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Trends in Research Methods

Q as Methodology: Theoretical Underpinnings and Key Considerations in Its Practical Applications in Applied Linguistics and TESOL Research

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Abstract
In recent years, Q methodology has become increasingly popular in applied linguistics and language education research, as a surge of Q studies published in these two fields could be spotted especially in the past five years. Nonetheless, most of these Q studies only present the procedures of Q in a descriptive manner without discussing or justifying the theoretical underpinnings or rationale of Q in depth largely due to the word limit of journals or their empirical focuses. To date, Q still remains contentious in academia, and the debate on Q's theoretical underpinnings and practical application are still ongoing. Therefore, there is a dire need for more articles to offer a theoretical illustration of Q and to justify several key steps during implementing Q in applied linguistics and language education, which is the primary aim of this article. In this article we elucidated the historical background of Q and its form of inference as well as the research paradigm. In addition, we also addressed some key practical issues in applying Q, including its study design, factor extraction and factor rotation. We hope that this article serves as a resource or reference to novice Q researchers in applied linguistics and TESOL as well as other related areas and contribute to the hot debate on Q.

Keywords
Q methodology, Q in applied linguistics, Q in language education, Qualiquantology, inference of abduction, Concourse Theory, factor extraction in Q, Q for TESOL

1 Introduction

Introduced in 1935 by Williams Stephenson, Q methodology (Stephenson, 1935) enables researchers to investigate participants' subjectivity in a systematic fashion (Brown, 1980, 1993), and it has been widely employed in the fields of psychology (Watts & Stenner, 2005) and health care (e.g., Valenta & Wigger, 1997). In recent years Q has become increasingly popular in applied linguistics or language education,

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as witnessed by a surge of studies adopting such methodology in these fields (Dieteren et al., 2023). For instance, Zheng and her colleagues (2020) tracked a group of English L2 and Spanish L3 learners' change in motivation in China via Q; Deignan and Morton (2022) utilised Q to investigate a group of English medium instruction (EMI) lecturers' perceptions regarding challenges in teaching EMI programmes; Lundberg (2020) applied Q in his doctoral research on teachers' viewpoints towards multilingualism in Sweden and Switzerland; Wang et al. (2024) explored Chinese EFL learners' enjoyment of learning English; and Raksawong et al. (2024) investigated factors of foreign language learners' unwillingness to communicate caused by their teachers. Furthermore, in their very recent, edited book, Fraschini et al. (2024) have collected 11 Q studies on popular topics in language education and applied linguistics. These 11 studies investigated issues of cognition, motivation, identity, emotion, teacher beliefs, and language education programmes and policies.

Despite such prevalence of Q in applied linguistics and language education research, only a few publications have presented a nuanced theoretical background, rationale, or principle of Q (e.g., Lundberg et al., 2020; Irie, 2014). Regarding the research articles in applied linguistics and language education adopting Q, largely due to the word limit of journals or the empirical focus of these articles, very few of them have they sufficiently elaborated on the theoretical underpinnings of Q or justified the steps taken when Q is used. Instead, they treated Q as a pure simple data collection and analysis method and illustrated it in a pure descriptive fashion. Moreover, some studies either made diverse claims of Q (e.g., claiming Q as a mixed method or a qualitative method) or even took erroneous steps when conducting Q studies (e.g., calculate significant loadings incorrectly), which, in our view, severely deviate from the original principle and theoretical grounding of Q. This, in our opinion, could be partially attributed to those dedicated software packages designed for conducting Q studies such as PQMethod (Schmolck, 2014), PCQ, Ken-Q (Banasick, 2023) and KADE that dramatically simplify the process of analysing and even collecting Q data. Researchers are assisted in such a way that they simply follow the steps in these software packages by merely clicking the button to carry out a Q study without fully acknowledging the rationale or theoretical fundamentals behind the software packages or even Q itself. It has to be made clear that we are not criticising these Q software packages; rather we give credit to them for their contribution. It is these packages that have made it more convenient for researchers to conduct Q studies, which is a real feat that we should celebrate. Having said that, we think that there is a dire need of more critical reviews that should provide the justification or rationale, background and principles of Q to which future Q studies could adhere, which is the primary purpose of this article.

Ontologically, Q methodology emphasises operant subjectivity, challenging traditional Newtonian paradigms whereas epistemologically, it aligns with Gestalt psychology, viewing knowledge as a holistic and emergent system (Zheng, 2023). Indeed, we aim to highlight that Q itself stands for a single, comprehensive and unique methodology as well as a theoretical framework. To justify this argument, we draw on multiple sources, principles and theories regarding Q to elucidate its historical background, form of logic and research paradigm. Furthermore, we intend to discuss the steps of performing Q in a simplified manner given that one piece of article would not be sufficient to unpack the practical steps of conducting Q in detail. In addition, we intend to denote several practical concerns and issues when implementing Q for empirical studies, including the collection and analysis of Q data. We hope to provide more details on Q for those who are interested in using Q. Specifically, we are interested in explaining how Q works in addition to presenting key terminologies used in Q. We now turn to the historical background and the story behind Q. Lastly, beyond its research function and purposes, we think Q could offer significant potential for pedagogical practice in TESOL, particularly in curriculum planning and formative assessment during the class. As Q systematically elicits and analyses learners' subjective viewpoints, it can reveal students' underlying attitudes, motivational orientations, and perceived learning challenges that are often overlooked by traditional surveys or tests.

2 Background of Q

Q methodology made its first appearance via a letter to the journal *Nature* in 1935 by a British scholar William Stephenson who possesses two PhDs in Physics and Psychology respectively. This letter depicted an innovative adaption of factor analysis, a method invented by Charles Spearman that unravels patterns of association and variance between a set of correlated variables. The adaption in this letter proposed by Stephenson was deemed as a response to the limitations of the traditional R methodology, an aggregate of all research methods using tests or traits as variables and carrying out research with a set of participants using instruments such as Likert-scale questionnaires (Watts & Stenner, 2012). The original R methodology adopts by-variable factor analysis with a large number of human participants and a relatively limited number of variables. These variables would be intercorrelated and produce a variable-by-variable correlation matrix in order to identify the group differences. This normally follows with a standardisation of scores to make different variables measurable. Factor analysis, in R methodology, is essentially a data reduction technique as it aims at revealing the manifest association among the correlation of matrix via identifying a greatly reduced number of latent variables, and these latent variables are known as factors (Watts & Stenner, 2012).

During the mid-1930s, by-variable factor analysis had become prevalent in psychology as it claimed to be related with individual differences. It was suggested that R methodology focuses on individual differences regarding specific psychological traits or characteristics (Lundberg, 2020). Nonetheless, the limitations of the by-variable factor analysis was spotted by William Stephenson. Whilst the standardisation of scores enables different variables to be measurable, it simultaneously disassociates the scores gathered from the participants.

According to Stephenson (1936a), R methodology "can certainly tell us if, and how the various attributes vary proportionately in a population of persons. But it can tell us little or nothing about… any individual person. It supplies information of a general kind" (p. 201). Watts and Stenner (2012, p. 11) used a vivid example to illustrate the above limitation in a simpler manner. They used height as a variable in a data matrix comprising three participants: 171 cm, 174 cm and 180 cm. Whilst the standardisation of the absolute score, such as standard deviations (see Kline, 1994) demonstrates that the attribute of heights differs proportionally across the participants, a notable 9 cm height difference is not indicated. In other words, R methodology or by-variable factor analysis, focuses on the association or the differences between variables on the large population scale but ignores the specific individual differences. If adopting R methodology for issues concerning perceptions, for instance, using a Likert-scale questionnaire, it would produce an overarching general perception or trend of perceptions from a large number of participants but marginalising the voices or perceptions of particular individuals (Stephenson, 1935). Lundberg (2020) expressed a similar concern of R methodology, suggesting that it "could not define individuals in a holistic fashion and was therefore considered insufficient for a full and genuine comparison of individual differences" (p. 64).

In order to surmount the limitation of R methodology and to depict the feelings or perceptions shared within a group of participants or community (Irie, 2014), Stephenson proposed to invert the by-variable factor analysis into by-person factor analysis, shifting the analytical focus from variable to person via an adaption of Spearman's by-variable factor analysis. This inversion of by-variable factor analysis into by-person factor analysis serves as the fundamental of the Q. In his paper, Stephenson explained how this inversion could be achieved:

> Factor analysis…is concerned with a population of n individuals each of whom has been measured in m tests or other instruments or estimates. The (m)(m-1)/2 correlations for these m variables are subject to … factor analysis. But this technique … can also be inverted. We may concern ourselves with a population of N different tests (or other items), each of which is measures or scaled relatively, by M individuals. The (M)(M-1)/2 correlates again can be factorised by appropriate theorems. (Stephenson, 1936b, p. 344).

It can be seen from the above excerpt that the data gathered for R methodology could not be subjected to this by-person factor analysis (Watts & Stenner, 2012). Therefore a new form of data is required for Q. This new form of data is called Q sort, which we elucidate later in the ensuing sections after discussing the research paradigm behind Q and its form of inference.

3 Research Paradigm of Q: Qualiquantology

According to Denzin (2008), "research paradigm" refers to a theoretical framework that provides conceptual and empirical guidance for a study that manifests in researchers' thinking habit and rules of study procedures. When it comes to the research design of an empirical study in applied linguistics and language education, it normally begins with determining the type of the research paradigm as well as the philosophical underpinnings, such as whether the study is qualitative, quantitative or mixed-methods. For researchers, determine the research paradigm at the initial stage of a study could be deemed as a safe practice, which afford them the comfort because of the clear direction and guidance for the next steps. Q, however, does not follow this rule since it could be problematic to categorise it into either qualitative, quantitative, or mixed methods. Existing Q studies have either placed Q as mixed-methods (e.g., Morea & Ghanbar, 2024) or as qualitative study (e.g., Pan & Lei, 2023). These, in our view, may not be exactly appropriate. On the one hand, whilst the final factors extracted and rotated from the Q study are interpreted qualitatively, and the establishing of participant samples generally adopts a qualitative study manner, the statistical calculation and technique involved during factor extraction and factor rotation, for instance, are eminently quantitative techniques (see Kline, 1994). Thus, placing Q as a qualitative research method seems to be inappropriate. On the other hand, claiming Q as mixed-methods is also inappropriate or even incorrect.

Despite Q containing elements of both qualitative and quantitative, unlike mixed-methods, it does not involve two separate sets of data during the data collection and analysis. According to Creswell and Creswell (2017), researchers use a mixed-methods design to seek integration or connection of two different sets of data: qualitative data and quantitative date, such as data collected via a Likert-scale questionnaire combined with data from semi-structured interviews, and both sets of data are collected and analysed either concurrently or sequentially. In the similar vein, Cohen et al. (2018) indicated that the "mixed" in mixed methods reflects the integration of analysing both qualitative data and quantitative date. Therefore, mixed methods have to contain two different sets of data: qualitative and quantitative. Q, however, does not involve two separate sets of data, the only data collected in Q is Q sort. Therefore, it would not be possible to conduct concurrent or sequential data collection and analysis in Q. Having said that, we think that there might be an issue in the data collection process in Q studies. Q sorting usually is followed by post-sorting interview, and hence it might seem that Q contains two sets of data. Nonetheless, it has been denoted that whilst post-sorting interview is critical in a Q study (Brown, 1980), it is not compulsory (Watts & Stenner, 2012), which means that Q methodology is not typically a mixed-methods approach. The only purpose of the post-sorting interview is to provide further information to support factor interpretation. Also, whilst the data collected from the post-sorting interview is qualitative, it remains to be tricky to define the Q sorts as qualitative or quantitative data, as they are neither descriptive nor have the sufficient quantity to be deemed as quantitative, as the number of participants in a Q study tends to be fewer than the number of statements in Q sets, which normally would not exceed 80 (Brown, 1980).

We spare ourselves from discussing the details of the procedures in Q and would like to put across the key message that placing Q in either these methodological categories discredits its own uniqueness and charm. What attracts Q methodologists is that Q brings down the polarisation of qualitative and quantitative and place itself on a qualitative-quantitative continuum (Lundberg, 2020). This is why Q methodology has been disliked by qualitative and quantitative researchers alike, as Q leads, or forces them to jump out of their so-called "comfort zone" (Stenner & Stainton Rogers, 2004). Q violates the paradigm or the principle of quantitative, qualitative and mixed-methods, leading to perturbations among qualitative and quantitative researchers (Stenner & Stainton Rogers, 2004). For qualitative researchers, seeing the grid-shaped distribution of Q sorts, hearing about the quantitative techniques in factor analysis (including factor loadings, variance and eigenvalues etc.), having to follow mathematic equations to calculate significant loadings and perform varimax factor rotations would undoubtedly perturbate them or even stop them from adopting such a method at the very beginning.

Meanwhile, whilst these quantitative techniques may not disturb quantitative researchers, who possess solid statistical knowledge and expertise, Q would still perturbate them. As it has been indicated in the previous section, Q adheres to the logic of abduction, and the factors identified in Q via factor analysis do not claim to prove any hypothesis or measure anything, rather than pure exploration and explanation. Since Q does not aim at measuring anything, discussing or considering the issues of validity and reliability, as conventional quantitative researchers would do, does not apply in Q. In other words, whilst Q involves quantitative techniques, it violates the conventions or principles that quantitative experts seen as "golden standard", hence perturbation is not unexpected.

As shown in our earlier explanation, the traditional quantitative and qualitative paradigm would not fit with Q. This is because Q stands for a unique paradigm. Stenner and Stainton Rogers (2004) gave this paradigm a "monstrous" (p. 99) name: qualiquantology, a name that expresses the "mixing" element of qualitative and quantitative methods encapsulated in Q whilst distinguishing Q from mixed-methods. The nature of qualiquantology is embedded in each steps of any Q study. One thing that needs to be borne in mind so far is that Q quantifies the subjectivities collected from the participants and analyses them through statistics techniques, and interprets them in a qualitative manner (Kamal et al., 2014). In our view, Q could be deemed as revolutionary as it blurs the boundary of the quantitative-qualitative dichotomy. Q frees the researchers from the doctrine of polarisation of research designs and purely focuses on the research itself, turning researchers' attention to solving the problems or addressing research topics, which is what research studies are supposed to be in the first place.

Meanwhile, there are still voices asserting that Q should be categorised as mixed methods. Ramlo and Newman (2011, p. 183) vividly illustrate the position of Q in the qual-quant continuum. Yet, they did not acknowledge that in a mixed method study, there has to be two different sets of data. Q, however, quantifies participants' subjectivities that are collected qualitatively and interprets them qualitatively, which showcased a peculiar hybrid characteristic. In the same volume with Ramlo and Newman (2011), Stenner (2011) rebutted the assertion of Q belonging to mixed methods, underscoring that the term qualiquantology better captures such hybrid characteristics of Q (p. 192), which we resonate with. Whilst Ramlo and Newman (2011) responded to Stenner (2011) in the same volume and insisted that Q is mixed methods, in our view, they failed to acknowledge the concept of "methods" in a research context. Creswell and Creswell (2017) denoted that methods involve "the forms of data collection, analysis and interpretations that researchers propose for their studies" (p. 51). In other words, a method should contain data collection, data analysis and data interpretation in order to be defined as a method. Under this notion, a mixed methods study needs to contain both qualitative data collection, analysis and interpretation and quantitative data collection, analysis and interpretation. Q, on the other hand, does not fit such a notion of mixed methods as it only contains qualitative data collection and interpretation (Q sorting, factor interpreting) and quantitative data analysis (factor extraction and factor rotation). Therefore, the term qualiquantology, in our view, is more in line with the hybrid characteristics of Q. In fact, whilst qualiquantology is a relatively niche concept compared with mixed methods, it is gaining increasingly recognition in Q studies in recent years. In his PhD thesis, Lundberg (2020) acknowledged the concept of qualiquantology in Q. Similarly, in their paper, Wang et al. (2024) defined Q as a "qualiquantological method" (p. 5).

4 Inference of Abduction and Q Methodology

Inference is one of the kinds of performance which is guided and regulated by logic (Rumfitt, 2012). In research methodology, deduction and induction are the two most common forms of inference. Deduction manifests as top-down. It begins with proposing a formal hypothesis or theory, followed by the collection of empirical data or evidence to prove, support or reject the original hypothesis or theory. In terms of research methodology, deduction serves as the fundamental of quantitative research designs (Cohen et al., 2011) underpinned by the postpositivist worldview (Creswell & Creswell, 2017). Induction, contrary to deduction, is bottom-up and it serves as the fundamental of qualitative research designs (Cohen et al., 2011) underpinned by the interpretivist worldview (Creswell & Creswell, 2017).. Instead of proposing a formal theory or hypothesis, induction approaches the object or issue by researchers' own standard rather than through a priori lens, and the empirical data gathered serves to accumulate a pool of information or a theory that could generalise or describe the object or issue.

Abduction, a form of inference distinct from deduction and induction, was first formed and proposed in the late 19th century by American philosopher and logician Charles Peirce. Yet it was not until the beginning of the 21st century that this form of inference began to attract increasingly attention from scholars (Watts & Stenner, 2012). The essence of abduction, according to Peirce (1955), is to devise a theory or likely theory to explain the fact being studied. Unlike induction, which generalises patterns, abduction proposes causal or conceptual explanations for anomalies. Watts and Stenner (2012) further elaborated on Peirce's idea, arguing that abduction starts with capturing "surprising empirical facts" (p. 45) and continues with a process to pursue a hypothesis or likely theory to explain such facts. Therefore, abduction is different from deduction, as neither does it require to propose a pre-determined hypothesis nor does it aim at proving any theory or hypothesis. It is in fact the beginning process with no formalised or existing theory, or in other words, no prior knowledge, but purely focusing on the facts themselves that makes the abduction unique and attractive. It seeks an in-depth, ultimate explanation of a surprising empirical fact. In other words, the purpose of abduction is not to test or verify a theory or hypothesis but to discover and generate an explanatory hypothesis that turns those surprising facts into a "commonplace example of some more general phenomenon" (Shank, 1998, p. 846).

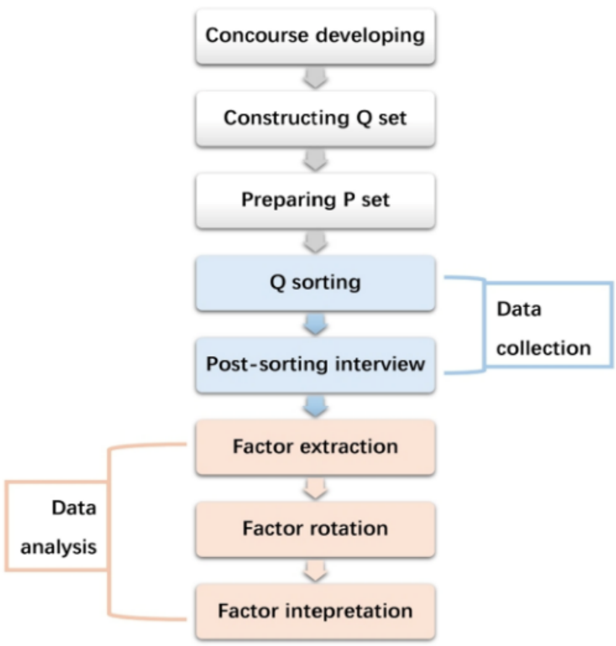
Meanwhile, abduction seems to be similar to induction, as both these inferences follow a bottom-up manner or half of it, as both of them begin with observing or studying the facts (Huang, 2014). However, induction, at its ultimate stage, pursues a theory accumulated from the empirical facts or data collected, and this theory serves as the overarching description of the facts being studied and the wide facts alike (Huber, 2018). A typical example could be the grounded theory in qualitative studies (see Charmaz, 2015). That said, induction is characterised as descriptive. Abduction, meanwhile, does not pursue a descriptive theory which could be applicable to the study of the wider phenomena. Instead, it seeks, generates and refers to the available evidence to produce a hypothesis or theory which could explain the fact being studied or observed (Haig, 2008). Therefore, unlike induction, abduction is characterised as explanatory and exploratory, and producing a generally applicable theory is not its objective (Shank, 1998).

Having discussed the inference of abduction so far, we have to move on to address a question that may arise therein: How does abduction relate to Q methodology? In his work, Stephenson (1961) discussed the relationship between abduction and factor analysis in Q and highlighted abduction as an important part of the Q methodology framework. According to him, factor in Q is not something being found but being abducted, a "creative abduction" (Stephenson, 1961, p. 10). From our perspective, two factors contributed to the bond between abduction and Q. The first factor could be attributed to the research purpose of Q. According to Brown (1980), Q methodology focuses solely on subjectivity, including issues such as perceptions, beliefs and attitudes. Brown (1986) further noted that subjectivity is not something provable, yet it "can nonetheless be shown to have structure and form", and it is Q's task to "render this form manifest for the purpose of observation and study" (p. 58). Therefore, it could be concluded that the aim and the function of Q align with abduction as both in essence are to explore and seek explanations. The second factor that ties abduction and Q is the fact that abduction is encapsulated in almost all stages of a Q study. In other words, abduction is manifested in literally every step in Q. Brown (1980) depicted factor analysis in Q as the technical extension or manifestation of the logic of abduction. In fact, the Q sorts collected during the Q study could be seen as those "surprising factors", and because of the exploratory nature of abduction, centroid factor analysis is preferred over principal component analysis by Q methodologists during factor extraction (Ramlo, 2016; Watts & Stenner, 2012). In addition, the interpretation of factors also reflected abduction. We now turn to several practical issues in relation to carrying out a Q study.

5 Practical Issues in Conducting a Q study

As presented in the introduction, the procedures would not be depicted in detail given the word limit. In this article, we focus on certain key issues in conducting a Q, including concourse and Q set, Q sorting, factor extraction and factor rotation. Figure 1 shows the procedures of conducting a Q study. The subsections in this section are divided in accordance with the steps listed in Figure 1. For those interested in procedures of performing Q in detail, see Watts and Stenner (2012), for factor analysis, Kline (1994) and for post-sorting interviews, Yuan (2024).

Figure 1
Procedures of Conducting a Q Study



5.1 From concourse to Q set

The theoretical basis of the sorting activities in Q is concourse theory of communication proposed by Stephenson (1986). It conceptualises communication not merely as a process of information transmission but as a collection of conversational and informal possibilities existed among any concept, statement, or object (Stephenson, 1986), and such a collection of possibilities or discourses is referred to as concourse, a universe of statements for any contexts or concepts. Rather than viewing individual viewpoints as isolated or internally generated, concourse theory posits that subjectivity emerges through individuals' interaction with these shared communicative structures (Brown, 1980; Watts & Stenner, 2012), and therefore it serves as the fundament for the implementation of Q by supporting Q methodology's epistemological orientation towards operant subjectivity (Stephenson, 1953), aligning with Gestalt principles and the abductive logic of inquiry. In practice, Q sorting is not a mechanical item ranking task. It is a contextual, interactional meaning-making process where participants engage with a subset of the concourse to express their singular viewpoint within the items or statements regarding a topic or context. This subset of the concourse is a Q set.

A Q set in a Q study refers to a collection of items to be sorted onto a distribution grid by participants. The items in a Q set could be in different forms, such as statements, visuals, sounds, traits and the like, depending on the research topic or questions (Stephenson, 1952). A generally accepted rule of the number of items in a Q set is between 40 to 80 items (Curt, 1994). The rationale behind this rule is that a Q set with too many items would make the sorting taxing and demanding, whereas a Q set with a small number of items might fail to cover the research topics sufficiently (Watts & Stenner, 2012). Nonetheless, it can be seen that in some Q studies, especially those published in recent years, the number of items in their Q sets was fewer than 40, yet the factors yielded in those studies were still satisfying (e.g., Watts & Stenner, 2005; Lundberg, 2020; Bonar et al., 2024; Fraschini & Lundberg, 2024). This, in our view, could be explained by two reasons. The first is that the number of items depends on the research topic itself. If the research topic has a relatively novel niche, it may not be possible to construct a large number of items that meet the rule set by Curt (1994). Another reason is that a small number of items could reduce the comprehension difficulty by, and sorting burden on, participants such as children (e.g., Fraschini & Lundberg, 2024), individuals with reading disabilities such as dyslexia, or those who would be asked to complete multiple Q sorts or tasks in one study. Therefore, Curt's (1994) rule should be seen as a rule of thumb, and the number of items in a Q set should depend on the research topic, the attributes and dispositions of participants, and the range of communications on the topic.

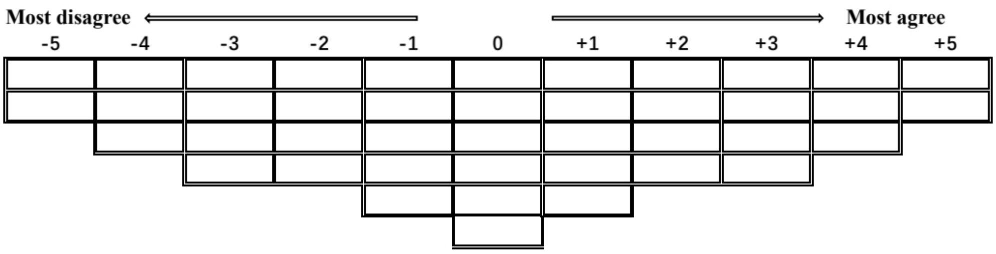
The items in a Q set are derived from the concourse. That said, a Q set is to the concourse what a participant sample is to a population. Therefore, the number of items in the concourse is typically greater than in the Q set. As shown in Figure 1, developing the concourse is usually the first step in a Q study once the research questions are formulated. There is no standard or limit regarding the source of items in the concourse. The items can be drawn from multiple sources (Watts & Stenner, 2012), including but not limited to academic articles, existing empirical studies, news and podcasts, informal or formal interviews or conversations with experts or peers on the research topic, data collected in previous studies, and self-reflections based on personal experiences or assumptions. As in the case of the Q set, there is no specific limit on the number of items in a concourse. All depends on the research topic and the researcher's judgment on whether saturation in the concourse has been reached, that is, whether the items in the concourse have demonstrated holistic and comprehensive coverage of the research topic. Compared with administering Q sorting and data analysis, which typically take a few days or weeks, developing the concourse can take several months (Curt, 1994). Therefore, concourse developing is generally the most time-consuming and labour-intensive stage in a Q study.

In practice, Watts and Stenner (2012) suggested that concourse and a Q set be developed in two ways: structured and unstructured, resulting in a structured Q set and an unstructured Q set respectively. The structured Q set follows Fisher's balanced-block approach of factorial design which ensures a representative sample. It divides the topic into several themes, and the number of items on each theme is equally allocated. Whilst not all Q scholars will agree that the themes (categories) must have equal items, such a way of constructing the concourse and the Q set has its own benefits. It could provide researcher with a relatively clear and logical guideline, as the dissection in a structured Q set could ensure the research topic to be covered in a balanced manner. In contrast, an unstructured way of constructing the concourse and a Q set sees the topic in a holistic manner. Instead of dividing the research topic into subsections, the unstructured way of developing the concourse and a Q set allows for more freedom and fluidity. An unstructured Q set provides a sample of items that represents the topic as a whole and simultaneously maintains the coverage and balance of the items being sampled from the concourse. There is no definitive right or wrong approach when constructing the concourse and the Q set. The choice of approach can be attributed to the researcher's background. Researchers with a quantitative background might favour a structured approach due to its similarities to designing an R-methodological questionnaire; whereas researchers with a qualitative background may prefer an unstructured fashion. In terms of interpreting "unstructured" in unstructured concourse and Q sets, Watts and Stenner (2012) suggested that "unstructured" only refers to the process of developing the concourse and the Q set, and it does not imply or condone a lack of structure in the final Q set.

5.2 Q sorting and forced distribution grid

Q sorting refers to the activity where participants sorting the items from the Q set on a distribution grid in a ranking order and a completed sorting activity produce a Q sort. The sorting pattern revealed in the Q sort reflected participant's subjectivity towards the research topic or question. The shape of the distribution grid is determined by the number of items in the Q set. Figure 2 is an example of a distribution grid for a Q set with 42 items.

Figure 2
Example of Distribution Grid for Q Set with 42 Items



As it could be seen it Figure 2, the distribution grid is designed in a symmetric shape and it consists of a number of grids. The number of these small grids corresponds to the number of items in the Q set. The symmetric shape is adopted primarily for the convenience and effectiveness of identifying sorting patterns in the factor analysis in Q. In fact, the shape of the distribution grid has virtually no effect on the results in factor analysis in Q. Brown (1980, pp. 288-289) analysed and compared 14 different distributions, including skewed left and right, inverted, and bimodal shapes, and found that the factor loadings and factor structures produced by each distribution showed no statistical differences.

Another concern over the distribution grid in Q is that it forces the participants to sort the items in a restricted manner, which appears to be "deviated" from abduction that the Q beholds. For instance, in Figure 2, participants could only place two items in the pole -5 and +5 according to the shape of the distribution grid. Brown (1980) contended this concern, arguing that whilst the distribution grid is pre-determined, participants are far from being forced or restricted during Q sorting activity. In the similar vein, Watts and Stenner (2012) illustrated that a Q set with 33 items coupled with a nine-point range distribution would provide them "roughly 11 times as many [sorting] options…as there are people in the world" (p. 78), therefore the forced distribution still adheres to the logic of abduction as it allows for numerous options for the sorting of items. Nonetheless, despite the fact that theoretically and statistically forced distribution does not distort the data structure or pattern, participants may still perceive it as constraining when they are doing Q sorting and they have every reason to feel that way. This highlights the importance of debriefing and post-sorting interviews to capture these subjective experiences.

Turning to the slope and the range of the distribution grid, Brown (1980) suggested a nine point range (-4 to +4) for a Q set that contains fewer than 40 items, an 11 point range (-5 to +5) for 40 to 60 items in a Q set, and a 13 point range (-6 to +6) for a Q set with more than 60 items. Nonetheless, it is only a suggestion rather than a stipulation. In practice, the point range in a distribution grid is determined by whether participants are familiar with the items in the Q set or the topic of study. A different point range on the same number of items would produce a different shape, or kurtosis: the degree of flatness and steepness (Brown, 1980) of the distribution grid. For instance, if a symmetric distribution grid for a Q set contains 42 items, when a nine-point range is adopted, more small grids would be placed in the centre and fewer in the two extreme values; therefore, a relatively steep or near normal shape of distribution grid would be produced. Such a shape of distribution is suitable for the complex Q sets that participants are unlikely to be familiar with since it allows participants to sort more items near the middle of the grid. Meanwhile, if these 42 items are distributed on a 11-point scale, a much flatter or platykurtic shape of distribution grid would be produced, as shown in Figure 2. Such a shape of distribution is designed for the relatively straightforward Q set that participants are likely to be familiar with, particularly its items, or the topic that falls within participants' knowledge and expertise. Hence it would be relatively easier for participants to sort items into two extreme sides of the distribution grid.

Before discussing the factor extraction, we would like to clarify several features in the distribution grid for Q sorting. To begin with, as shown on the top of the distribution grid in Figure 2, the expressions chosen in two extreme sides are *most disagree* and *most agree*. These expressions, however, are not fixed. The expressions on the top of the grid are normally determined by the research topic. For instance, expressions such as *most important* and *most unimportant*, or even *most tasty* and *most tasteless* for Q studies investigating participants' perceptions towards food, are all appropriate as long as they are appropriate for the research topic. Another thing that needs to be noticed on the top of the Figure 2 is that the opposite expression of *most agree* is *most disagree* but not *least agree*. This is because *most agree* and *least agree*, whilst seem to be in contrast with each other, still refer to the extent of agreeing. For an item which participants strongly disagree with, it would not make sense to place it under the *least agree* column as it indicates that this particular item is still what the participant agrees with, which deviates from the participant's real perception.

The second thing to be clarified is how the numbering on the top of the distribution grid is interpreted in Q. Whilst the number *-5, 0,* or *+2* on the top of the grid seems to be analogous with the numbering in Likert-scale questionnaires or other data collection instruments alike, it should be noted that Q does not measure anything. These numbers only serve to code participants' subjectivity towards the items in Q, not to quantify them. In terms of the distribution of numbering in the grid, Watts and Stenner (2012) justified for adopting near-normal symmetric distribution numbering from a negative value at one pole to the equivalent positive value at the other pole via zero, such as -5 to +5 in Figure 2, rather than from 1 to 11 in a 11-point range. In this near-normal symmetric distribution, a rather limited number of items could be placed at the two poles (e.g., 2 items in -5 and +5 in Figure 2); whereas a relatively larger number of items could be placed at the centre of the grid (e.g., 6 items in 0 in Figure 2). Such a distribution indicates that people would normally show very strong perceptions or feeling, either positively or negatively, towards a comparatively limited number of issues (Watts & Stenner, 2012). Therefore, using -5 to +5 appears to be more reasonable than using 1 to 11 for the numbering of the point range. Furthermore, the value zero in Q does not indicate indifferent or neutral towards an item perceived by the participants. In Q, nothing could be defined as absolute. Instead, Q works by "eliciting an inherently connected series of relative evaluations from its participants" (Watts & Stenner, p.79). Zero in the distribution grid only indicates one more than -1 and one less than +1. The same principle applies to all other numerical values in Q.

Last but not the least, while placing an item that a participant agrees with at a negative position (or vice versa) due to the constraints of the distribution grid may seem to contradict the participant's actual perceptions, this concern can be alleviated as long as researchers understand that negative rankings do not necessarily indicate negative perceptions, and positive rankings do not imply positive perceptions. Participants may perceive all items in the Q set as either positive or negative. Therefore, an item ranked at -3, for instance, only indicates that this item is valued slightly less than those ranked at -2 and slightly more than those at -4 by the participant, nothing more. We now turn to another issue in applying Q: factor extraction.

5.3 Factor extraction in Q: PCA vs. CFA

Once the Q sorts are collected and uploaded to any of the Q analysis software packages, the first thing these software packages would do is to intercorrelate the Q sorts with each other and produce a correlation matrix. The correlation matrix demonstrates the relationship between each Q sort in a data set, thereby representing the total variability present in the study (Watts & Stenner, 2012). In other words, a correlation matrix reflects the extent of similarities of the sorting patterns among all the Q sorts collected. The extent of similarities, or the relationships between those Q sorts are indicated within the range of [-1, 1] or [-100%, 100%] in the correlation matrix. This range of meaning and variability is known as study variance (Watts & Stenner, 2012). For instance, a 0.56 correlation between Q sort 1 and Q sort 3 indicates the sorting pattern of these two Q sorts of 56% of similarities. Once the correlation matrix is composed, factor extraction would be performed.

According to Brown (1993), factor analysis in Q aims to identify shared patterns of subjectivity among participants by grouping individuals based on the similarity of their viewpoints as expressed through their Q-sorts, not necessarily to account for the maximum variance in the dataset as is the case in factor analysis in R. As one of the steps in factor analysis, factor extraction identifies and removes a sizeable amount of study variance within the correlation matrix by extracting the Q sorts with high study variance, or high similar sorting patterns, and clusters these Q sorts. Each cluster extracted from the correlation matrix is known as a factor or viewpoint. Compared with the number of Q sorts in the data set, the number of factors extracted from the data set would be dramatically fewer. Therefore, factor analysis is a data reduction technique (Watts & Stenner, 2012).

There are two methods for factors extraction in Q: Principal Component Analysis (PCA) and Centroid Factor Analysis (CFA), both of which are available in any Q analysis software packages. Whilst the results produced by two factor extraction methods with the same data set are almost identical (Watts & Stenner, 2012; Lundberg, 2020), there are nonetheless differences in the rationale behind these two methods since they are operated based on different fundamentals and principles. PCA, on the one hand, relies on rigorous statistical calculation and produces a single, most mathematically appropriate solution, which might be attractive especially for researchers with a quantitative research background. It is one of the most commonly adopted factor extraction method in factor analysis and it could be performed in almost all statistical programmes (Akhtar-Danesha, 2017). In the third chapter of his book, *An Easy Guide to Factor Analysis*, Kline (1994) illustrated the computation and mathematical equations of PCA in a step-by-step manner. CFA, on the other hand, has a longer history than PCA. It was adopted prior to the invention of the computer and is still widely adopted by Q methodologists at present (Watts & Stenner, 2012). Whilst CFA also involves mathematical calculations such as the use of correlation matrices and factor loadings, unlike CFA, it does not restrict itself in seeking a single mathematically optimal solution. Instead, it allows researchers to explore the correlation structure more flexibly, guided by abductive reasoning that aims at integrating and justifying ideas to develop new knowledge (Ramlo, 2016). In practice, CFA requires researchers to observe the correlation closely and extracts Q sorts with high study variance in an exploratory fashion. In conducting CFA, once a factor is identified and extracted from the correlation matrix, factor loading, a measure of the extent of each Q sort is typical of or exemplified with the extracted factor, would be provided. The extraction of a factor from the correlation matrix would change the intercorrelations within the correlation matrix, and the remaining relationship of Q sorts in the matrix would be captured by the residual correlations. Once the residual correlations are calculated, the exploratory extraction would be repeated until no more factors of shared meaning could be identified.

The matter of considerable contentions in Q methodology is the issue of which factor extractions should be used when conducting Q studies. A number of Q methodologists, including Stephenson himself, have made a stand for CFA as it reflects the abductive reasoning, and using PCA over CFA may seems to deviate from the abduction that Q closely adhere to (Stephenson, 1953; Ramlo, 2016; Watts & Stenner, 2012), even though both factor extraction methods could provide nearly equivalent solutions (see McKeown & Thomas, 1988 for comparison of the factors extracted by CFA and PCA). In his work, Choulakian (2003) provided mathematical proofs that favour the use of CFA. However, among recent Q studies in language education and applied linguistics, PCA has been adopted predominantly, as evidenced in a number of recently published Q studies (e.g., Raksawong et al., 2024; Wang et al., 2024; Lundberg, 2020).

Among the 10 Q studies collected in the edited book (Fraschini et al., 2024), eight of them opted for PCA for factor extraction. The reason behind this trend is perhaps that some researchers, particularly those with a quantitative research background, favour PCA because of its statistical rigour and accuracy. Another reason is that compared with using CFA, PCA could extract more factors and provide a much clearer solution. Since it is deeply-rooted in more complicated mathematical calculations, PCA could detect more patterns or factors among a set of Q sorts as it seeks maximum variance explanation. In practice, when carrying out a Q study, researchers may encounter ambiguous or insufficient solutions by CFA whilst solutions by PCA are clearer and abundant. In order for the Q analysis to be carried on, they would select the solutions from PCA. To make our point more explicit, we use the data from the first author's current Q study to illustrate this.

Table 1
Unrotated Matrix of Dataset One by CFA

Nm ↑	Participant	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
1	L1	0.3613	-0.4265	0.1786	-0.2379	0.0562	0.2471	-0.0258	0.0592
2	L2	0.3797	0.2399	0.056	0.3836	0.238	-0.3275	-0.3032	0.1317
3	L3	0.6653	0.0366	0.0018	0.0113	0.0006	-0.0198	0.2169	0.0341
4	L4	0.6053	0.2518	0.0619	0.0495	0.0047	0.1585	-0.1402	0.0405
5	L5	0.642	0.0863	0.0078	0.1684	0.0395	-0.3571	-0.0034	0.073
6	L6	0.5508	-0.1484	0.017	0.0151	0.0008	0.2564	-0.3525	0.1634
7	L7	0.5545	-0.2977	0.0773	0.1186	0.0206	-0.4588	0.1154	0.1463
8	L8	0.6146	0.3599	0.1327	-0.2619	0.0702	0.0306	0.2943	0.0679
9	L9	0.6789	0.1519	0.0228	-0.3167	0.111	0.0916	-0.2078	0.0411
10	L10	0.7123	-0.1239	0.0117	0.0907	0.0128	0.2853	0.0832	0.0829
11	L11	0.673	-0.1213	0.0111	-0.0947	0.0061	-0.056	-0.208	0.0287
12	L12	0.7549	0.32	0.103	0.1539	0.0333	0.2351	0.0551	0.0564
13	L13	0.5726	-0.0568	0.0019	0.0722	0.0087	0.0942	0.0633	0.0148
14	L14	0.3121	-0.4749	0.2357	-0.2846	0.0863	-0.3116	0.2384	0.0984
15	L15	0.6845	-0.1739	0.0242	0.0419	0.0036	0.3914	0.1926	0.1774
16	L16	0.719	0.3425	0.1192	-0.3171	0.1112	-0.002	-0.0535	0.0016
17	L17	0.7215	0.2346	0.0539	0.1208	0.0213	0.1801	0.0282	0.0343
18	L18	0.3636	-0.2174	0.0389	0.2507	0.0872	-0.5172	-0.0013	0.1803

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Eigenvalues	6.5393	1.186	0.149	0.7247	0.1083	1.3059	0.5816	0.1693
% explained variance	36	7	1	4	1	7	3	1
cumulative % explained variance	36	43	44	48	49	56	59	60

Table 2

Unrotated Matrix of Dataset One by PCA

Nm ↑	Participant	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
1	L1	0.3833	0.1084	0.6595	-0.0357	0.1133	-0.2541	0.3894	0.2848
2	L2	0.416	0.2393	-0.6633	-0.1958	-0.0539	-0.141	0.2319	0.3496
3	L3	0.6833	0.0698	-0.0586	0.2087	-0.1227	0.4949	0.1503	0.1296
4	L4	0.6632	-0.3262	-0.1655	-0.1562	-0.2527	0.1454	0.1981	-0.1334
5	L5	0.6551	0.2966	-0.4295	-0.0055	0.1095	-0.2529	-0.2916	0.0374
6	L6	0.5846	-0.095	0.2477	-0.5994	-0.2292	-0.0908	0.0978	0.0641
7	L7	0.5335	0.6851	-0.0404	0.032	0.0824	0.0576	-0.0414	0.1094
8	L8	0.6687	-0.288	-0.0186	0.4966	-0.1679	0.1412	0.0587	0.1872
9	L9	0.7126	-0.1938	0.0272	0.1785	-0.0825	-0.4076	0.2108	-0.2439
10	L10	0.7419	-0.1106	0.2299	-0.2145	0.073	0.2012	-0.2222	-0.1619
11	L11	0.6829	0.1544	0.139	-0.146	-0.3855	-0.2331	-0.2365	-0.0973
12	L12	0.796	-0.2804	-0.1585	-0.0052	0.0596	0.1606	0.0103	-0.0184
13	L13	0.6009	0.0937	0.0935	0.0372	0.6913	-0.0431	0.1618	-0.1615
14	L14	0.3151	0.5764	0.4769	0.3503	-0.2164	-0.0379	-0.2019	0.0558
15	L15	0.7139	-0.1385	0.3423	-0.1715	0.1563	0.2603	-0.1552	0.0917
16	L16	0.7526	-0.195	-0.1133	0.3641	-0.0502	-0.2201	0.0499	-0.1721
17	L17	0.7695	-0.2537	-0.1547	-0.0552	0.2308	-0.0984	-0.31	0.1817
18	L18	0.3604	0.7121	-0.1715	-0.1253	-0.0472	0.2248	0.2303	-0.3373

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Eigenvalues	7.1461	1.9514	1.6711	1.1187	0.9657	0.9125	0.7595	0.5999
% explained variance	40	11	9	6	5	5	4	3
cumulative % explained variance	40	51	60	66	71	76	80	83

The two unrotated matrixes in Table 1 and Table 2 are extracted from the same set of data. The dataset in these two tables contains 18 Q sorts from 18 participants and a Q set with 42 statements. Table 1 shows the factors extracted via CFA whereas Table 2 uses PCA. By observing the eigenvalues of the two tables, or judging based on their significant loadings (Watts & Stenner, 2012) or Humphrey's rule (Brown, 1980), we can see that only two factors could be retained via CFA in Table 1, whilst in Table 2, four factors could be extracted via PCA. All four factors extracted via PCA could produce meaningful interpretation and new knowledge. However, does this indicate that, in this case, we should still stick to CFA as advocated by some Q experts?

To answer the above question, we would like to reiterate that the primary goal of data analysis is to serve the purpose of answering the research questions appropriately and adequately. Q, in general, is about finding and identifying multiple viewpoints and generating ideas or knowledge rather than testing hypotheses inductively or deductively. In this regard, any method that could produce sufficient, meaningful factors should be selected during analysing Q data. Therefore, using PCA, in our view, would not defy the principles of Q as long as PCA could produce satisfying results to answer the research questions. There is little point in arguing which extraction methods should be preferred, nor does it mean that using PCA deviates from the abduction inference. In fact, as the Tables 1 and 2 above show, sometimes researchers may not have that luxury to opt for the CFA, the "purest" fashion in conducting Q analysis, as the solution provided by CFA is not as neat as PCA. This could partially justify the prevalence of using PCA in Q studies published in recent years, as solutions provided by PCA could better answer the research questions as shown in Tables 1 and 2. Furthermore, as it has been discussed in previous sections, Q is a qualiquantological method, and using PCA during data analysis represents the "quan-" aspect in Q. Hence, using PCA during analysing Q data, in our view, is acceptable.

It should be noted that in Q analysis software packages, when researchers select CFA as the factor extraction option, a question would pop up: how many factors would you like to extract?. This question may confuse or even intimidate the researchers and would lead them to turn to another option, PCA, which only takes a click of the mouse and the calculation would be automatically completed in seconds. Brown (1980) suggested a "magic number seven" (p. 223) when it comes to how many factors to extract via CFA in those software packages. In PQMethod, the default number of factors extracted via CFA is seven, whilst the maximum number of factors to be extracted in Ken-Q or KADE is eight. Therefore, in practice, we suggested researchers who choose to extract factors via CFA by extracting as many factors as possible (set to the max), then inspecting them and making a judgement on how many factors to keep (e.g., its eigenvalue, significant loadings). This leads to the last issue of factor extraction we would like to highlight: Not all factors extracted should be kept. Some factors, whether extracted by CFA or PCA, may not offer meaningful information or knowledge despite meeting the criteria to be extracted. In this regard, using PCA again does not violet the abduction, as abductive reasoning is involved in making sound decisions on the number of factors to be kept rather than purely relyimg on mathematical solutions. In terms of the number of extracted factors to retain, several rules could be adhered to by referring to the unrotated factor matrix produced by the factor extraction, which we do not have space for further elaboration, as it has been abundantly explained by a number of scholars using Q method. Instead, we would like to highlight factor rotation, a practical consideration in Q.

5.4 Factor rotation in Q

Factor extraction in Q is to extract the factors from the collected Q sorts that are worthy to be interpreted, whereas factor rotation makes those extracted factors easier and more effective to be interpreted. Factor rotation aims to identify the Q sorts in the database whose positions are in close proximity to a particular factor or viewpoint (Watts & Stenner, 2012), and it is commonly performed via varimax rotation or by-hand/theoretical rotation (judgemental rotation in Ken-Q) in Q. Similar to PCA in factor extraction, varimax rotation adopts statistics computation to maximise the sum of variances in the unrotated factor matrix produced by factor extraction (Akhtar-Danesha, 2017). Therefore, it leads to the factor loadings of the Q sorts in each factor either near one or zero.

In contrast, by-hand rotation, as its name suggests, requires the researchers to rotate the factors manually to observe a position where the Q sorts are clustered approximately to a particular factor. Similar to factor extraction, factor rotation would only take minutes to complete via those dedicated software packages with a simple click of the mouse, but the rationale of how rotation works is not included. Watts and Stenner (2012, p. 115-120) and Kline (1994, p. 57-59) have depicted the rationale of factor rotation in a simple and comprehensive fashion, which we do not need to reiterate. One thing that deserves mention is that the rotation of factors only changes the Q sort's factor loading in relation to the factor, but it does not change the original intercorrelation between the Q sorts. In terms of which factor rotation approach ought to be adopted, Ramlo (2016) insisted on using theoretical rotation as it closely adheres to the abduction inference, whereas Akhtar-Danesh (2017b) criticised judgemental rotation as "not scientifically sound" and could lead to unreliable or invalid results. Nonetheless, one most commonly accepted way is to apply both rotation approaches in factor rotation (e.g., starting with varimax rotation, then observing and adjusting the rotated factor matrix by-hand where necessary) as asserted by Watts and Stenner (2012). In practice, when we use Q study software to perform factor rotation, we see that PQmethod and Ken-Q only allow researchers to use one rotation approach whereas KADE allows researchers to start with Varimax rotation and further adjust using theoretical rotation.

Leaving this aside, we now address factor rotation approaches. Both approaches derive the Q sorts to closely approximate to a factor from the unrotated factor matrix and synthesise them into a whole single Q sort that represents this particular factor. This synthesised representative Q sort is called a factor array. That said, if five factors are extracted from the correlation matrix and rotated, five factor arrays comprising the Q sorts closely approximated to the respective factors will be produced by factor rotation. Meanwhile, it should be indicated that whichever rotation approach is adopted, the rotated factor matrix may not be perfect. One issue could be that not all Q sorts would be perfectly located close to the extracted factors. This would produce confounded Q sorts, and those Q sorts are significantly loaded on more than one factor, which need to be removed when factor arrays are constructed. The final product of factor rotation will be a table that has all factor arrays and all the items from the Q set, or in most Q studies this table is named factor arrays.

6 Conclusion

In this paper, we have provided a relatively detailed explanation of Q methodology, a unique research method that is thriving in applied linguistics and language education in recent years. We have presented the historical background of Q, its abductive form of logic and the qualiquantology research paradigm. We have also justified certain practical procedures and considerations in conducting the Q, including designing a Q set, a distribution grid for Q sorting, and a method adopted for factor extraction and factor rotation. The justification and explanation of these issues are rarely reported in extant applied linguistics and language education studies employing the Q, and we have attempted to fill this gap by reviewing the theoretical underpinnings and key considerations in Q applications.

Meanwhile, as it has been mentioned at the beginning, in this article we have only addressed several steps and issues in conducting a Q study, instead of providing a step-by-step menu on how to carry out a Q study. Therefore, we are not expecting this article to serve as a guideline or handbook on how to conduct a Q study. Rather, we think that our article could be a resource or at least a theoretical reference for those who are interested in deepening their understanding of the rationale of Q or employing Q in their own research. In addition, for TESOL practitioners, Q could be adopted as a powerful tool for pedagogical purposes such as lesson planning and formative assessment during the class. As an ultimate goal, we hope that our review could further ignite the debate on the theoretical underpinnings and practical concerns of Q so that more studies will be conducted in accordance with what Q is supposed to be used for achieving the intended research purpose or objective.

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