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# A Novel Sequential Mixed-method Technique for Contrastive Analysis of Unscripted Qualitative Data: Contrastive Quantitized Content Analysis

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**Abstract**

Between-subject design surveys are a powerful means of gauging public opinion, but critics rightly charge that closed-ended questions only provide slices of insight into issues that are considerably more complex. Qualitative research enables richer accounts but inevitably includes coder bias and subjective interpretations. To mitigate these issues, we have developed a sequential mixed-methods approach in which content analysis is quantitized and then compared in a contrastive fashion to provide data that capitalize upon the features of qualitative research while reducing the impact of coder bias in analysis of the data. This article describes the method and demonstrates the advantages of the technique by providing an example of insights into public attitudes that have not been revealed using other methods.

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Between-subject design survey is a powerful instrument within the researcher's tool kit. In this type of design, also known as independent measures, each participant is assigned only one condition while blinded on the existence of other experimental conditions. In this way, the between-subject design mitigates the several ways in which subjects are exposed to demand characteristics (Nichols and Maner 2008; Orne 1962), that can impact participants' responses, including social desirability bias (Crowne and Stephens 1961; Fisher 1993; Randall and Fernandes 1991) and being aware of what the experimenter expects to find, also known as reactive arrangements (Campbell 1957). Because these effects can be expected to be similar in each of the experimental conditions, they effectively cancel each other. One example of a between-subject design technique used with considerable success in experimental philosophy, legal studies, behavioral economics, medical sociology, psychology, and more (Aspinwall, Brown, and Tabery 2012; Cabrera, Fitz, and Reiner 2015a, 2015b; Felsen, Castelo, and Reiner 2013; Finch 1987; Fitz et al. 2014; Link et al. 1999; Roskies and Nichols 2008) is the contrastive vignette technique (CVT; Burstin, Doughtie, and Raphaeli 1980).

In the CVT, two or more minimally contrastive variants of a vignette crucially differ in at least one detail (independent variables). Each respondent is randomly assigned one of the different versions of a contrastive vignette and asked a number of closed-ended questions. The key outcome measure is always the difference between contrastive condition responses, rather than the stated preference offered by the participant. This contrastive approach is "an indirect-structured methodology designed to overcome many of the shortcomings inherent in current techniques" (Burstin et al. 1980:147). The hypothesis commonly investigates how a small modification of the details of the vignette (e.g., enhancement vs. restoration or Susan vs. Steven) might influence participants' quantitative answers.

One well-justified critique of between-subject designs with closed-ended responses is that these are *thin*, that is, the responses are mostly descriptive without any additional evaluative component. Thus, closed-ended responses provide only slices of insight into issues that are often considerably more complex. While qualitative research enables richer accounts, it inevitably brings to the analysis the coder's subjective interpretations (Glaser and

Holton 2004; Saldana 2008). In an attempt to address these issues, we have developed a novel sequential mixed-method technique which we referred hereafter as contrastive quantitized content analysis (CQCA). This technique uses quantitization of classical content analysis that is analyzed contrastively. Such complementarity maximizes the benefits of both the quantitative and qualitative domains (Giordano, Rossi, and Benedikter 2013). While there has been a great deal of effort in developing integrated mixed-method designs (Johnson and Onwuegbuzie 2004), to the best of our knowledge CQCA is the only method that systematically analyzes qualitative data (e.g., free-response comments) in a design that allows for a *contrastive* comparison, such as in the between-subject design of the CVT. This contrastive comparison makes CQCA an innovative way to mitigate inherent coder bias, the inevitable result of coder's subjective interpretations and judgments in the process of coding.

The goal of this article is to provide a practical guide; as such, in what follows, we first describe and deconstruct the method. We then discuss some of CQCA's benefits and caveats, and we conclude with an example of the method in action from our research in experimental neuroethics.

## The Method: CQCA

CQCA is a sequential mixed-method technique that incorporates both quantitative and qualitative data analysis techniques, developed to analyze in a contrastive fashion qualitative data that are suitable for contrastive analysis, such as data from between-subject design surveys in which participants are asked both closed- and open-ended questions. CQCA basically builds up on three main analytical techniques: content analysis, quantitization, and contrastive analysis. While these techniques are applied sequentially, the key innovation of CQCA emerges from the synergy of these different approaches. In particular, it gives way to a method that integrates qualitative data to inform quantitative responses, quantitizes qualitative data to enable statistical analysis, and breaks apart contrastive conditions to enable the researcher to carry out meaningful comparisons.

In what follows, we will use the CVT as an example of how CQCA can be implemented.

## Data Collection

In the CVT, several minimally contrastive variants of a vignette are carefully designed by the researcher describing a particular situation. The vignettes are crafted in such a way to insure that they are plausible, comprehensible, and capture the essence of the issue to be explored as fully as is practical. Once the final version of the vignettes is ready, researchers can implement the survey (i.e., online or on paper). Each participant is randomly assigned to read one (an only one) vignette, and subjects are unaware that a contrastive condition exists. Participants then answer questions regarding their attitudes to the issue presented, with responses commonly recorded as a numerical rating on a Likert-type or continuous scale.

A key addition to the traditional closed-ended (quantitative) questions from CVT surveys is the incorporation of a "forced" open-response question following the question that constitutes the main quantitative outcome measure. By forced, we mean that only those who have responded this question can continue with the rest of the survey. In order to elicit detailed responses from participants, a minimum-character threshold is recommended as well as developing questions that entice rich qualitative responses. In terms of a minimum-character threshold, a reasonable minimum used by our group is that of 25 characters, which seems to keep a balance between being a burden to the participant and providing sufficient space for answers with enough content to be analyzed.

The following four main steps are applied, once the experimenters have gathered the quantitative and qualitative data from the respective contrastive vignette survey. The first stage is data preparation. The second stage is the *content* analysis of the unscripted qualitative data. The third stage is the *quantitization* of the qualitative codes. The final stage deals with the *contrastive* analysis of the quantitized data set.

## Data Preparation

A best practice in the analysis of qualitative data (e.g., coding free-response answers) used in order to reduce coder bias and improve reproducibility and generalizability is blinding coders to the specific condition they are coding for. Thus, in CQCA, coders are blinded to the specific contrastive vignette read by the respondent. In order to do so, a file is prepared by a noncoding researcher containing only the responses to be coded, which have been randomized with respect to contrastive condition and which have been assigned with an identifier for future reference; contrastive conditions are omitted. Treating the data in this manner reduces the likelihood that coder knowledge of the contrastive condition influences coding of the comments.

## Content Analysis Stage

This stage of the method follows conventional content analysis methodology, including generating initial codes, searching for categories, reviewing categories, and applying the analytical framework to the full data set (Braun and Clarke 2006; Hsieh 2005; Saldana 2008). There are several choices that must be made by the experimenter when carrying out content analysis, and these may affect what results are achieved as well as their interpretation (Carley 1993). A key decision relates to level of analysis. In the case of CQCA, the level of analysis normally employed is the individual response.

A different set of decisions relates to developing the coding strategy. One can either develop a list of concepts incrementally during the process of coding (interactive) or use a predefined set of concepts. There are also decisions around choosing the right level of generalization and the implication for concepts is likely to be dictated both by theoretical concerns and by the type of analysis in which the experimenter wishes to engage. Thus, the experimenters should be transparent in their chosen level of generalization, and whether they are using explicit or implied concepts, making notes of what is to be included and excluded, and what concepts are going to be used in a similar fashion and which ones are not.

Traditional code validation strategies such as interrater reliability or interpretive convergence can be used (Lombard, Snyder-Duch, and Bracken 2002; Onwuegbuzie et al. 2007; Saldana 2008). Kappa is commonly used to measure interrater reliability; when $\kappa < 0.6$, it is customary to revise or abandon the coding system (Chi 1997). Interpretive convergence relies upon intensive group discussion and consensus. These code validation strategies have been well accepted as a means of assuring the reliability of the codes and mitigating coder bias.

While these code validations are important, CQCA is designed as an innovative way to mitigate coder bias, as the key outcome measure is always the difference between contrastive condition results rather than the specific coding result. Thus, any coder bias inherent in the coding process can be expected to be similar in each of the contrastive conditions, effectively canceling each other.

## Quantitization Stage

Content analysis is a method of data reduction, but a further step, quantitization, is required to render the data amenable to statistical analysis. Quantitization, numerical transformation of coded qualitative data (Onwuegbuzie

2003; Sandelowski, Voils, and Knafl 2009; Tashakkori and Teddlie 1998), enables one to capture the frequency of occurrence of emergent codes or categories. However, quantitization also comes with downsides, in particular it can result in losses of variance on the original variables (Cohen 1983) as well as undercutting the nuance and subtlety of particulars within given contexts of meaning (Sandelowski et al. 2009). Quantitization can be carried out by binarizing codes such that a score of 1 is given for a code "if it represents a significant statement or observation pertaining to that individual" (Onwuegbuzie 2003:396); otherwise a score of 0 is given. An alternative approach toward quantitization based on binary assignments is that of giving a different number to each code within a given category. Both of these approaches render the data into a format ready for graphical representations of the relationships and differences between different codes. For an example of how we have implemented quantitization, please see "CQCA and Neuroethics in Practice" section.

The types of statistics that experimenters might decide to use for a particular quantitized data set would be dependent on the type of quantitization scheme chosen.

Depending upon the researcher's objectives, quantitization can be used to document the percentage of codes associated with a given category of respondent, the percentage of participants selecting specific codes, or other features of the data set (Onwuegbuzie 2003).

## Contrastive Analysis Stage

Once the data have been coded for content and quantitized without reference to the specific contrastive condition encountered by participants, the next step is to resort the coded and quantitized data according to contrastive condition, tabulating the number of times each code or category is mentioned by respondents in each condition. The frequency of codes within a given category can then be compared across contrastive conditions, with descriptive statistics used to characterize the composition and properties of the sample (Sandelowski et al. 2009), and inferential statistics used to make judgments regarding the probability that any observed differences between groups are statistically meaningful. Chi-squared test or Fisher's exact test can be used to demonstrate which nominally measured variables are related to each of the codes (Mehta and Patel 2011). Cramer's V can serve as a measure of latent effect size. Furthermore, odds ratios (ORs) can be utilized to compare prevalence rates among categories (Onwuegbuzie 2003). Graphs and tables can be constructed to provide a visual depiction of the contrast between arms of the experiment.

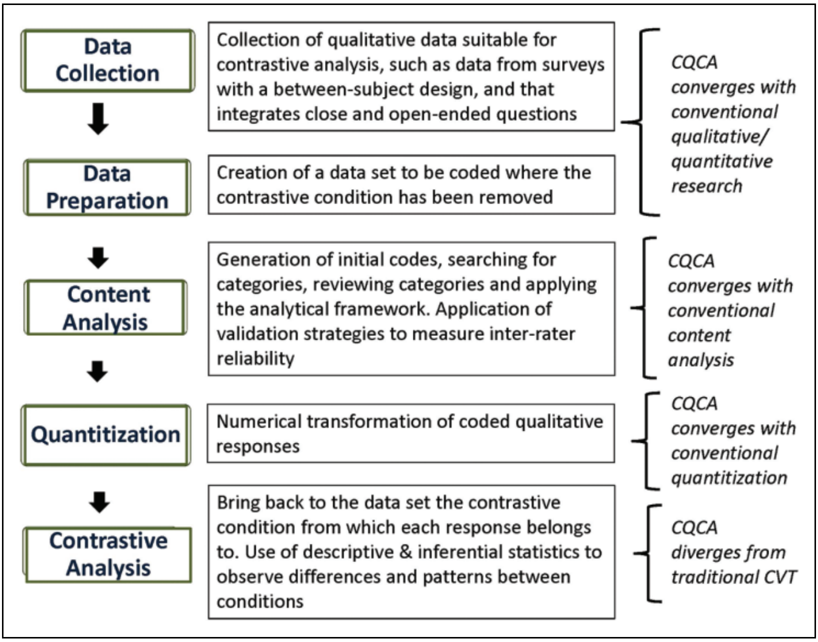


**Figure 1.** Contrastive quantitized content analysis steps.

While CQCA takes several insights from the CVT, it is at this stage where they diverge. While the key outcome measure in the CVT is the difference between contrastive condition responses, in CQCA the key outcome measure is the difference between occurrences of a certain code across conditions. Thus, in CQCA, the focus is on contrasting the occurrences of certain code for a given condition compared with the occurrences of that same code in another condition rather than the average rate of overall occurrences for a certain code. Figure 1 summarizes the different steps involved.

## Benefits and Caveats

### *The Benefits*

By integrating quantitative and qualitative analysis, CQCA captures some of the richness of free-response comments, thereby providing a more in-depth description of contrastive data than using quantitative measures alone. Furthermore, the design of CQCA mitigates coder bias while introducing the advantages of quantitative rigor: reproducibility and generalizability of results.

In the process of coding comments during content analysis, researchers bring their subjectivities, personalities, and predispositions (Glaser and Holton 2004; Saldana 2008). In CQCA, coder bias is mitigated by allowing the subjective approach brought forward into the analysis of the comments being essentially identical in each arm of the contrastive design. That is why it is important that the coders are blinded to the contrastive condition as they are coding.

Reproducibility and generalizability are essential features of sound quantitative research methods. The former indicates that the research process can be replicated in order to verify research findings (O'Leary 2004). The latter indicates that the findings of a sample show statistical probability of being representative and thus applicable to a larger population (Braun and Clarke 2006; Hsieh 2005; O'Leary 2004; Saldana 2008).

CQCA, if used on a representative sample of the general population, can be regarded as generalizable. But even when used in a nonrepresentative sample, it already enables researchers to make a different level of inferences than those from conventional qualitative research which typically relies in small sample sizes.

The reproducibility of CQCA is worthy of consideration. On the one hand, because the data set is based on content analysis with the inherent coder's subjectivities, one might argue that CQCA is not reproducible. However, one can still achieve consistency, meaning that another researcher can still follow the "decision trail" used by the study's coders (Sandelowski 1986). On the other hand, both the ability of CQCA to reduce coder bias and the large data set involved might overcome this limitation. We look forward to this issue being tested empirically as CQCA is adopted by others.

Another benefit of CQCA, when used for survey data, is that it can be used to measure the internal validity of the experiment. One can correlate the results of a contrastive survey question (whose subject is the same or similar to the issue discussed in the CQCA data) with those obtained using CQCA. Known as triangulation (Greene, Caracelli, and Graham 1989; Lombard et al. 2002; Onwuegbuzie et al. 2007; Saldana 2008), this approach can be used to test if the responses offered in different parts of the experiment are consistent. Such correlation could be regarded as a form of internal validity. In addition, one can create a scatter plot to identify outliers that might alert the researcher to the possibility that those individual data points might be unreliable and further comparison may be used as a comprehension check.

Identification of outliers can also be useful in highlighting internal contradictions between the quantitative and qualitative responses of participants.[1] In studies relevant to public opinion on moral issues, these tensions within subjective accounts can help shed light into participant's conflicting moral values or beliefs.

Finally, while we have used this approach for experimental data, that does not preclude its use in analyzing other types of qualitative data, such as comments about images or short video clips or even time-series contrastive comparisons. Our team has used CQCA to analyze changes of attitudes in public comments from online media publications in two different time periods (Cabrera and Reiner 2015). However, the technique works best when there is a well-matched set of data, as exemplified by its use in association with the CVT. Such stringent criteria are more difficult to obtain when there is no experimental manipulation but can be applied reasonably to time-series data. For example, if one were to investigate the text of comments made in response to media publications about the genome editing technique clustered regularly interspaced short palindromic repeats (CRISPR) in the first days after publication and contrast this with comments made after a week of the first media release, one could reasonably apply CQCA to this approach.

## *The Caveats*

A major drawback of the CQCA technique derives from the quantitization step as transforming qualitative data into quantitative carries the risk of losing critical information and analytical power contained in the raw qualitative data (Chi 1997; Cohen 1983; Driscoll and Appiah-Yeboah 2007).

A second drawback is the use of relative short comments. Written accounts provide a venue in which participants can articulate in their own words their viewpoints and attitudes toward a specific issue. Some scholars have warned about the possibility of participants being less thorough with their answers in open-ended questions that enable only relative short accounts (Denscombe 2007; Onwuegbuzie 2003; Sandelowski et al. 2009; Tashakkori and Teddlie 1998). This could lead to vague comments, making difficult to capture a comprehensive picture of the set of beliefs at hand as well as the strength of the argumentation. Similarly, some commentators have provided thoughtful critique about the quality of these type of responses (Israel 2010; Onwuegbuzie 2003; Smyth et al. 2009) as they can be seen as the result of "quick and dirty" (Kahneman, Slovic, and Tversky 1982) or "fast and frugal" (Goldstein and Gigerenzer 2002) heuristics, thus lacking reflective insight. However, other commentators have also provided evidence suggesting that reflection and analysis do not necessarily lead to wiser choices than relying on intuitions, which have the advantage to be faster and often more accurate (Bortolotti 2011).

CQCA, as we have implemented it, mines data from short comment responses, which provides a snapshot of the public's opinions. The length of these comments can be regarded as a limitation of our current use of CQCA. Of course, in principle, researchers can use written accounts of any length, but analysis of large numbers of longer comments may be onerous. While such longer accounts may provide a more detailed description of respondent views, thus mitigating vagueness, there has been little methodological research regarding response length and quality of responses (Deutskens et al. 2004; Smyth et al. 2009). This is an area that merits further investigation.

## CQCA and Neuroethics in Practice

The final section of this article is focused on a practical example of CQCA in action.

### *Public Attitudes Regarding Discomfort for Different Enhancement Conditions Experiment*

This survey aimed to explore public attitudes regarding discomfort for different enhancement conditions.

### *Data Collection and Quantitative Analysis of Slider Answers*

Our implementation of CQCA involved data collection from a convenience sample of respondents from Canada and the United States recruited via Amazon's Mechanical Turk. We compensated respondents with US$0.25 for completion of the online survey. Once participants accepted the assignment, they were directed to an external survey site (FluidSurveys.com), where they were randomly assigned to read one and only one version of a vignette describing the use of a pill to enhance 1 of 12 cognitive, affective, or social domains. While the vignettes differed with respect to the specific domain under study, the primary contrastive feature of the experiment was enhancement condition: For each cognitive, affective, and social domain, a version of enhancement was described which represented enhancement *toward* the norm (ETN) while a contrastive version described enhancement *above* the norm (EAN).

Following each vignette, participants were asked three questions with the opportunity to provide their answers on a 101-point slider scale. The first question asked participants to rate how comfortable they felt with the individual (John) having taken the pill, with anchors at *not at all comfortable* ($-50$) and *completely comfortable* ($+50$). The open-response question that followed asked participants to provide, in their own words, their reasons for answering as they did. Importantly, the free-response question immediately follows the first (primary outcome) question, before any potential prompting of participants with further questions that could act as demand features influencing their open-ended responses. Question 2 asked participants to rate the degree to which the use of the pill changed the individual, with anchors at the same person and a changed person, while question 3 asked participants to rate how much the use of the pill contributed to the individual's success in life, with anchors at a very small change and a very large change. These two last questions were peripheral to the main outcome measure, and so we will only discuss question 1 and its associated open-response question in order to illustrate the CQCA method. For further details on the experimental design, please refer to Cabrera, Fitz, and Reiner (2015a).

Data from the slider questions were analyzed using the statistical software SPSS 20.0. In order to provide results ranging from 0 to 100, responses to the slider question were adjusted by adding 50 points to each data point. With respect to the primary independent variable of enhancement condition, 1,368 participants read vignettes describing ETN, while 1,408 participants read vignettes describing EAN, providing 2,776 unique responses. This stage involved the use of descriptive and inferential statistics. A two-way, between-subject analysis of variance revealed a statistically significant main effect of enhancement condition on comfort level of participants (Cabrera, Fitz, and Reiner 2015a).

*CQCA.*

Stage 1: Data Preparation

In order to blind coders to the experimental condition, a file was prepared containing only the responses to be coded and an identifier for future reference.

Stage 2: Qualitative Analysis of Qualitative Data

In the second stage, responses from the free-response box were subjected to content analysis and codes emerged. Based on the overall meaning of the comment, codes were clustered into one of four categories: *not comfortable*, *comfortable*, *ambivalent and others*.

Stage 3: Quantitization of Qualitative Data

As an example of the kind of data that we observed, we will focus on the *not comfortable* category. Codes within a given category were quantitized, each one representing a reason for discomfort. We found that for both enhancement conditions, ETN and EAN, NO NEED ($n = 835$), SAFETY CONCERNS ($n = 614$), and CONCERNS ABOUT PILLS ($n = 539$) were the three most frequently mentioned codes. SOCIAL PRESSURE TO FIT IN ($n = 31$), LEGAL OR PRESCRIBED ($n = 35$), and RELIGIOUS CONCERNS ($n = 5$) were the least frequently mentioned codes in our data set (Figure 2). The full set of categories and results can be found in Cabrera, Fitz, and Reiner (2015a).

Stage 4: Contrastive Analysis of Quantitized Data

At this point using the identifier from stage 1, the data were unblinded regarding the key contrastive features of the experiment, which in this case was enhancement condition. This provided us with a data set suitable to carry out contrastive analysis of codes across enhancement conditions. We carried out statistical analysis on codes that represented more than 5 percent of the total number of coded comments (from both ETN and EAN) mentioning that specific code. The 5 percent inclusion limit was chosen in order to ensure having a well-powered sample. Five codes within the *not comfortable* category fulfilled this criterion. Using the case of NO NEED as an example, when the condition was framed as EAN, 43 percent of participants within that group viewed NO NEED as their reason for discomfort with the situation, while only 17 percent of participants within the ETN group felt similarly. The effect size associated with this relationship as measured by Cramer's V was 0.29. The odds of participants providing NO NEED as a reason for discomfort in the EAN group was 3.8 times higher than for the ETN group (OR 3.8, 95 percent confidence intervals [3.2, 4.6]). We used Fisher's exact test to determine which differences between enhancement conditions presented statistical significant differences[2]. Only NO NEED and SAFETY presented statistically significant differences between enhancement conditions ($p < .001$, two-tailed Fisher's exact test, with Bonferroni correction).

We calculated the number of codes used within the *not comfortable* category per participant and correlated this with each participant's rating of comfort level (question 1). We found a strong positive correlation ($r = .80$) between these two measures, suggesting that our qualitative analysis

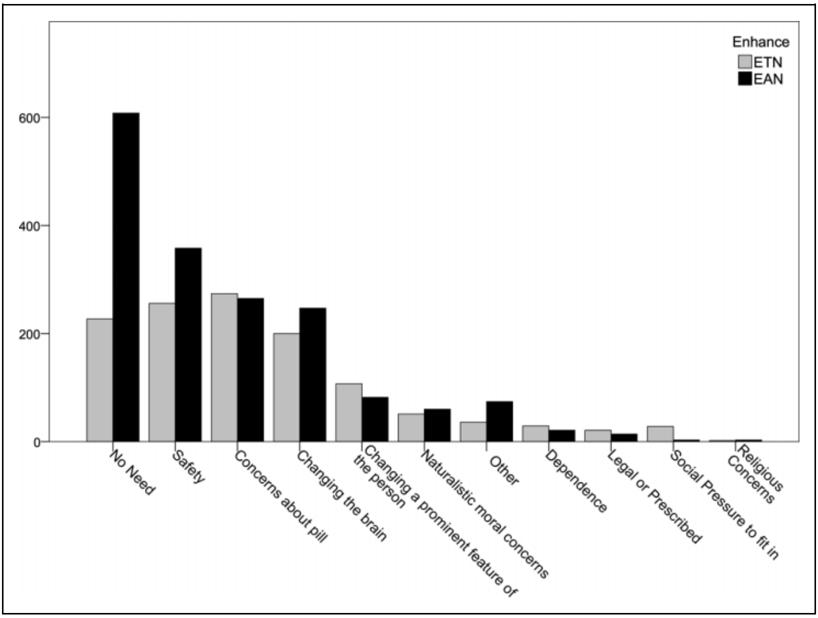


**Figure 2.** Codes under *not comfortable* category according to enhancement condition.

results were consitent with our quantitative results. In other words, the more discomfort participants reported in their quantitative responses, the greater number of reasons they provided in their open-response question box, providing a measure of internal validation for the consistency of participant responses.

Overall, the use of CQCA provided one important insight. Regardless of enhancement condition, NO NEED, a concern that is hardly touched within the neuroethical literature, is a primary concern shaping people's discomfort toward enhancement. Whereas concerns that are widely dicussed in the neuroethics literature, such as RELIGIOUS CONCERNS or DISTRIBUTIVE JUSTICE, turn out to be not salient in people's reasons for discomfort with someone taking a pill for enhancement. Thus, by incorporating qualitative data into the analysis of participants quantitative answers, CQCA has enriched and deepened our understanding regarding people's feelings toward cognitive, affective, and social enhancement in a way that previous methods on their own have not attained before. This is clearly a valuable insight, with positive implications for future survey designs.

## Conclusions

This article introduced a novel sequential mixed-method design that has successfully been used within experimental neuroethics. As a mixed-method approach, it provides analytical advantages when exploring complex research questions. The qualitative aspect of CQCA provides a deeper understanding of vignette survey responses while the quantitization provides the opportunity to analyze the patterns of responses statistically. Furthermore, the contrastive nature of CQCA insures that both respondent's and coder's biases are mitigated, resulting in a novel way to analyze data that has heretofore been absent from the literature. CQCA opens up new avenues of survey design and analysis, helping researchers explore complex research questions with rigour.

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### Notes

1. We would like to thank one of our reviewers for pointing out such an interesting possibility.
2. While Fisher's exact test can be used for groups with less than five responses, we decided to only carry out statistical analysis on codes, where for all groups (domain and enhancement), five responses were present.

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