Article

Field Methods
2018, Vol. 30(3) 241-257

DOI: 10.1177/1525822X18781756
journals.sagepub.com/home/fmx
SAGE

A Formal Method for Detecting and Describing Cultural Complexity: Extending Classical Consensus Analysis

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Abstract

The most widely used formal approach to culture, the cultural consensus theory (CCT) of Romney, Weller, and Batchelder, originally relied on a priori definitions of cultural groups to map their unity and diversity. Retaining key features of classical CCT, we provide techniques to identify two or more cultural subgroups in a sample, whether those groups are known in advance or not. Our method helps CCT practitioners connect to contemporary approaches to culture in anthropology and related disciplines, which emphasize complexity. We suggest that our method provides reasonable and easily implementable approximations of cultural unity and diversity

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within a sample. In pursuing these matters, we contribute to other ongoing efforts to bring CCT closer to contemporary theorizing on cultural multiplicity, thus rendering CCT potentially more useful to a wider range of practicing social scientists.

Cultural consensus theory (CCT; Romney et al. 1986) is well known and widely used to estimate and describe cultural unity and diversity within a group (Hruschka et al. 2008), having accumulated over 1,500 citations to date in anthropology and other disciplines since its formulation in 1986 (Google Scholar, retrieved August 28, 2017). While retaining the essential features of the original methods of CCT, we extend this classic formal approach by providing researchers with a technique and metric to address a long-standing question faced in CCT, namely, whether known groups within the informant population (e.g., women vs. men) differ substantially in their consensus about a domain of understanding, even having their own answer key (what are understood to be the most salient, meaningful, and culturally correct ideas about a domain of knowledge). This provides the foundation for the second part of our analysis that employs a genetic algorithm (Whitley 1994) to allow researchers to systematically detect multiple cultural groups/perspectives within a sample of informants without these cultural groups being known in advance, with multiple CCT answer keys provided. In pursuing these matters, we contribute to other efforts that systematically use CCT-based approaches to identify and analyze multiple cultures (e.g., Anders and Batchelder 2012; Borgatti 2002; Garro 1986). And we aim to bring the CCT tradition closer to contemporary theorizing in anthropology and other related disciplines, where cultural complexity and multiplicity are emphasized, thus rendering CCT potentially more interesting and useful to a wider range of practicing social scientists (Abu-Lughod 1991; Clifford 1994; Hannerz 1992; Marcus 1995).

Acknowledging cultural difference among informants does not contradict the fundamentals of CCT and has been done since its inception, with various scholars within this tradition having analyzed patterns of cultural sharing and divergence within groups (Boster 1986; Garro 1986; Weller 1983; Weller and Baer 2001, 2002). Classic CCT presumes that informants vary in their individual cultural competence—that is, in their knowledge of a culturally framed domain of understanding—so even conventional CCT analyses reveal cultural variability within the sample and thus some divergence from cultural sharing (Dressler et al. 2015). CCT scholars have also developed sophisticated residual analysis procedures to estimate the amount of cultural variation across a priori defined subgroups not explained by, and thus residual to, consensus estimates (Dressler et al. 2015; Handwerker 2001; Ross 2004; Ross et al. 2007). Nevertheless, residual analysis extensions of CCT tend to treat cultural differences as deviation from a *single* culturally correct set of responses to items within a cognitive domain, thus retaining a more homogeneous view of culture than its practitioners might desire or the data may warrant (Lacy and Snodgrass 2016).

Of note, two of the originators of the CCT did suggest shortly after publishing their original article the possibility of identifying *multiple* cultural truths—that is, answer keys—though they didn't initially formally develop the properties of such a model (Batchelder and Romney 1989). In fact, other work in the CCT tradition has acknowledged that subgroups may draw on distinct cultural knowledge source models to frame their responses to cultural consensus items (Boster and Johnson 1989; Caulkins and Hyatt 1999; Chavez et al. 2001; Chavez et al. 1995; Garro 2000; Handwerker 2001). Typically, such approaches compare multiple answer keys derived from aggregate and a priori groupings of informants to ascertain areas of inter/intragroup agreement and variation (Keller and Loewenstein 2011; Schrauf and Iris 2011). For example, the quadratic assignment procedure provides a way of testing for hypothesized differences between known subgroups, with subsequent CCT analyses run on identified subgroups providing their distinctive answer keys (e.g., see Borgatti 2002; Garro 1986). However, in a recent and distinct advance in the CCT tradition, Batchelder and his colleagues have developed a formal mathematical generalization of CCT, accompanied by theorems, proofs, and fit diagnostics, that permits an analyst to discover the presence of multiple previously unknown groups within the sample (Anders and Batchelder 2012; Oravecz, Faust, et al. 2014; Oravecz, Vandekerckhove, et al. 2014). While some of this work deals with binary choice data (e.g., T/F, yes/no, and option 1 & option 2), these researchers have also developed CCT techniques for other response categories such as ordinal and continuous data (Anders and Batchelder 2015; Anders et al. 2014; Batchelder and Anders 2012). In addition to providing an approach to detecting unknown cultural groups within a sample, their mathematical methods address other limitations of the original CCT model (e.g., allowing for different guessing models and varying difficulty of individual items, with various publications accompanied by available software packages; Anders 2017; France et al. n.d.; Oravecz 2017; Purzycki and Jamieson-Lane 2017).

The work presented here offers an alternative approach to identifying multiple cultural subgroups within a sample, which is based in part on a genetic searching algorithm (Whitley 1994) and also on a new measure of model fit. Like other recent approaches, our method explicitly recognizes that independent sources of cultural variation may underlie the responses of a sample of informants, and thus that multiple answer keys may better account for the observed responses within a sample about a given domain of understanding. We first offer a way to compare multiple CCT keys within known groups or categories such as gender, age, or ethnicity. Then, we extend that to detecting unknown groups, so that sub- or countercultural groupings need not be identified a priori or by existing demographic categories.

We begin by addressing the simpler problem of comparing two *known* groups within a sample—such as women and men, the young and the old—to determine whether they might be better categorized as belonging to separate cultures with separate keys. This initial piece is in the spirit of both classic and contemporary CCT work that offers a systematic way to explore how group membership is related to informants' differing belief or knowledge systems (Borgatti 2002; Boster 1985; Garro 1986; Gatewood and Cameron 2009; Weller 1984). We illustrate that with data drawn from our recent fieldwork among the Sahariya of central India (Snodgrass 2015; Snodgrass et al. 2016; Snodgrass, Lacy, et al. 2017; Snodgrass, Most, et al. 2017; Zahran et al. 2015). The second part of our presentation describes a procedure based on a genetic searching algorithm (Whitley 1994) to find a division of the sample into two different but *unknown* culture groups that show maximum internal consensus. We again illustrate that technique with a Sahariya example.

This empirical work is followed by a more general discussion of our technique in relation to the CCT field more generally. As we show throughout, our approach unites with a single measure of model fit—the total competence score (TCS), the sum of informant competence scores as estimated from a conventional cultural consensus model—techniques for identifying both known and unknown cultural groups within a sample. And we position this method and metric collaboratively alongside a family of new multiple culture CCT approaches for understanding cultural complexity, hoping that this body of work as a whole will push consensus analysis practice in newly productive directions, thus aligning CCT more firmly with contemporary theorizing on culture. Unlike other new multiple CCT methods (Anders and Batchelder 2012), we have not attempted to solve problems associated with the relatively simple response model of the original CCT model (e.g., equiprobable guessing and equal item difficulties) but have focused only on the problem of analyzing and identifying multiple cultures. For economy of reference, we name the family of multiple culture techniques, including our approach and those of Batchelder and his collaborators and others as cultural consensus, multiple keys (CCMK, pronounced "see-mac"), retaining CCT to designate the traditional one group/one key model. (Interested readers can consult Online Appendix 1 for a discussion on the method and theory behind classical CCT, which provides context for our extension of this model and approach to culture).

TCS and a Comparison of Two Known Groups

For comparing how well a one- versus a two-culture group model accounts for a set of data, some kind of measure of fit is necessary. Cultural consensus practitioners have traditionally relied on informal (and sometimes ad hoc) rules such as comparing the ratio of the first to the second eigenvalue, examining the average competence scores, and ensuring no negative competence scores exist within a group (Dressler et al. 2015). For the current purpose, we propose a simpler and intuitive measure, the TCS to describe the fit of a one-group CCT model to a set of data. Besides being simple, this measure conveniently extends to summarizing the fit of a two or more group/key model of the data, something not readily done with the eigenvalue ratio. This allows a direct statistical comparison of a one-group model versus two-group model. Using TCS to measure fit has the further advantage of being independent of the particular method by which competence scores are derived, which is relevant given the rise of a range of other estimation methods currently available (Anders and Batchelder 2012; Aßfalg and Erdfelder 2012; Karabatsos and Batchelder 2003; Oravecz, Vandekerckhove, et al. 2014). TCS is the sum of informant competence scores as estimated from a conventional one-group/key cultural consensus model, formally represented as:

$$\mathrm{TCS}_{1\mathrm{key}} = \sum_{i=1}^{N} D_i,$$

where D_i is the competence score for the ith of the N individuals in the sample, and the subscript "1key" indicates that this obtains assuming a single key. The rationale is that to the extent a single-key cultural consensus model fits informants' responses well, they would all have high(er) competence scores. TCS_{1key} always lies between 0 and N, since $0 \leq D_i \leq 1.0$ for each of the N individuals.

As a first step toward methods for comparing latent (unknown) cultural groups within the sample, consider first using TCS to examine how much two *known* groups (say women and men) differ regarding consensus in some domain. After obtaining the baseline TCS_{1key} for the sample as a whole, one conducts conventional CCT consensus analyses separately on each *known* subgroup. This gives two (potentially) different answer keys and sets of competence scores, and a TCS value for each group, say TCS_1 for the sum of the first group's competence scores on their own key and TCS_2 for the second group. We measure the fit of this two-group model to the data by summing the TCS values, $TCS_{2key} = TCS_1 + TCS_2$. To the extent that members of each group better fit their own group's key, rather than a procrustean one group key, the individual competence scores will be higher under the two-group model, and TCS_{2key} will substantially exceed TCS_{1key}. We measure the superiority of a two-group to a one-group model as:

$$TCS_{diff} = TCS_{2key} - TCS_{1key}.$$

Presuming the two groups do have different keys, with $TCS_{diff} > 0$ in the sample, a formal hypothesis test for this comparison is of interest. The substantive null hypothesis is that all informants share a common key, with $TCS_{diff} = 0$, versus the alternative that underlying each informant group's responses is a distinct key, so that $TCS_{diff} > 0$. Even if this null hypothesis were true, an observed sample value of TCS_{diff} might nevertheless exceed 0 due to the randomness introduced by informants guessing when they do not know the culturally correct answer to an item, per traditional CCT assumptions (Romney et al. 1986). A formal hypothesis test of whether TCS_{diff} exceeds its null value beyond chance is possible by computer simulation, using a parametric bootstrap method (Manly 2006. The interested reader can find details of this procedure in Appendices 2 and 3, which respectively describe the parametric bootstrap test for comparing two known groups and the procedure for obtaining competence scores and answer key estimates from individuals' responses). What would matter to the practicing user here, though, is that this technique yields a p value to test the null hypothesis that both groups' answers arise from a common single key.

Example: Use of a Bootstrap Test to Compare Two Known Groups

We illustrate this *known* groups test by applying it to data we collected in 2011 in Sahariya villages in the Indian state of Madhya Pradesh (Snodgrass

2015; Snodgrass, Most, et al. 2017). Sahariyas are classified in India as Adivasis—literally, first inhabitants and thus natives or indigenous persons who continue to live near forestlands, subsisting on agriculture, herding, wage labor, and government assistance along with some foraging of wild foods and other forest products. Part of the sample ($N = 80$) lived in Behruda, which remains in its traditional location, adjacent to a relatively rich forest. The other part of the sample resided in Maziran ($N = 77$), which the Madhya Pradesh Forest Department relocated in 1998 to a different (and materially inferior) area to protect wildlife and plants in the original location from human influence. After extensive fieldwork, Snodgrass and his field collaborators developed and administered a Hindi questionnaire to village residents. It solicited responses about various aspects of social and material well-being of the villagers including perceptions of village quality. This set of survey items asked informants to rate their perceptions of the quality (bad, ok, and good) of various aspects of the facilities and conditions of local life (see Table 1 for details, paying attention to results columns total sample, Behruda village, and Maziran village).

A conventional CCT, treating the responses as nominal (multiple choice) data, was conducted on the total sample ($N = 157$ completed interviews). (We treated the data as multiple choice to use the formal and more mathematically rigorous cultural consensus model, which can only handle T/F or multiple choice data [Weller 2007].) This analysis indicated low consensus for a one-group model, with a total sample $\mathrm{TCS}_{\mathrm{1key\text{-}TS}}$ of 57.5, corresponding to a mean competence score of only 0.37. The two-group solution gave $\mathrm{TCS}_{\mathrm{1key}}$ values of 46.6 and 37.0 for separate analyses of each village (abbreviated in the table as $\mathrm{TCS}_{\mathrm{1key\text{-}B}}$ and $\mathrm{TCS}_{\mathrm{1key\text{-}M}}$), summing to a $\mathrm{TCS}_{\mathrm{2key\text{-}BM}}$ of 83.6 (mean competence 0.53). By this criterion, a two-group model fit about 45% better than a one-group model, with $\mathrm{TCS}_{\mathrm{diff\text{-}BM}} = 26.1$. We formally tested this observed value against the null value of $\mathrm{TCS}_{\mathrm{diff}} = 0$ using a bootstrap procedure described in Online Appendix 2. The results clearly contradict the null hypothesis, supporting a two-group solution, as the observed $\mathrm{TCS}_{\mathrm{diff\text{-}BM}} = 26.1$ exceeded *any* of the values obtained from 1,000 random simulations performed assuming the one-group null hypothesis as true. This example shows the use in practice of the TCS-based measures to summarize fit and compare a two-answer key model with cultural groups known in advance, which is a first contribution of the current work.

Table 1. Consensus Results for Combined and Separate CCT Analyses of Sahariya Regarding "Quality" of Village Conditions.

	Answer Keys and Summary Statistics for:				
Conditions/Facilities	Total Sample ($N = 157$)	Behruda Village ($N = 80$)	Maziran Village ($N = 77$)	Group 1, Genetic Algorithm ($N = 87$)	Group 2, Genetic Algorithm ($N = 70$)
Q1. Soil	3[a]	3	1	$\underline{3}$[b]	$\underline{1}$
Q2. Jungle/forest	3	3	1	$\underline{3}$	$\underline{1}$
Q3. Irrigation	1	1	1	1	1
Q4. Human drinking water	1	1	1	1	1
Q5. Animals' drinking water	1	1	1	1	1
Q6. Animals' fodder	3	3	1	$\underline{3}$	$\underline{1}$
Q7. Electricity	1	1	2	$\underline{1}$	$\underline{2}$
Q8. Hospital	1	1	3	$\underline{1}$	$\underline{3}$
Q9. Road	1	1	3	$\underline{1}$	$\underline{3}$
Q10. Fuelwood	3	3	1	$\underline{3}$	$\underline{1}$
Q11. Village security	3	3	3	3	3
Q12. Village council (panchayat)	2	2	2	2	2
Q13. Forest department	1	1	1	1	1
Q14. NGO	1	1	1	1	1
Summary Statistics on Competence Scores	$TCS_{1key\text{-}TS} = 57.5$	$TCS_{1key\text{-}B} = 46.6$	$TCS_{1key\text{-}M} = 37.0$	$TCS_{1key\text{-}1} = 47.43$	$TCS_{1key\text{-}2} = 36.65$
		$TCS_{2key\text{-}BM} = 83.6$ $TCS_{diff\text{-}BM} = 26.1$		$TCS_{2key\text{-}GA} = 84.1$ $TCS_{diff\text{-}max} = 26.6$	

Note: NGO = nongovernmental organization.
[a]1 = bad, 2 = ok, 3 = good.
[b]Underlined items in group 1 and 2 key columns indicate differences between latent group 1's and group 2's answer keys.

Using a Genetic Algorithm with TCS to Identify Unknown Cultural Subgroups in a Sample

Accepting this test for known groups as valid, we move to our more ambitious goal, to formally examine and test whether a sample contains *unknown* subgroups, such that separate CCT models for each latent group would fit the data substantially better than a single-key model for the entire sample. As before, for simplicity of presentation, we restrict our description to two rather than three or more groups.

The first part of this procedure entails a method to discover what division of the sample of *N* informants into two groups would give the best fit (i.e., display maximum consensus within each of the two groups). This is a difficult computational task, since examining each possible division to find the best one is impractical for all but small samples, at least with current computing technology. Our procedure addresses this difficulty by using a genetic algorithm, an accepted approach to computational problems like this in which a complete enumeration is challenging and potentially impossible (Whitley 1994). Briefly, a genetic algorithm presents a method for solving optimization problems based on a natural selection paradigm. The technique mimics biological processes by iteratively selecting the best offspring in iterative generations of a population that has been allowed to randomly change or mutate in some prescribed way. In this way, the overall optimization or fitness increases over subsequent generations of iterations of the procedure.

Relying on a genetic algorithm, we developed computer code (described in Online Appendix 4) to discover what division of a sample into two groups would give the largest possible value for TCS_{diff}. We term this largest possible value of TCS_{diff} as "$TCS_{diff\text{-}max}$," and it measures the extent to which a sample shows evidence of containing *latent* cultural subgroups. $TCS_{diff\text{-}max}$ will, in general, greatly exceed the TCS_{diff} in the known-group case described previously, as a huge number of possible arrangements are considered in finding it. To judge whether a given sample's $TCS_{diff\text{-}max}$ value is large enough to support concluding that two different keys/groups underlie the responses in the sample, one must consider whether $TCS_{diff\text{-}max}$ might arise from the random features of the response process inherent in CCT and the vast search opportunities within a sample. This points to the second part of our procedure that allows for detecting *unknown* subgroups, a formal test for the null hypothesis that the observed responses derive from a single key, as opposed to the alternative that they originate from two latent groups of informants answering from their own different answer keys. This test uses an approach resembling the known-groups hypothesis test in combination with the genetic algorithm technique to find the $TCS_{diff\text{-}max}$, again using a bootstrap approach to hypothesis testing (see Online Appendix 5). Here, the practical analyst need only to attend to this procedure's result, which is a *p* value for a test of the hypothesis that the responses of individuals in the sample derive from two latent groups with different keys, versus the null assumption that their responses come from a single common key with any difference in the two groups' responses arising only from the random component of the CCT model. (The interested reader may consult Online Appendix 6 for a detailed numerical example of finding multiple latent groups within a simulated data set.)

CCMK Applied to Actual Data: Sahariya Village Quality

We now apply the CCMK method to our Sahariya data to detect two unknown subgroups. The genetic algorithm procedure identified two latent groups with TCS_{1key} values of 47.4 and 36.6, giving a summed $TCS_{2key\text{-}GA}$ of 84.1 and a $TCS_{diff\text{-}max}$ of 26.6 versus the total sample. Group 1's key found through the genetic algorithm was the same as for the total sample, but group 2 differed on the answer key for seven items: soil, jungle/forest, fodder, electricity, hospital, road, and fuelwood (different answers are underlined in Table 1). This sample difference in fit of the two-key versus the one-key model strongly suggests that two latent cultural groups exist within the sample, which was confirmed by a p value of .001 from our simulation test comparing the two models. (The first/second eigenvalue ratios for each group under the two-key model were much higher, 5.99 and 4.78, vs. 1.30 for the one-key model.)

A reasonable question is whether the derived groups 1 and 2 correspond to some sociocultural reality. In this case, the derived (latent) group assignment closely aligned with the external facts of actual village membership in Behruda or Maziran, with Table 1 showing that latent group 1 had the same key as Behruda, and group 2 the same as Maziran. Likewise, 79 of the 87 persons in the CCMK-derived group 1 resided in Behruda, and 69 of the 70 in group 2 came from Maziran, again showing our technique's ability to accurately replicate an external real fact. (As noted, there are 157 villagers total, 80 in Behruda and 77 in Maziran. This means that 79 of the Behruda's 80 villagers are placed in the latent group 1, while 8 of Maziran's 77 individuals are found there. Sixty-nine of the Maziran's 77 villagers are in the latent group 2, accompanied by only one Behrudan.) As Table 1 also shows, the key for group 1 (and thus also for Behruda) generally favored natural resources (soil, jungle, fodder, and fuelwood) as better than group 2 (which matches Maziran), while the reverse is true regarding modern resources (electricity, hospital, and roads). These patterns are also consistent with the realities of the villages' situation at the time of the study, with the more traditional Behrudans displaying greater connection to forests and their resources; the relocated villagers of Maziran having more access to modern amenities. So, while the CCMK method identified groups purely on the basis of response patterns, without external reference to what we knew ethnographically, the statistical results here correspond closely with local cognitive, social, and environmental realities.

Discussion

Conventional CCT allows researchers to identify patterns of cultural sharing and thus consensus, as its name implies; however, it also documents cultural diversity by giving each individual a competence score. Nevertheless, even when cultural complexity is a focus of CCT research, recent studies have tended to focus on how group members diverge from a single set of culturally correct answers to questions about a domain of knowledge, which, for example, can be precisely estimated via methods of residual analysis (Dressler et al. 2015). Although important, such techniques have more limited ability to reveal other forms of cultural diversity, such as how members of a subgroup might uniquely frame a domain of knowledge, rather than simply being more or less concordant with a dominant cultural frame.

By contrast, our method aligns itself with a growing family of other CCMK techniques that explicitly recognize that alternative and distinguishable cultural perspectives may exist across previously identified subgroups (Boster 1985; Garro 2000; Handwerker 2001; Hruschka et al. 2008), with some providing explicit formal methods, accompanied by theorems, proofs, fit diagnostics, and so on, to identify and compare how multiple even *latent* groups of informants not known ahead of time might inform the responses observed in a sample (Anders and Batchelder 2012, 2015). As our examples reveal, our data-driven CCMK approach allows for the comparison of two *known* groups in an effort to decide whether they're sufficiently different to be categorized as distinctive cultures. When such information is available, the known-groups test we described provides a formal way to compare these groups and should be widely useful. However, our technique does not require external or a priori information about which informants might represent another culture or follow a different model. Rather, our method further allows one to discover potentially hidden and thus *unknown* groups within the data itself.

Although a member of a growing family of CCT and CCMK techniques for identifying multiple cultures, our method's TCS metric offers a simple way to measure model fit and does so in a way that unites techniques for identifying both *known* and previously *unknown* subgroups in a sample. Of note, our CCMK technique as described in this article uses a statistical approach closely resembling that described in the original CCT article, retaining standard CCT assumptions about respondents' competence, guessing, and question–answer behavior (Romney et al. 1986). However, others have shown that classical CCT assumptions oversimplify response processes (Anders and Batchelder 2012). The extent to which our methods and those would give similar results would be a useful task for future work.

Although developing methods to estimate a cultural consensus model that relaxes those assumptions was not the focus of our work here, we see in principal no reason why our CCMK approach could not be applied using any method of estimating the competencies and key for a cultural consensus model. That is, our TCS fit measure does not depend on the analyst using a particular method to derive competence scores, so our CCMK method could be used in combination with any recent technique for estimating competence scores of a cultural consensus model, including recent novel techniques that accommodate varying item difficulty or the presence of response bias (Anders and Batchelder 2012). To clarify, we have used maximum likelihood estimation to obtain competence estimates, but the method could just as well be used with the original factor analysis estimation procedure, with Markov chain estimation, within a Bayesian framework, and so on, which others have usefully developed (Anders and Batchelder 2012, 2015; Anders et al. 2014; Aßfalg and Erdfelder 2012; Karabatsos and Batchelder 2003; Oravecz, Vandekerckhove, et al. 2014).

Similarly, we would not presume that the TCS measure is not the only possible fit measure that could be used within the broader framework we use here. While TCS has the advantage of being easily comparable between one-key and multiple key models, other measures might be made usable as well. Finally, while we have for simplicity of presentation restricted discussion of our CCMK technique to two groups, our approach, whether in the known group or unknown group form, applies in principle to any number of groups.

Finally, our approach could be combined or used in parallel to other CCT and CCMK techniques commonly used in cultural consensus analyses. We would still recommend that a classical one-key CCT analysis remains as a first straightforward and well-established description of cultural unity and diversity (Romney et al. 1986). Then, if the analyst had reason (ethnographic or theoretical) to think the sample at hand could be described as a single-culture group with particular deviating individuals, then residual analysis would be a fitting follow-up (Dengah 2013; Dressler et al. 2015; Handwerker 2001; Ross 2004; Ross et al. 2007). Or, if the researcher believed that a multiple culture description would have theoretical advantages, then we would view our method or the recent CCMK work of Batchelder and colleagues as alternative approaches to pursue.

Conclusion

In a well-known CCT analysis, Ross et al. (2007:511) compellingly argue for moving beyond culture as shared norms, ideas, and values: "Rather than treating agreement as a cultural norm and disagreement as noise, we propose a focus on both disagreement and agreement, for exploring both the origins and consequences of intragroup as well as intergroup differences." Similar ideas are found in other work in the CCT paradigm, as in Dressler and his collaborators' use of residual analysis methods to carefully document cultural variability (Dressler et al. 2015). They are also found in an expanding body of techniques for identifying even more drastically differing subgroups in a sample—for example, who don't share the same answer keys and thus knowledge about a domain of understanding—whether those groups are identified ahead of time or rather revealed to be latent in the response data (Anders and Batchelder 2012; Boster 1985; Garro 2000; Handwerker 2001; Hruschka et al. 2008). If we take seriously those ideas and other work emphasizing the diverse and competing models resident within many contemporary cultures, the ability to estimate multiple keys and competences offered by our CCMK and other multiple culture consensus analysis approaches should be very desirable. Among other things, they bring CCT practice and theory closer to contemporary theories of culture, which emphasize diversity, complexity, and cultural opposition and disagreement within social groups (Abu-Lughod 1991; Clifford 1994; Hannerz 1992; Marcus 1995).

To conclude, our technique offers an alternative method for a multiple consensus group analysis, using the simple TCS metric to identify both known and unknown cultural groups within a sample. At this point, we propose our method as one alongside other CCT and CCMK approaches in the hope that together they will push cultural consensus practice in a direction where considerations of cultural multiplicity, complexity, conflict, and even "dissensus" are considered more the norm than the exception. That is, we position our work collaboratively as part of an increasingly well-established CCMK extension of CCT, which we hope will become increasingly commonplace. To that end, the CCMK method described here has been implemented in an *R* (version 3.4.1) statistical package and is freely available to users (Meyer et al. 2013). We also direct readers to the packages of other researchers cited in our article. We plan to further test our technique by comparing it to similar ones in future work, and we hope that others will join us in the important endeavor of helping get CCMK techniques more into the mainstream of formal cultural anthropological practice.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was funded in part by a grant from the National Science Foundation, "Environmental Displacement and Human Resilience: New Explanations Using Data from Central India," BCS-1062787, June 1, 2011 to May 31, 2014 (PI Jeffrey G. Snodgrass; co-PI Sammy Zahran).

Supplemental Material

Supplementary material for this article is available online.

References

Abu-Lughod, L. 1991. Writing against culture. In *Recapturing anthropology: Working in the present*, ed. R. G. Fox, 137–62. Santa Fe: School of American Research Press.

Anders, R. 2017. CCTpack: Consensus analysis, Model-based clustering, and cultural consensus theory applications (version 1.5.1). https://cran.r-project.org/web/packages/CCTpack/index.html (accessed April 19, 2018).

Anders, R., and W. H. Batchelder. 2012. Cultural consensus theory for multiple consensus truths. *Journal of Mathematical Psychology* 56:452–69.

Anders, R., and W. H. Batchelder. 2015. Cultural consensus theory for the ordinal data case. *Psychometrika* 80:151–81.

Anders, R., Z. Oravecz, and W. H. Batchelder. 2014. Cultural consensus theory for continuous responses: A latent appraisal model for information pooling. *Journal of Mathematical Psychology* 61:1–13.

Aßfalg, A., and E. Erdfelder. 2012. CAML—Maximum likelihood consensus analysis. *Behavior Research Methods* 44:189–201.

Batchelder, W. H., and R. Anders. 2012. Cultural consensus theory: Comparing different concepts of cultural truth. *Journal of Mathematical Psychology* 56: 316–32.

Batchelder, W. H., and A. K. Romney. 1989. New results in test theory without an answer key. In *Mathematical psychology in progress*, ed. E. E. Roskam, 229–48. Berlin: Springer. http://link.springer.com/chapter/10.1007/978-3-642-83943-6_15 (accessed April 19, 2018).

Borgatti, S. P. 2002. A statistical method for comparing aggregate data across a priori groups. *Field Methods* 14:88–107.

Boster, J. S. 1985. Requiem for the omniscient informant: There's life in the old girl yet. In *Directions in cognitive anthropology*, ed. J. W. D. Doughterty, 177–97. Champaign: University of Illinois Press.

Boster, J. S. 1986. Exchange of varieties and information between Aguaruna manioc cultivators. *American Anthropologist* 88:428–36.

Boster, J. S., and J. C. Johnson. 1989. Form or function: A comparison of expert and novice judgments of similarity among fish. *American Anthropologist* 91:866–89.

Caulkins, D., and S. B. Hyatt. 1999. Using consensus analysis to measure cultural diversity in organizations and social movements. *Field Methods* 11:5–26.

Chavez, L. R., F. A. Hubbell, J. M. McMullin, R. G. Martinez, and S. I. Mishra. 1995. Structure and meaning in models of breast and cervical cancer risk factors: A comparison of perceptions among Latinas, Anglo women, and physicians. *Medical Anthropology Quarterly* 9:40–74.

Chavez, L. R., J. M. McMullin, S. L. Mishra, and F. A. Hubbell. 2001. Beliefs matter: Cultural beliefs and the use of cervical cancer-screening tests. *American Anthropologist* 103:1114–29.

Clifford, J. 1994. Diasporas. *Cultural Anthropology* 9:302–38.

Dengah, H. F. I. 2013. The contract with God: Patterns of cultural consensus across two Brazilian religious communities. *Journal of Anthropological Research* 69: 347–72.

Dressler, W. W., M. C. Balieiro, and J. E. Dos Santos. 2015. Finding culture change in the second factor stability and change in cultural consensus and residual agreement. *Field Methods* 27:22–38.

France, S. L., M. Vaghefi, and W. H. Batchelder. n.d. FlexCCT: Software for continuous CCT. https://pdfs.semanticscholar.org/ab47/ad043960b066c82e9574d5e04bda42bd34a3.pdf (accessed April 18, 2017).

Garro, L. C. 1986. Intracultural variation in folk medical knowledge: A comparison between curers and noncurers. *American Anthropologist* 88:351–70.

Garro, L. C. 2000. Remembering what one knows and the construction of the past: A comparison of cultural consensus theory and cultural schema theory. *Ethos* 28: 275–319.

Gatewood, J. B., and C. M. Cameron. 2009. Belonger perceptions of tourism and its impacts in the Turks and Caicos Islands. http://www.lehigh.edu/~jbg1/Perceptions-of-Tourism.pdf (accessed April 19, 2018).

Handwerker, W. P. 2001. *Quick ethnography: A guide to rapid multi-method research*. Walnut Creek, CA: AltaMira.

Hannerz, U. 1992. *Cultural complexity: Studies in the social organization of meaning*. New York: Columbia University Press.

Hruschka, D. J., L. M. Sibley, N. Kalim, and J. K. Edmonds. 2008. When there is more than one answer key: Cultural theories of postpartum hemorrhage in Matlab, Bangladesh. *Field Methods* 20:315–37.

Karabatsos, G., and W. H. Batchelder. 2003. Markov chain estimation for test theory without an answer key. *Psychometrika* 68:373–89.

Keller, J., and J. Loewenstein. 2011. The cultural category of cooperation: A cultural consensus model analysis for China and the United States. *Organization Science* 22:299–319.

Lacy, M. G., and J. G. Snodgrass. 2016. Analyzing cultural consensus with proportional reduction in error (PRE) beyond the eigenvalue ratio. *Field Methods* 28: 153–69.

Manly, B. F. 2006. *Randomization, bootstrap and Monte Carlo methods in biology*, Vol. 70. Boca Raton, FL: CRC Press.

Marcus, G. E. 1995. Ethnography in/of the world system: The emergence of multi-sited ethnography. *Annual Review of Anthropology* 24:95–117.

Meyer, M. C., J. C. Snodgrass, and M. Lacy. 2013. SubCultCon: Maximum-likelihood cultural consensus analysis with sub-cultures (version 1.0). https://cran.r-project.org/web/packages/SubCultCon/index.html (accessed April 19, 2018).

Oravecz, Z. 2017. Hierarchical Condorcet modeling toolbox. https://sites.psu.edu/zitaoravecz/hierarchical-condorcet-modeling/ (accessed April 17, 2017).

Oravecz, Z., K. Faust, and W. H. Batchelder. 2014. An extended cultural consensus theory model to account for cognitive processes in decision making in social surveys. *Sociological Methodology* 44:185–228.

Oravecz, Z., J. Vandekerckhove, and W. H. Batchelder. 2014. Bayesian cultural consensus theory. *Field Methods* 26:207–22.

Purzycki, B. G., and A. Jamieson-Lane. 2017. AnthroTools: An R package for cross-cultural ethnographic data analysis. *Cross-Cultural Research* 51:51–74.

Romney, A. K., S. C. Weller, and W. H. Batchelder. 1986. Culture as consensus: A theory of culture and informant accuracy. *American Anthropologist* 88:313–38.

Ross, N. 2004. *Culture and cognition: Implications for theory and method*. Thousand Oaks: CA: Sage.

Ross, N., D. Medin, and D. Cox. 2007. Epistemological models and culture conflict: Menominee and Euro-American hunters in Wisconsin. *Ethos* 35:478–515.

Schrauf, R. W., and M. Iris. 2011. Using consensus analysis to investigate cultural models of Alzheimer's disease. In *A companion to cognitive anthropology*, eds.

D. B. Kronenfeld, G. Bennardo, V. C. de Munck, and M. D. Fischer, 548–68. Oxford, UK: Blackwell.

Snodgrass, J. G. 2015. Festive fighting and forgiving: Ritual and resilience among indigenous "conservation refugees." In *Global mental health: Anthropological perspectives*, eds. B. A. Kohrt and E. Mendenhall, 173–90. Walnut Creek, CA: Left Coast Press.

Snodgrass, J. G., M. G. Lacy, and C. Upadhyay. 2017. Developing culturally sensitive affect scales for global mental health research and practice: Emotional balance, not named syndromes, in Indian Adivasi subjective well-being. *Social Science & Medicine* 187: 174–83.

Snodgrass, J. G., D. Most, and C. Upadhyay. 2017. Religious ritual is good medicine for indigenous Indian conservation refugees: Implications for global mental health. *Current Anthropology* 58:257–84.

Snodgrass, J. G., C. Upadhyay, D. Debnath, and M. G. Lacy. 2016. The mental health costs of human displacement: A natural experiment involving indigenous Indian conservation refugees. *World Development Perspectives* 2:25–33.

Weller, S. C. 1983. New data on intracultural variability: The hot–cold concept of medicine and illness. *Human Organization* 42:249–57.

Weller, S. C. 1984. Cross cultural concepts of illness: Variation and validation. *American Anthropologist* 86:341–51.

Weller, S. C. 2007. Cultural consensus theory: Applications and frequently asked questions. *Field Methods* 19:339–68.

Weller, S. C., and R. D. Baer. 2001. Intra-and intercultural variation in the definition of five illnesses: AIDS, diabetes, the common cold, empacho, and mal de ojo. *Cross-Cultural Research* 35:201–26.

Weller, S. C., and R. D. Baer. 2002. Measuring within-and between-group agreement: Identifying the proportion of shared and unique beliefs across samples. *Field Methods* 14:6–25.

Whitley, D. 1994. A genetic algorithm tutorial. *Statistics and Computing* 4:65–85.

Zahran, S., J. G. Snodgrass, D. G. Maranon, C. Upadhyay, D. A. Granger, and S. M. Bailey. 2015. Stress and telomere shortening among central Indian conservation refugees. *Proceedings of the National Academy of Sciences* 112:E928–36.