and representing distinct portions of shared meaning (Watts & Stenner, 2012)
Factor loading	A measure of the extent to which each Q-sort is typical of a given factor (McKeown & Thomas, 2013)
Factor rotation	A process to simplify structure and optimise factor loadings (Valenta & Wigger, 1997)

Section Summary

- Field notes and post-sort interviews during data collection can help inform factor interpretation.
- Data analysis can be described in terms of three transitions: Q-sorts to factors, factors to factor arrays, and factor arrays to factor interpretation.

Practical Lessons Learned

This section of the case details the lessons learned from the quantitative aspects of data analysis I performed at the three key transitions. To illustrate them, I refer to the data derived from the Q-sorts of the 21 participants in Strand 2 of my study.

Transition 1: Q-sorts to Factors

Correlation Matrix

In Q methodology, data analysis begins with the creation of a correlation matrix, which Watts and Stenner (2012) stress represents all of the meaning and variability contained within the dataset. Derived by the intercorrelation of each Q-sort with all the other Q-sorts in the study, it provides a measure of the similarities and differences between them. Table 2 illustrates the correlation matrix for Q-sorts 3, 7, 15, 16, and 19.

Table 2. Example correlation matrix

Q-sort	3	7	15	16	19
3	100	*21*	*8*	*14*	*26*
7		100	*3*	*4*	*15*
15			100	**67**	**72**
16				100	**50**

Q-sort	3	7	15	16	19
19					100

The text formatting highlights the relative strengths of the relationships. Bold highlights relatively strong correlations between Q-sorts 15, 16, and 19, while those in italics highlight relatively weak correlations with Q-sorts 3 and 7. This indicates that the participants who completed Q-sorts 15, 16, and 17 sorted the items in similar ways to each other and differently from those participants who completed Q-sorts 3 and 7. Q-sorts that correlate with each other significantly were revealed through factor analysis.

Factor analysis is crucial in Q methodology because it is the means whereby Q-sorts are grouped together to reveal shared viewpoints. I found the analogy drawn by Watts and Stenner (2012) between the process of factor analysis in Q methodology and a cake particularly helpful in understanding factor extraction. In the same way, different ingredients come together to make a cake, and different Q-sorts come together to communicate a shared meaning. Just as a cake can be divided into different ways, so too can the shared meaning within the completed Q-sorts. Effectively, each of the factors extracted from the Q-sorts in this study equates with a slice of cake: a portion of the shared meaning extracted from the whole.

The first step in this process toward an effective factor solution is factor extraction. Two approaches to factor extraction are commonly referred to in the literature: Principal Component Analysis (PCA) and Centroid Factor Analysis. Both are offered as options for data extraction in PQMethod. The next step is factor rotation; commonly performed in Q-methodology by means of Varimax or “by-hand”— also known as “judgmental”—rotation. My study used Centroid Factor Analysis with a Varimax rotation for the reasons discussed below.

Factor Extraction

Factor analysis is crucial in Q methodology because it is the means whereby Q-sorts are grouped together to reveal shared viewpoints.

One of my first decisions was to decide which option for factor extraction to choose. Subject to great debate within the Q methodology community, I was guided, again, by Watts and Stenner (2012) who advise novice Q-methodologists use of Centroid Factor Analysis in the first instance. Using PQMethod (Schmolck, 2012), a traditional Centroid Factor Analysis of the data was performed.

Extracted factors are displayed by PQMethod as a table of unrotated factor loadings. Factor loadings are a measure of the extent to which a Q-sort is typical of a factor; in effect, how much a given Q-sort has in common with a factor (Watts & Stenner, 2012). Interpreting the table of unrotated factor loadings is a key step in determining how many factors to retain. Table 3 shows loadings—rounded to two decimal points—for some Q-sorts from my study. I considered the following issues in relation to factor loadings: communality (h^2), the nature of the correlation, eigenvalues (EVs), and factor variance.

Table 3. Unrotated factor loadings

	Unrotated factor loadings					
Q-sorts	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	h^2	h^2 **%**
3	0.38	0.39	-0.18	0.03	0.33	33
7	0.32	0.01	0.52	−0.05	0.37	37
15	0.56	−0.58	−0.18	0.10	0.70	70
16	0.56	−0.33	−0.06	0.18	0.45	45
19	0.76	−0.30	−0.03	0.27	0.74	74
Eigenvalue	5.98	1.62	1.21	0.94		
Variance %	28	8	6	4		

Communality (h^2)

Communality is a measure of the extent to which the extracted factors account for the variance of any given Q-sort and is calculated as the sum of a Q-sort's squared factor loadings on each factor (Watts & Stenner, 2012). This is provided automatically by PQMethod but can be calculated manually, and Table 4 illustrates this calculation for Q-sort 3.

Table 4. Calculation of communalities

h^2 **(Q-sort 3)**	
=	(Q-sort 3 loading on Factor 1)^2 + (Q-sort 3 loading on Factor 2)^2 + (Q-sort 3 loading on Factor 3)^2 + (Q-sort 3 loading on Factor 4)^2
=	$0.38^2 + 0.39^2 + -0.18^2 + 0.03^2$
=	0.14 + 0.15 + 0.03 + 0.00
=	0.32 (h^2 % = 32%)

Note: The discrepancy between this manually calculated figure of 0.32, and the automatically calculated figure of 0.33 is accounted for by rounding the factor loading to two decimal places.

This means that 32% of the variance in Q-sort 3 has been accounted for by the four extracted factors. Essentially, 32% of the variance in Q-sort 3 is a common variance; that is, it is shared with all the other Q-sorts in my study. In comparison, the 74% communality score of Q-sort 19 in Table 3 shows how much more Q-sort 19 has in common with all the other Q-sorts in my study and how much more typical it is of the study group than Q-sort 3. Table 5 shows the communalities in ascending order and illustrates the wide range in communalities from 14% (Q-sort 13) to 77% (Q-sort 5).

Table 5. Communality range

Number of Q-sort	h^2 %
13	14
8	27
5	77

Watts and Stenner (2012) note that the Q-sorts with a lower communality are less likely to be significantly loaded on any particular factor because they do not have enough in common with any of the extracted factors. This was supported by the subsequent analysis detailed below which found that Q-sorts 8 and 13—with their relatively low communality scores of 27% and 14%, respectively (Table 5)—were nonsignificant; that is, they did not load significantly on any of the four factors extracted.

I also considered the presence of positive and negative factor loadings because these are suggestive of the presence of opposing viewpoints (Watts & Stenner, 2012). This is illustrated in Table 3 by the relative factor loadings for the example Q-sorts on Factor 2. The positive and negative factor loadings on Factor 2 suggested that opposing viewpoints were present. No such opposing viewpoints were evident in Factor 1. This indicated that the viewpoint captured by Factor 1 was one of consensus, while the other three factors seemed to capture viewpoints incorporating some disagreement.

To identify the extent to which each Q-sort is typical of each factor, the factor loadings were squared (Watts & Stenner, 2012). This can be illustrated with reference to Q-sorts 3 and 7 in Table 3. The factor loading for Q-sort 7 Factor 1 in Table 3 accounted for 14% (0.38 × 0.38) of the variance of Q-sort 7 but 57% (0.76 × 0.76) of the variance of Q-sort 19. This indicated that Q-sort 19 was more typical of and explained more about Factor 1 than Q-sort 7. Essentially, Q-sort 19 had more in common with Factor 1 than Q-sort 7.

Eigenvalues (EVs)

While communality scores provide information regarding each Q-sort, eigenvalues (EVs) provide information regarding each factor (Watts & Stenner, 2012). Typically, in Q methodology a factor with an EV greater than one is considered significant (Baxter et al., 2009). EVs are automatically calculated by PQMethod but can be calculated manually by summing the squared factor loadings for each Q-sort on each factor (Brown, 1980). I found it useful to perform a manual calculation of a selection of EVs to enhance my understanding of the process. This is illustrated with reference to Factor 1 in Table 6.

Table 6. Eigenvalue calculation

EV (Factor 1)	
=	(Q-sort 1 loading on Factor 1)^2 + (Q-sort 2 loading on Factor 1)^2 +… + (Q-sort 21 loading on Factor 1)^2
=	$0.54^2 + 0.36^2 + … + 0.58^2$
=	0.29 + 0.13 + …+ 0.34
=	5.98

In Table 3, it is worth noting that before rotation, Factor 1 had an EV of 5.98 and accounted for 31% of everything that the 21 Q-sorts held in common. Similarly, Factors 2 and 3 also had EVs in excess of one, but the EV for Factor 4 was just under 0.94, so it did not meet this criterion. This added to my uncertainty about Factor 4’s retention.

Factor Loadings

Determining the significance of factor loadings is a key step in establishing which factors to accept. Watts and Stenner (2012) recommend that consideration should be given for factors that have two or more Q-sorts loading at a significant level. To calculate a significant factor loading at the 0.01 level, Brown (1980) provides the following equation shown in Table 7 and illustrated with reference to the study with 44 items in the Q set.

Table 7. Significant factor loading calculation

Significant factor loading	= 2.58 × (1 ÷ √number of items in the Q-set) = 2.58 × (1 ÷ √44) = 2.58 × (1 ÷ 6.6332) = 2.58 × 0.1508 = 0.3890 rounded-up to **0.39**

I then checked this significance level of 0.39 against the factor loadings. This enabled me to identify the significant factor loadings on each factor. An example of this process is shown in Table 8 with the significant unrotated factor loadings bolded.

Table 8. Unrotated factor loadings

	Unrotated factor loadings			
Q-sorts	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**
1	**0.7351**	−0.1194	−0.1960	−0.0177
3	0.3776	**0.3909**	−0.1803	0.0272
7	0.3191	0.0133	**0.5158**	−0.0470
8	**0.4019**	0.1247	0.2371	−0.1971
12	0.3039	0.3163	−0.2845	−0.2735
20	0.2000	**0.4459**	0.0502	0.0232
21	0.2403	0.0754	**−0.4614**	−0.2198

Significance level = 0.39, bold.

When this process was completed for all 21 Q-sorts and factors, Factors 1, 2, and 3 all had two or more significantly loading Q-sorts, but Factor 4 had none. Consequently, I wondered whether I should retain Factor 4 for further analysis.

Humphrey’s Rule

Another guide to decision-making in this regard is Humphrey’s Rule. This rule states that a factor is significant if “the cross-product of the two highest loadings…exceeds twice the standard error” (Brown, 1980). The standard error was calculated using the equation provided and shown in Table 9.

Table 9. Standard error calculation

Standard error for study	**= 1 ÷ (√number of items in the Q-set)**
	= 1 ÷ (√44)
	= (1 ÷ 6.6332)
	= 0.1508 rounded-up to 0.15
Twice the standard error	= 0.30

Watts and Stenner (2012) note, however, that Humphrey's Rule can be applied less strictly so that it is satisfied by cross-products of highest loadings merely exceeding the standard error. This was calculated for all four factors by multiplying the two highest loadings on each factor, and the results are shown in Table 10, with the significant factors in bold. Only Factor 1 satisfies the strictest application of Humphrey's Rule, but Factors 2 and 3 meet the criterion in its more relaxed form by exceeding 0.15. Once again, Factor 4 failed to meet this criterion and, therefore, made me more doubtful still about retaining it.

Table 10. Humphrey's Rule

Factor	Humphrey's Rule	Exceeds 0.30?	Exceeds 0.15?
1	0.7798 × 0.7882 = 0.6146	**Yes**	**Yes**
2	0.5793 × 0.4459 = 0.2583	No	**Yes**
3	0.5158 × 0.4614 = 0.2780	No	**Yes**
4	0.3828 × 0.3637 = 0.1392	No	No

As discussed, Factors 1, 2, and 3 all met core criteria for retention prior to rotation. Factor 4 did not, but its EV was borderline at 0.94 (Table 3). Watts and Stenner (2012) remind researchers that EVs may well improve following rotation and advise against abandoning factors too soon because significant perspectives may be lost. Instead, they advocate retaining borderline factors for rotation and "taking a good look" at the result (Watts & Stenner, 2012, p. 110). Indeed, this was the case for Factor 4, the EV of which increased to 1.05. The risk of abandoning Factor 4 prior to rotation—perhaps missing a significant perspective—did seem to outweigh the risk of retaining too many factors. Consequently, I retained Factor 4 for rotation.

Factor Rotation

Factor rotation is a means of simplifying the structure and optimizing factor loadings with a view to enhancing the interpretability of the factors. In effect, the factor loadings are used—like coordinates in a map—to map the factors against each other in theoretical, multidimensional space (Watts & Stenner, 2012). In Q methodology, two approaches to rotation are commonly used: automated Varimax and/or manual "by-hand" rotation.

The approach to factor rotation is the subject of great debate within Q methodology (Akhtar-Danesh & Mirza, 2017). Some argue that a "by-hand" rotation is best because it is most in keeping with Stephenson's original vision (McKeown & Thomas, 2013), while others argue that its very subjectivity renders it unreliable (Akhtar-Danesh & Mirza, 2017). Watts and Stenner (2012, p. 122) note that manual rotation is an acquired skill and suggest that Varimax rotation may be preferred if a study is focused on the majority perspectives of the participants (Watts & Stenner, 2012). For these reasons, I used Varimax rotation.

Regardless of which approach or combination of approaches is used, factor loadings are crucial to the process. PQMethod—and other dedicated programs for Q methodology such as KenQ (Banasick, 2017)—will automatically "flag" Q-sorts with significant factor loadings. However, I also performed this manually because this enabled me to engage meaningfully with the data analysis process. As shown in Table 11, 16 of the 21 participants who completed a Q-sort loaded significantly on one of the four factors. These Q-sorts were "flagged" as significant and used to generate the factor arrays. The Q-sorts of four participants were confounded; that is, they loaded significantly on more than one factor and one was nonsignificant.

Table 11. Significant Q-sorts by factor

Q-sort #	**Factors**				**Comment**
	1	**2**	**3**	**4**	
1	0.6195*				
2		0.7803*			
3		0.5226*			
4	**0.6118***		**0.4393***		**Confounded**
5	**0.5482***	**0.5721***			**Confounded**
6	**0.6409***			**0.4355***	**Confounded**
7			0.5455*		
8			0.4811*		
9	**0.5598***		**0.4661***		**Confounded**
10		0.4182*			
11	0.4729*				
12					
13	*−0.0135*	*0.0967*	*−0.0128*	*−0.3599*	*Nonsignificant*
14	0.5717*				

Q-sort #	Factors				Comment
	1	**2**	**3**	**4**	
15	0.8191*				
16	0.6623*				
17			0.5211*		
18			0.5987*		
19	0.8105*				
20		0.3951*			
21				0.4939*	

Note: * Significant factor loading >0.39. Confounded Q-sort—significant loadings on more than one factor; nonsignificant Q-sort—did not load significantly on to any factor.

Of the 21 completed Q-sorts, 16 were retained to generate the factor arrays. This is summarized regarding specific Q-sorts below in Table 12.

Table 12. Factors by Q-sort

	Factors				Confounded	Nonsignificant	Total
	1	**2**	**3**	**4**			
Q-sort #	1, 11, 14, 15, 16, 19	2, 3, 10, 20	7, 8, 17, 18	12, 21	4, 5, 6, 9	13	
Total	6	4	4	2	4	1	21

Note: Q-sort # = Q-sort number.

Transition 2: Factors to Factor Arrays

Based on the significant factor loadings flagged above, a factor array was generated in PQMethod for each factor. A factor array is an estimate of the perspective represented by the factor and is generated by means of a weighted average of the Q-sorts—called a *z-score*—that load significantly onto a given factor. Weighting for each Q-sort, loading significantly on a factor, is determined by its factor loading; the greater the factor loading, the greater the weighting. This means that, of the significant Q-sorts loading onto a factor, those with the highest factor loading will make the greatest contribution to the factor array (Watts & Stenner, 2012). Factor arrays are often presented as exemplar Q-sorts in sorting grids and in tables such as the one shown in Table 13 which provides an overview of all the factor arrays (generated by PQMethod for this example case).

Table 13. Overview of factor arrays

Stat. #	Statements	Factors			
		1	2	3	4
1	Being able to tell how the person is feeling when they can't speak out	0	1	2	−4
2	Being able to take time with the person	−1	−2	1	−1
3	Being well-prepared to deliver care	−2	−2	0	1
4	Being able to care for the person in a clean environment	-3	0	−4	1
5	Never leaving the person in a vulnerable position	4	3	2	5
6	Responding promptly when the person reports pain	0	2	0	−2
7	Pulling curtains around when the person's upset	3	−1	0	3
8	Speaking to the person as an adult, not a child	3	0	1	−1
9	Listening to the person	3	3	3	0
10	Welcoming everyone's ideas about care	−2	−3	−2	−3
11	Helping the person with their personal hygiene	1	−1	−2	2
12	Being able to access whatever equipment is needed	−5	0	−4	−3
13	Giving the person the information they need to make their own choices	1	4	3	0
14	Working well with others in a team	−2	0	−2	−4
15	Finding out what the person wants	5	−1	0	−3
16	Being genuinely interested in the person	0	1	5	3

Stat. #	Statements	Factors			
		1	2	3	4
17	Keeping the person covered as much as possible during care	4	3	0	−1
18	Keeping good records of care	−3	2	−1	4
19	Speaking to the person as an individual	4	1	4	−2
20	Being passionate about care	−2	5	4	4
21	Helping the person look their best before their loved ones come in	2	−4	−1	−4
22	Caring for the person in an environment that feels safe	−1	−2	1	−1
23	Being honest with the person	3	2	1	1
24	Being able to use single rooms when necessary	−4	−3	−4	−1
25	Knowing how to move and handle the person well	−4	1	−1	2
26	Being patient with the person	2	2	2	1
27	Showing kindness to the person's loved ones	−2	0	1	0
28	Being in-tune with the person's needs	−1	−1	2	−2

I then used these factor arrays to develop what Watts and Stenner (2012) describe as "crib sheets"; detailing my preliminary thoughts about the perspective captured in each array.

In addition, the relative ranking tables produced by PQMethod—see Table 14— provide a further guide to the similarities and differences between factors by identifying "*distinguishing*" and "*consensus*" statements. Described clearly by Newman and Ramlo (2010), distinguishing statements for each factor array with at least $p > 0.05$; that is, their ranking in a factor array is significantly different from other factors and indicates opposing perspectives. Conversely, consensus statements are statements that are not ranked significantly differently and so do not distinguish between factors and indicate agreement (Newman & Ramlo, 2010).

Table 14. Relative rankings table for factor 1

Stat.#	Statements	Factors				
		1		2	3	4
Highest ranking statement						
15	Finding out what the person wants	**5**	D*	−1	0	−2
Statements ranking higher than in other factors						
19	Speaking to the person as an individual	**4**		1	4	−1
5	Never leaving the person in a vulnerable position	**4**	C	3	2	4
17	Keeping the person covered as much as possible during care	**4**		3	0	2
7	Pulling curtains around when the person's upset	**3**		−1	0	3
9	Listening to the person	**3**		3	3	0
23	Being honest with the person	**3**		2	1	−2
8	Speaking to the person as an adult, not a child	**3**	D	0	1	0
26	Being patient with the person	**2**	C*	2	2	1
21	Helping the person look their best before their loved ones come in	**2**	D	−4	−1	0
38	Asking if it's OK to pass information on to their next-of-kin	**1**	D	−1	−3	−4
40	Helping loved ones to spend time with the person	**0**	C	−2	−1	−1
Statements ranking lower than in other factors						
6	Responding promptly when the person reports pain	**0**		2	0	2
43	Being approachable	**0**		2	3	1
16	Being genuinely interested in the person	**0**		1	5	1
28	Being in-tune with the person's needs	**−1**		−1	2	−1

Stat.#	Statements	Factors				
		1		2	3	4
27	Showing kindness to the person’s loved ones	**−2**		0	1	−1
20	Being passionate about care	**−2**	D*	5	4	4
14	Working well with others in a team	**−2**		0	−2	−1
3	Being well-prepared to deliver care	**−2**		−2	0	2
30	Feeling confident enough to express opinions about care	**−3**		1	−2	3
18	Keeping good records of care	**−3**	D*	2	−1	0
24	Being able to use single rooms when necessary	**−4**	C*	−3	−4	−4
25	Knowing how to move and handle the person well	**−4**	D*	1	−1	3
41	Being specially trained in the type of care required	**−4**		−4	3	1
Lowest ranking statements						
12	Being able to access whatever equipment is needed	**−5**		0	−4	−4

C, consensus statement; D, distinguishing statement; Stat.#, statement number.

Note: D, p > 0.05; D*, p > 0.01; C, p > 0.05, C*, p > 0.01

Transition 3: Factor Arrays to Factor Interpretation

In my study, analysis of this transition point revealed four factors. Their interpretation required me to integrate the quantitative data provided by the factor arrays and relative rankings tables, with the qualitative data collected via my field notes, post-sort interviews, and crib sheets. The purpose of this integration is to develop a holistic understanding of the perspective captured in each factor. While this case focuses on the quantitative aspects of data analysis in Q methodology, I think it is important to acknowledge the importance of qualitative data in the interpretation process. Steven Brown summarizes this memorably when he notes that Q methodology was designed to reveal “life as lived from the standpoint of living it” and not “life measured by the pound” (Brown, 1996).

Of the44 statements in the Q-set, four consensus statements were identified, indicating general agreement among the participants, and these statements are shown below in Table 15.

Table 15. Consensus statements

Stat. #	Statement	Factors				
		*	1	2	3	4
5	Never leaving the person in a vulnerable position		4	3	2	4
24	Being able to use single rooms when necessary	*	−4	−3	−4	−4
26	Being patient with the person	*	2	2	2	1
40	Helping loved ones to spend time with the person		0	−2	−1	−1

Stat.#, statement number.

Note: All listed statements are nonsignificant at $p > 0.01$, and those flagged with * are also nonsignificant at $p > 0.05$.

To interpret the differences between the perspectives, I again began by considering the factor arrays and relative ranking tables—such as the examples shown in Tables 13 and 14—noting, in particular, the distinguishing factors. The process is illustrated with reference to Factor 1 in my study. Following Varimax rotation, Factor 1 had an EV of 4.41 and explained 21% of the study variance. In total, six participants loaded significantly on to this factor, and distinguishing statements are shown in Table 16.

Table 16. Factor 1 distinguishing statements

Stat.#	Statements	Factors				
		1		2	3	4
Highest ranking statement						
15	Finding out what the person wants	**5**	D*	−1	0	−2
Statements Ranking Higher than in Other Factors						
8	Speaking to the person as an adult, not a child	**3**	D	0	1	0
21	Helping the person look their best before their loved ones come in	**2**	D	−4	−1	0

Stat.#	Statements	Factors				
		1		2	3	4
38	Asking if it is OK to pass information on to their next-of-kin	**1**	D	−1	−3	−4
Statements Ranking Lower than in Other Factors						
20	Being passionate about care	**−2**	D*	5	4	4
18	Keeping good records of care	**−3**	D*	2	−1	0
25	Knowing how to move and handle the person well	**−4**	D*	1	−1	3

Abbreviations: D, distinguishing statement; Stat.#, statement number.

Note: D, $p > 0.05$; D*, $p > 0.01$.

By considering the factor arrays and relative ranking tables in light of the qualitative data gleaned from my field notes and post-sort interviews. This enhanced my insight and enabled me to enrich the findings with participant comments and identify areas of interest for further study.

Section Summary

- Transition 1—Q-sorts to factors—involves deriving the correlation matrix, factor extraction and factor analysis.
- Transition 2—factors to factor arrays—involves factor rotation and consideration of factor loadings to develop factor arrays.
- Transition 3—factors to factor interpretation—involves integrating factor arrays and relative rankings tables with qualitative data from field notes, post-sort interviews, and crib sheets.

Conclusion

The process of data analysis in Q-methodology can be daunting, and this case provides a step-by-step account of the process with reference to real data collected as part of my doctoral study. It is hoped that this case will help novice Q-researchers develop their confidence and skill in applying Q-methodology techniques to their own data.

Classroom Discussion Questions

1. To what extent do you agree that subjectivity is amenable to objective analysis?
2. How does Q methodology provide “by-person” rather than “by-trait” factor analysis?

3. In what ways might field notes and post-sort interviews inform the subsequent interpretation of factor arrays?
4. Are there areas of your own practice amenable to investigation through Q methodology? If so, what are they? If not, why not?

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