chapter 9

Some observations on meta-analysis of MTMM studies

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Although the results of analyzing different multitrait multimethod (MTMM) data sets are described in Andrews (1984, tables 4, 5, and 6), more detailed remarks about the approach and some special considerations relevant to it will be made in this contribution.

ON THE "CASES" FOR THE META-ANALYSIS

One needs to remember that a "case" in the meta-analysis consists of data for a particular trait, assessed using a particular method, for a particular group of people. In my analysis each case had the following information associated with it:

- a. the measurement quality estimates for that case (i.e., estimates of validity, method effect, and random error)
- b. the thirteen survey design/content features that characterize that measure and that are discussed in Andrews (1984)
- c. the type of respondent for whom the measurement quality estimates were computed.

In principle, the maximum number of cases in the meta-analysis would be the number of traits times the number of methods times the number of groups on which the analysis was performed; however, in actuality one does not need to use complete MTMM data designs (if there are more than the minimum of traits and methods, some "holes" are permissible), and one does not have to use all or the same groups for every MTMM data set. In my study the actual number of cases for the meta-analysis was 2,115. (Across my six MTMM data sets, there were an average of about 6 traits and about 3 methods, and estimates were computed for an average of about 20 groups.)

The smallest identified MTMM model depends, of course, on the constraints one imposes. With the constraints I used (method factors independent from each other¹ and from the trait factors, and all method effects from a single factor constrained to be equal), models for four traits and two methods (or two traits and four methods) and models with three traits and three methods are identified. Models with only three traits and two methods may also be identified under these conditions, but I have not rigorously examined this or tried to use models this small. If we take the 3x3 model as an example of a useful small model, it will generate measurement quality estimates for 9 measures, i.e. 9 validity estimates, 9 method effect estimates, and 9 estimates of random error variance.

For any significant meta-analysis, one needs a large number of cases, certainly more than nine. There are three ways to increase the number of cases, and I have used all three in my own work.

An obvious first approach is to combine results from several MTMM data sets. One can combine results from different surveys and/or incorporate more than just one MTMM data design in a single survey.

A second way to generate more cases is to use bigger MTMM designs. The number of traits represented in an MTMM model can easily be expanded in a survey setting. However, survey respondents tend to find repeated questions about the same topic that differ only with respect to the measurement method tedious, so as a practical matter the maximum number of different methods is three or four. Six traits each assessed by four methods would provide twenty-four sets of measurement quality estimates.

A third way to increase the number of cases is to generate measurement quality estimates not only for the sample as a whole, but also for subgroups characterized on the basis of age, and again for three subgroups based on education would provide 63 sets of measurement quality estimates (=3*3*[1+3+3]). In addition to increasing the number of cases available for the meta-analysis, this approach makes it possible to examine the relations between the selected subgrouping characteristics and the measurement quality

¹ Although the research reported in Andrews (1984) consistently constrained method factors to be independent of one another, more recent work I have done with Herzog and Rogers has relaxed this constraint. Allowing method factors to be related to each other has conceptual appeal and sometimes improves the fit of a model. However, when all the traits are also substantially interrelated, an ambiguity arises as to what portion of the relationships among the observed measures should be attributed to correlated traits versus correlated methods. If methods are allowed to relate to one another, it seems important to include at least one trait that is independent of other traits and/or one method that is independent of other methods.

estimates, a topic of considerable interest in its own right. (One could find out, for example, wether more educated respondents provided more precise answers.) Of course, analyzing overlapping subgroups produces some theoretically messy dependencies, but from a practical standpoint the messiness has not (so far) proven problematic. Some new results on this are presented below.

ON DESIGNING THE DATA FOR A META-ANALYSIS AND CHOOSING AN ANALYSIS TECHNIQUE

I have called the analysis of the cases described above a "metaanalysis" or a "stage 2 analysis" because it involves the analysis of measurement quality estimates obtained from prior causal modeling analyses. The meta-analysis is a straightforward analysis that attempts to explain each dependent variable (the estimates of validity, method effect and random error) on the basis of a set of multiple predictor variables (the survey design/content features and/or population subgroup).

As in any such analysis, several aspects of the data need to be considered and will affect one's choice of analysis technique. These aspects have to do with assumptions about (a) multicollinearity, (b) additivity, (c) linearity, and (d) metric variables. The analysis technique that I used, Multiple Classification Analysis MCA (Andrews et al., 1973), was chosen because it can appropriately handle data with substantial correlations among the predictors (multicollinearities), certain nonadditivities, nonlinearities, and nonmetric predictor variables.² An alternative but less convenient technique would have been to use dummy variable multiple regression.

Multicollinearity

Multicollinearity refers to the fact that there may be correlations among the predictor variables. Unless the correlations are very high, multivariate techniques such as multiple regression and multiple classification analysis handle it routinely and provide parameters (regression's b's and β 's and MCA's effect coefficients) that "hold constant" the effects of all other predictors.

In a study such as this, however, high or even perfect multicollinearity can easily occur and must be guarded against. The

² MCA is included in OSIRIS, MICROSIRIS, and SPSS.

problem can be easily illustrated: if the combinations of item characteristics (which are the predictor variables in the meta-analysis) are always as given below, one could not distinguish the effect of the number of categories and the position of the item in the interview because these two characteristics always go together:

- 3 categories and near the beginning of the interview
- 4 categories and in the middle of the interview
- 5 categories and near the end of the interview.

This is an extreme example of overlap that completely confounds number of categories and position in questionnaire. However even the following involves a problematic instance of multicollinearity:

- 3 categories and near the beginning of the interview
- 4 categories and at the middle or end of the interview
- 5 categories and at the middle or end of the interview.

In this case, the effects of using a four- or five-category scale and the effects of being in the middle or at the end of the interview can be distinguished, but the effects of using a 3-category scale cannot be distinguished from a position near the beginning of the interview.

It is helpful to consider this situation as a bivariate frequency table. In table 1, the X's indicate cells in which some cases (survey measures) fall, and the O's indicate cells that have no cases.

table 1: A problematic instance of multicollinearity

	3 categories	4 categories	5 categories	
beginning	X	0	0	
middle	О	X	X	
end	О	X	X	

The problem arises because the only cases in the top row also fall only in the left column. Whenever there is a unique row-column combination, the respective categories will be confounded, and it will be impossible to distinguish their separate effects. (Other problems of multicollinearity involving three or more predictors can also arise, but if one has guarded against the occurrence of two-variable problems such as that illustrated above, the more complex ones will be quite rare.)

The "solution" to the multicollinearity problem is, ideally, to prevent it from occurring. This requires that one has control over the design of the data set and that one thinks through in advance the nature of the meta-analysis that will eventually be performed. The literature on experimental designs includes potentially useful suggestions on this matter.

If prevention is not feasible, then one must examine the data one has actually obtained to identify instances of overlapped categories. One can then collapse predictor variable categories or eliminate whole predictor variables to eliminate any problems that appear.

For the meta-analysis reported in Andrews (1984), several predictor variables had to be eliminated and several categories collapsed (as described in footnote 18 of that article). Although all the most serious problems were solved, I have since come to suspect that the surprising empirical results for the "20+" category of number of scale categories might be a multicollinearity artifact involving the predictor that records category labeling.

Nonadditivity

A technique that would handle anticipated statistical interactions (nonadditivities) was needed because it was expected that the effect of the length of the question on validity would depend on the length of the introduction to that question. If a long introduction was used, it was expected that question length might relate negatively to validity, but if the introduction was short the length of the question could relate positively to validity. The underlying idea is a simple one: that there is an optimal amount of information to be presented to a respondent, and that long introductions combined with long questions may present too much information, while short introductions combined with short questions may not present enough.

To allow this interaction effect to be handled within MCA, the two original predictor variables (question length and Introduction length) were combined into a single "pattern variable", and the pattern variable was then used as one of the predictor variables in the MCA analysis. The pattern variable was constructed by first bracketing each original variable into three categories (long, medium, and short, the exact definitions for these appear on page 431 of Andrews, 1984), and then representing the nine possible combinations of these two sets of three categories as a single 9-category variable. Using the pattern variable, the MCA analysis did show the expected interaction.

Nonlinearity

Some nonlinear effects were also expected. For example, the very first questions in a survey are frequently suspected of providing less good measurements than later questions because the respondent and interviewer are just beginning to learn how to work together and establishing rapport. Similarly, the final questions in a long interview may provide poorer measurements because the respondent and/or the interviewer may have become fatigued. Thus one would expect a curvilinear (an inverted-U) relationship between validity and the position of the question in the interview. This did appear in the MCA analysis.

Nonmetric variables

Another problem in the meta-analysis is that many of the predictor variables are nonmetric variables. Some are pure nominal variables (e.g., wether the data were collected using face-to-face interviews, telephone interviews, or group-administered questionnaires) and other predictors had a limited set of ordered categories. MCA is designed for such predictor variables.

SUBGROUP ANALYSIS

In the next part of this presentation I will discuss the subgroup analysis that was included in the original study and present some results that have never been published so far.

As noted above, developing measurement quality estimates for contrasting (and perhaps overlapping) subgroups of the respondents has two attractive features: it provides more cases for use in the meta-analysis and it provides an opportunity to see how subgroup membership relates to the measurement quality estimates.

All together I was able to look at 52 different subgroups. (Adding in estimates obtained from the total set of respondents brings the total to 53 groups.) These are shown in table 2. As one can see, groups were defined on the basis of a wide variety of sociodemographic and survey-processing variables. An attempt was made to define the same subgroups among respondents to each of the six surveys that I used, but this was not always possible and hence some subgroups are defined in only a subset of the surveys.

table 2: Effects of respondent characteristics on data quality

	number of estimates	validity	method effect	residual error
group:				
all respondents together	106	.011	.00	.00
education:				
0-11 years	82	04	.01	.06
high school (or HS plus tech.)	63	.00	.01	01
some college	63	.03	04	02
bachelors degree or more	87	.03	.00	05
grade school to some college	24	00	.01	.00
some college or more	19	.04	03	03
age:				
18-34 (or 18-30)	106	.02	02	02
35-54 (or 31-56)	87	.00	01	00
55-90	82	04	.03	.05
65-70	19	06	.05	.05
71-90	19	08	.11	.03
race:				
white	82	.01	01	01
black	82	04	.01	.04
sex:				
female	106	00	.00	.00
male	106	.01	.00	01
where respondents grew up:				
rural	24	01	01	.01
suburban	24	01	04	.02
urban	24	.02	.01	04
seniority in firm X:				
0-4 years	24	.00	.01	01
5 or more years	24	00	01	.00
interviewer's ratings:				
resp.'s interest high	82	.02	01	03
resp.'s interest low	82	03	.02	.02
-	19	.03	02	03
resp.'s intelligence high resp.'s intelligence low	19	.03 00	02 .01	.03
•				
resp.'s sincerity high	19	.02	02	01
resp.'s sincerity low	19	01	.03	.01
resp.'s suspiciousness high	19	.01	01	02
resp.'s suspiciousness low	19	.01	04	00
resp.'s reluctance high	9	.01	08	.02
resp.'s reluctance low	9	00	.03	01
0.4				

SOME OBSERVATIONS ON META-ANALYSIS OF MTMM STUDIES

table 2: (continued)

table 2. (continued)	number of	validity	method	residual
	estimates		effect	error
respondents own ratings:				
interview seems long	9	03	.04	.03
interview seems short	9	.01	02	01
interest in survey high	9	02	06	.03
interest in survey low	9	.01	.04	03
importance of survey topics his	gh 24	00	.02	.00
importance of survey topics lov	w 24	00	02	00
survey's expected impact high	24	00	.01	00
survey's expected impact low	24	00	01	.01
assistance by interviewer:				
none or once	12	.02	01	02
twice or more	12	05	.08	.05
clarifications requested:				
none or once	9	.01	.03	02
two or more	9	03	12	.06
questions repeated:				
none	9	01	.04	00
a few to many	9	.00	01	01
was resp. interviewed by SRC before		210	nan-a	
no	54	.01	.00	01
yes within 6 months	54	.01	00	00
number of attempts to reach resp.:			0.4	0.4
one	73	.01	01	01
five or more	73	.01	01	01
special interviewing techniques:	~	04	00	01
none, standard methods	9	.01	03	.01
spec. instructions, commitment		01	.04	01
resp.'s concern for social desirability		01	01	02
high low	51 51	01 .02	.01 .01	.02 03
		.02	.01	03
explanatory power of 53 groups abo	ve:	10	14	0E
eta ² adj.		.12	.16.	.05

statistical significance:

By conventional tests of significance, a difference between these means is significant at the p=.05 level, if the difference is at least .02 and N's are at least 50, or the difference is at least .03 and N's are at least 25, or the difference is at least .05 and the N's are about 10. Standard errors for the coefficients are about .007 when N is 100, .010 when N is 50, and .020 when N is 10; see text.

¹ The coefficients show deviation from the mean associated with membership in the designated category after effects of 13 survey design characteristics have been removed.

Because the subgroups that could be defined differed from survey to survey, and because the design characteristics of the survey measures also differed from survey to survey, it was possible that the group-defining variables might be related to one or more of the design characteristics. This problem was solved by using a two-step analysis: The design characteristics were used first to explain all the variance they could in the measurement quality estimates, then the group characteristics were used to explain as much of the remaining (i.e., residual) variance as they could. The survey design variables explained 66% - 72% of the variance in the measurement quality estimates (as reported in table 5 of my 1984 article), and the group characteristics explained an additional 5% - 16% of the remaining variance (as shown in table 2).

On the whole, the subgroup analysis shows that the effects of the grouping variables are relatively small, but interesting results in expected directions are found in many instances. The largest effects are found for education and age. As one can see, less educated respondents and older respondents tended to provide somewhat less valid data. (Although table 2 does not report a multivariate analysis, another analysis, not shown, indicated that each of the above effects persisted even when the other was held constant.) The results of this analysis stimulated further research into the effects of age. Using other data, results reported by Andrews and Herzog (1986) and by Rodgers, Herzog, and Andrews (1988) show that this "age effect" is replicable, and we are currently trying to identify the conditions that affect its impact.)

One of the concerns that, very properly, has been raised about combining measurement quality estimates from overlapping subgroups analyses in single meta-analysis is that the measurement quality estimates are not independent of one another. This makes it very difficult to obtain a reasonable standard error for the subgroup differences and hence difficult to assess the statistical significance of any effects that emerge. Given the exploratory nature of my own work, I chose to disregard this problem and focus on the trends that emerged. However, recently I have obtained an answer to the question whether the trends shown in the entire data set I used (which included all the overlapping subgroups) would be the same as the trends in a "pure" data set consisting only of estimates from the total groups (i.e., excluding estimates from all the subgroups).³

³ I am indebted to participants at the Amsterdam conference in February 1989 and to my colleague Willard Rogers for pushing this issue, and to Rodgers for performing the analysis.

The answer is a reassuring "yes": the trends shown in a metaanalysis based only on the much smaller but "purer" set of cases from the total groups are virtually identical to those reported in table 6 of my 1984 article. Table 3 presents both the originally published results obtained from the large "messy" data set, and the new results obtained from the small but "pure" data set.

SUMMARY AND CONCLUDING COMMENTS

An abstract discussion about meta-analysis of MTMM data can make the matter sound complex and difficult. However, being clear about a few key ideas and applying standard procedures for the analysis of a dependent variable with multiple predictor variables will resolve most of the problems. This presentation has tried to emphasis these points.

One needs to recall that a "case" for the meta analysis consists of a survey measure as applied to a set of respondents. The measure is defined by a survey question that assesses a particular topic, which we call a "trait" in the multitrait multimethod parlance, and that uses a particular measurement method. Each case is described by a set of variables. The dependent variables are estimates of the measurement quality with which the given trait was assessed using the given method in the given group of respondents. The independent variables include characteristics of the survey design, of the topic being assessed, and of the respondent group.

The analysis itself is straightforward so long as one uses a multivariate technique that is appropriate for the data. There are likely to be multicollinearities among the predictor variables (perfect overlaps must be avoided), nonadditive effects, curvilinear relationships, and categorical predictor variables. Multiple Classification Analysis or Dummy Variable Multiple Regression, each in combination with pattern variables to handle the interaction effects, are appropriate techniques.

Analyzing overlapping subgroups of respondents is a useful way to generate more cases for the meta-analysis and to be able to explore the effects of subgroup membership on data quality. The overlaps among the subgroups create a statistically messy data set, but (so far) no evidence has emerged that the basic trends become seriously biased.

table 3: Comparison of MCA coefficients and MCA β's from metaanalyses using (1) "total" groups only (N=106) and (2) "all" groups (including overlapped subgroups (N=2115)

	concepts		met	methods		theta (sqrt)	
characteristic	total	all	total	all	total	all	
RESPONSE SCALE							
number of categories (β)	.61	.56	.88	.68	.77	.74	
2		06		.11	.11	.04	
3		13	04	05	.23	.22	
4-5	.03	.04		.01	05	06	
7	.01	.00	03	02	.01	.04	
9-19	00	.01	.19	.21	09	07	
20+ or actual	.13	.14	14	13	21	28	
explicit DK (β)	.32	.31	.56	.45	.22	.30	
no	03	04	.05	.04	.04	.06	
yes	.08	.09	10	11	10	14	
category labeling (β)	.32	.27	.30	.28	.14	.15	
all labeled	03	04	.03	.04		.03	
some labeled		.08	08	09	08	10	
explicit midpoint	.03	.01	.06	.06	.01	.00	
no	.03	.02	.04	.05	02	.01	
yes		01	01	02	.01	01	
ITEM CHARACTERISTICS							
absol. vs. comp. (β)	.30	.28	.08	.15	.38	.33	
absolute		04	.02	.01		.07	
comparative	.06	.07	03	02	10	11	
length intro/quest (β)	.10	.13	.37	.35	.09	.10	
sh/sh		05		01		02	
sh/med		05	.04	.03	.07	.08	
sh/long	.00	01	02	03	.02	.05	
med/sh	.01	.03	.07	08	03	04	
med/med	.04	.06	07	08	06	07	
med/long	.04	.06	08	09	02	05	
long/sh	.00	00		.05	01	00	
long/med		.00	.06	.07		00	
long/long		03	.06	.07	.05	.06	
QUESTIONNAIRE DESIGN							
battery length (β)	.17	.17	.24	.19	.28	.44	
1 item (not battery)		.03		04	06	10	
2-4 items		.05	.01	.02	09	11	
5-9	02	03	02	03	.06	.09	
10 or more	06	07	.09	.10	.08	.14	

SOME OBSERVATIONS ON META-ANALYSIS OF MTMM STUDIES

table 3: (continued)

	<u>con</u>	CHUIC				thata (sart)	
	concepts			methods		theta (sqrt)	
characteristic	total	all	total	all	total	all	
position in quaire (β)	.12	.13	.24	.18	.11	.16	
1-5	02	01				.03	
6-25		02		02	.04	.05	
26-35	.03	.04		01	.05	07	
36-39	.01	.02		03	.01	03	
40-100	.03	.04		05	06		
101-200	03	04		.07	.05	.08	
201-348	04	06	.05	.06	.04	.08	
data coll. procedure	.07	.03	.29	.24	.01	.02	
telephone		01	00	02		.01	
F-T-F		.00	.09	.10	.00	01	
group adm	.00	.04	07	05	02	.04	
TOPIC CHARACTERISTIC							
soc. des. sens. (β)	.07	.07	.01	.00	.08	.08	
low or medium	01	02		.00	.02	.03	
high	.04	.05	01	00	07	08	
content specificity	.08	.06	.01	.00	.06	.04	
low		03		.01	.03	.04	
medium		01		00		.02	
high	.03	.02		01	04	03	
experience vs. predict	.01	.01	.00	.00	.01	.01	
actual experience		.00	.00	00		01	
predictions		02	,,,,,,	00		.04	
content salience	.01	.01	.00	.00	.00	.00	
low	.00	.01		01		01	
medium		.01		00	00	.00	
high		01		.01	.00	.01	
R ²	.69	.66	.88	.72	.66	.67	

A blank in the "total" column means MCA coefficient matches the "all" column.

Meta-analysis of measurement quality estimates can provide extremely interesting answers to the questions of to what extent (and in what ways) does survey measurement quality relate to the design and administration of survey research.

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