Validating the Cross-Validation: A 3-Dimensional Model for Multiple Informant Data (3D-MMID)

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Conceptual validation is always an issue of measurement in social and clinical sciences. Social scientists and clinicians are of the view that sometime single source is not enough to cater a concept [1] either due to potential biasness or partial involvement/contact with the target population [2]. Although almost all social science disciplines face the issue at some time, mainly research in developmental psychology & psychopathology meets the said challenge often [5, 6]. That is because many of the researched constructs/variables in question can be measured only by involvement of more than one source [2]. For instance, to measure adolescents' behavioral problems data may be required from home environment as well from school environment. Another variation might be that from the same environment (i.e., home) data is required from both parents on the same construct as studies shows that father and mother reports differ for a child's underlying state [11]. This issue is of the concern in a situation where subjective involvement is required rather than objective measurement of a physical status or medical condition [10]. For instance, exploration on a question of interest "how much stress is faced by an individual?" may require involvement of all stake holders in one's life (i.e., self-report, parent / partner / practitioner report, teacher / colleague / boss report).

A variety of solutions to the multi-informant data have been presented [2,10]. Some suggested the use of optimal source [4,13], and ignoring others which actually means there is no need to collect data from other sources. The decision that which source is optimal shall be made at the time of designing the project [10]. Another frequently used method is to use data from all sources separately [7,9], which most of the time increases confusion rather than converging the problem. As concluded in a review article using multi-informant, that there is low to medium level of correlations between informants (i.e., Teacher-Parents = .27; Self-Peer = .26 etc.) [2]. Correlations only for the same informants appeared above .50 (i.e., Parent-Parent = .59; Teacher-Teacher = .64 etc.) [2]. Another way to combine multi-informant data is pooling. Various methods of pooling have been introduced and algorithms have been developed to commence a solution for multi-informant data [4,10 ,12]. For instance the "And" "Or" rules, the "And" rule suggest that information is accepted only if presented in reports of all informants whereas "Or" rule suggest that an information is considered if any of the source reported it [10,13]. The "And" rule costs sensitivity and the "Or" rule costs specificity. Although depending on the nature of the research question any of the method can be a more preferable solution over the other yet this type of pooling offer solution only for dichotomous scales/variables.

Another method of pooling is averaging the scores [3], which can be used for continuous scales but has its' own pros and cons. This type of pooling is seriously affected with outliers; additionally it loses a lot of information. Let's consider an example: on a five point Likert scale an adolescent (A) is rated at 4 by his teacher and rated 2 by his parent, the resulting average score will be 3, on the other hand an individual (B) who is rated 3 by both parent and teacher also results on an average score of 3. None of the informant rated the two cases as same but using the average method, the researcher considers both cases as same which is not only loss of information, rather it also indicates that to the researcher none of the informant is reliable as the method researcher used is not representative of any or both of the informants.

Others presented more complex algorithms, for optimal use of multi-informant data [8,10]. Most of the solutions presented for composite score and to the extent of my knowledge, so for there is not a single method addressing the issue at the scale level. This study is an effort to develop a method for use of multi-informant data at the scale level hence retaining all the scale characteristics. The study is aimed to advance the pooling methods by overcoming some of its shortcomings. In terms of optimal informant, a method is presented which accounts for informant error and in terms of averaging the method is modified to preserve the distinct position of each individual.

The example being used here include parent rated and teacher rated problem behaviors. Both parent and teacher reported on a 5 point Likert type scale. The pooling was conducted on three steps and is reported as such.

Step 1

An agreement scale was computed based on the following matrix. The matrix is produced by cross-tabulating the two informants.

Agreement		Parents				
		1	2	3	4	5
Teacher	1	5	4	3	2	1
	2	4	5	4	3	2
	3	3	4	5 (B)	4	3
	4	2	3 (A)	4	5	4
	5	1	2	3	4	5

Although the example presents two informants, the SPSS syntax to compute an agreement scale can be extended to as many informants as included in the study. This step accomplishes the horizontal stretch of the concept/construct.

Step 2

At the second step, the researcher needs to decide whether he/she want to use one optimal source or both sources. In case of using one optimal source the data can be corrected for potential bias simply by multiplying the agreement score with the score of the informant. For instance, in parent report, conflict on item was reported by parents as 4, whereas adolescent reported conflict on the same item as 3. Using the cross-tabulation, the agreement score for the item emerges as 4. If the researcher now wants to use parent report, the parent reported intensity i.e., 4 shall be multiplied with the agreement score hence 4*4=16. To use adolescent perspective, adolescent reported intensity shall be multiplied with the agreement score that is 3*4 =12. This type of pooling corrects report of an optimal informant for the potential biasness. But in case, the use of multi-informant is based on the fact that one informant is not sufficient to cater the concept, then this type of pooling is not useful. In such situation, the second step would be to generate an average intensity measure simply by averaging two reports i.e., (i1+i2)/2. An average report measure of such a five points Likert scale looks as shown below.

Intensity		Parents				
		1	2	3	4	5
Teacher	1	1	1.5	2	2.5	3
	2	1.5	2	2.5	3	3.5
	3	2	2.5	3 (B)	3.5	4
	4	2.5	3 (A)	3.5	4	4.5
	5	3	3.5	4	4.5	5

This step accomplishes the vertical stretch of the concept/construct.

Step 3

To grab the three dimensional sight of concept/construct, a final step involves combining the two matrices. This step can simply be accomplished by multiplying the agreement scale with the average scale, resulting into a 3D-MMID (a 3 dimensional model for multi informant data).

Agreement * Intensity	5	6	6	5	3
	6	10	10	9	7
	6	10	15 (B)	14	12
	5	9 (A)	14	20	18
	3	7	12	18	25

Considering the case reported earlier: on a five point Likert scale an adolescent (A) is rated at 4 by his teacher and rated 2 by his parent, the resulting average score will be 3, on the other hand an individual (B) who is rated 3 by both parent and teacher also results on an average score of 3. None of the informant rated the two cases as same but using the average method, researcher considers both cases as same. Now look at the situation, the first individual gets a score of (3*3)=9, whereas the second individual gets a score of (5*3)=15, both the individual are reported different by both the raters and their score as computed by 3D-MMID also presents them as different individuals compare to the average method which reports the two cases similar. Though not the perfect solution, the resulting matrix solves most of the issues of the average method yet a conceptual analysis of the resulting 3D-MMID matrix raises other issues. Analyzing the first row of the resulting matrix, we can see that 2nad and 3rd cell of the row presents two cases as similar but they are not similar. That is they are rated similar by teacher but rated different by teachers. Another more severe problem emerges by comparing 1st and 5th cells of first row. The 1st cell is presenting a subject for whom both teacher and parents agree on the lowest probability of presence of a problem behavior. Comparatively, 5th cell present a case where though one source (parent) report lowest probability of presence of that problem behavior yet at least one source (teacher) reports the highest probability of presence of the same problem behavior. A conceptual analysis of the two situation suggest that the child facing the situation in 5th cell is more vulnerable to have the particular problem behavior than the child facing the situation presented in 1at cell, yet our 3D-MMID matrix suggest opposite results i.e., rating the child in 1st cell at 5 and rating the child in 5th cell at 3. To solve these issues agreement matrix was revised by placing a magnitude of 0.6 for lowest agreement and 1.0 for highest agreement. The resulting agreement matrix is presented below:

Agreement		Parents				
		1	2	3	4	5
Teacher	1	1.0	0.9	0.8	0.7	0.6
	2	0.9	1.0	0.9	0.8	0.7
	3	0.8	0.9	1.0 (B)	0.9	0.8
	4	0.7	0.8 (A)	0.9	1.0	0.9
	5	0.6	0.7	0.8	0.9	1.0

Step 3 the multiplication step was revised to generate new interaction matrix which resulted as:

Agreement * Intensity	1	1.35	1.6	1.75	1.8
	1.35	2	2.25	2.4	2.45
	1.6	2.25	3 (B)	3.15	3.2
	1.75	2.4 (A)	3.15	4	4.05
	1.8	2.45	3.2	4.05	5

The final 3D-MMID-R matrix resolved all the issues raised in the previous version of the matrix. As presented in matrix 5, not only that subject A and B are rated differently, values in different cells are also more representative of the respective position of subjects.

Example Scales

Two data sets are presented as example cases. Adolescents with type 1 diabetes and their parents rated Parent-Child conflicts on a 17 items, 5 point Likert type scale and a 29 items family responsibility questionnaire. Descriptives of the scales are presented for 7 types of computed scores. 1. Parents reports, 2. Adolescents report, 3. Average score, 4. Parents report corrected for adolescents perspective, 5. Adolescent report corrected for parents perspective, 6. 3D-MMID scores using the 3rd matrix, and 7. 3D-MMID-R scores using the 5th Matrix.

Parent-Child Conflict:

	N	Mean	S.E	S.D	Variance	Skew	S.E	Kurt	S.E	Alpha
Adolescent report	411	29.30	0.36	7.24	52.43	0.92	0.12	1.49	0.24	0.84
Parent reported	432	30.44	0.43	8.98	80.57	0.86	0.12	0.46	0.23	0.81
Average score	408	29.79	0.35	6.99	48.87	0.86	0.12	1.28	0.24	0.84
Parents corrected for adolescent	408	27.11	0.32	6.42	41.17	1.06	0.12	2.44	0.24	0.82
Adolescents corrected for parents	408	27.83	0.36	7.28	53.04	0.79	0.12	0.87	0.24	0.93
3D-MMID Conflict	408	125.75	1.38	27.87	776.64	1.43	0.12	4.36	0.24	0.79
3D-MMID-R Conflict	408	27.47	0.30	6.09	37.04	1.14	0.12	2.76	0.24	0.82

Family Responsibility:

	N	Mean	S.E	S.D	Variance	Skew	S.E	Kurt	S.E	Alpha
Adolescent report	386	71.70	0.96	18.77	352.24	0.27	0.12	-0.20	0.25	0.92
Parent reported	386	93.96	1.01	19.77	391.00	-0.13	0.12	-0.19	0.25	0.93
Average score	322	83.35	0.33	5.93	35.11	-0.26	0.14	1.05	0.27	0.73
Parents corrected for adolescent	322	61.09	0.75	13.37	178.75	-0.35	0.14	-0.19	0.27	0.73
Adolescents corrected for parents	322	46.89	0.72	12.86	165.28	0.33	0.14	-0.03	0.27	0.88
3D-MMID responsibility	322	206.30	2.48	44.44	1974.91	0.04	0.14	-0.39	0.27	0.68
3D-MMID-R responsibility	322	53.99	0.33	5.86	34.39	-0.24	0.14	1.02	0.27	0.72

Conclusion

The polling method presented as 3D-MMID-R captures individual differences very well and as well presents a reliable solution to multi-informant data and shall be preferred on average method.

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