Psychological Test and Assessment Modeling, Volume 55, 2013 (4), 438-461

Multiple intelligences: Can they be measured?

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Abstract

This paper is about issues relating to the assessment of multiple intelligences. The first section introduces the authors' work on building measures of multiple intelligences and moral sensitivities. It also provides a conceptual definition of multiple intelligences based on Multiple Intelligences theory by Howard Gardner (1983). The second section discusses the context specificity of intelligences and alternative approaches to measuring multiple intelligences. The third section analyses the validity of self-evaluation instruments and provides a case example of building such an instrument. The paper ends with concluding remarks.

Key words: Giftedness, multiple intelligences theory, MIPQ, CFA, Bayesian modeling

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Introduction

In this paper, we introduce our work on building measures of multiple intelligences and moral sensitivities based on the Multiple Intelligences theory of Howard Gardner (1983, 1993). We have developed several instruments for self-assessment that can be used in educational settings (Tirri & Nokelainen, 2011). Gardner's theory of Multiple Intelligences (MI) focuses on the concept of an 'intelligence', which he defines as "the ability to solve problems, or to create products, that are valued within one or more cultural settings" (Gardner, 1993, p. x). Gardner lists seven intelligences that meet his criteria for an intelligence, namely linguistic, logical-mathematical, musical, spatial, bodily kinesthetic, interpersonal, and intrapersonal (Gardner, 1993, p. xi).

In a broad sense, Gardner views his theory as a contribution to the tradition advocated by Thurstone (1960) and Guilford (1967) because all these theories argue for the existence of a number of factors, or components, of intelligence. All these theories also view intelligence as being broader and multidimensional rather than a single, general capacity for conceptualization and problem-solving. Gardner differs from the other pluralists, however, in his attempt to base MI theory upon neurological, evolutionary, and cross-cultural evidence (Gardner, 1993, p. xii). In the first edition of his MI theory, thirty years ago, Gardner (1983) adopted a very individualistic point of view in exploring various intelligences. In a newer edition of MI theory, however, Gardner (1993) places more emphasis on the cultural and contextual factors involved in the development of the seven intelligences. Gardner retained the original seven intelligences, but acknowledged the possibility of adding new intelligences to the list. For example, he has worked on an eighth intelligence – the intelligence of the naturalist – to be included in his list of multiple intelligences (Gardner, 1995, p. 206).

Robert Sternberg identifies Gardner's MI theory as a systems approach, similar to his own triarchic theory. Although he appreciates Gardner's assessments at a theoretical level, he believes them to be a psychometric nightmare. The biggest challenge for advocates of Gardner's approach, then, is to demonstrate the psychometric soundness of their instrument. Sternberg is calling for hard data that would show that the theory works operationally in a way that will satisfy scientists as well as teachers. Sternberg's own theory promises the broader measurement implied by the triarchic theory (Sternberg, 1985). His theory provides "process scores for componential processing, coping with novelty, automatization, and practical-contextual intelligence, and content scores for the verbal, quantitative, and figural content domains" (Sternberg, 1991, p. 266).

Sternberg's observations on Gardner's theory should be kept in mind in attempts to create tests based on his theory. However, in the educational setting his theory can be used as a framework in planning a program that would meet the needs of different learners (Tirri, 1997). Gardner has shown a special interest in how schools encourage the different intelligences in students (Gardner, 1991). Gardner's theory has been applied in educational settings and in schools (see, e.g., Armstrong, 1993). Nevertheless, Gardner warns against using his theory as the only educational approach. There is no single way to adapt his theory, but he has given some guidelines for the possible uses of his theory in schools (Gardner, 1995, pp. 206-209).

Measuring multiple intelligences

According to Moran and Gardner (2006), multiple intelligences can interact through interference, compensation or catalysis. *Interference* means that weakness in one intelligence area may hinder the actualization of full potential on another intelligence area. For example, a musically gifted student with weak self-regulatory (intrapersonal) abilities may have difficulties learning piano compositions because she cannot concentrate during practice. By contrast, through *compensation* strong intelligence areas may support the weaker ones. We all know that some popular contemporary music artists are better at writing music than they are at writing lyrics – and *vice versa*. *Catalysis* is the third form of interaction where one intelligence amplifies the expression of another. In this case, a student may use his bodily-kinesthetic intelligence to play the drumset (bodily-kinesthetic intelligence catalyzes both musical and logical-mathematical intelligences).

These different interaction types indicate that multiple intelligences should neither be assessed solely in a linear fashion nor without considering the effect of context. For example, a student who receives low grades at school for sports (bodily-kinesthetic intelligence) may be a top ice hockey player outside school hours in a local team as she is interested in only one aspect of that school curriculum area. Shearer's (2009) review, based on data from 22 countries, shows many different context-specific ways of assessing multiple intelligences, for example, with structured interviews or self-report as well as using significant others as informants. His own Multiple Intelligences Developmental Assessment Scales (MIDAS) self-report questionnaire produces both a qualitative and quantitative profile of a student's multiple intelligences.

According to Moran and Gardner (2006), the context effect may also apply to students who do not perform well in tests: "their linguistic intelligence of reading and writing may interfere with the expression of whatever content the test is assessing" (p. 126). This might be an indicator of both multiplicative and additive effects of intelligences. Our studies showing correlations among intelligences support this assumption (e.g., Tirri & Nokelainen, 2008).

Self-evaluated multiple intelligences

In our instrument development work, Gardner's Multiple Intelligences theory (1983) is the framework to build tools for students' self-evaluation. Self-evaluated intelligence is closely related to a person's self-concept (SC). According to leading researchers, self-concept has a two-factor structure: general self-concept and academic self-concept (Shavelson, Hubner, & Stanton, 1976). Byrne and Gavin (1996) argue that SC is a multidimensional construct, which in their study comprised the four facets of general, academic, English, and mathematics self-concepts. Self-evaluated intelligence can reflect both the general and academic components of a person's self-concept. Furthermore, self-evaluated intelligence is closely related to a person's self-esteem and self-confidence. The concept of self-efficacy also needs to be acknowledged in the context of self-evaluation. According to Bandura (1978), self-efficacy is specific to a particular activity or situation, in contrast to global beliefs like self-concept.

In our research, we concentrated on self-evaluations of intelligence within the Gardnerian framework. We assumed that students reflect both general and academic self-concepts in their self-assessments of their strengths and weaknesses. According to Moran (2011), MI self-report measures filter assessment of the other intelligences through intrapersonal intelligence by providing indicators of both the intelligence that is being measured alongwith the person's perception of that intelligence. This information may help students to understand their self-regulation processes better.

Intelligence may be “a nightmare” as a target for self-evaluation. In addition to measurement issues related to reliability and validity, the creators need to define what they mean by the concept ‘intelligence’. In our work, we argue that students’ perceptions of and beliefs about themselves as learners, together with their intertwined affective experiences of self in relation to all areas of the seven intelligences presented in Gardner’s theory, are the primary dynamic aspects in their personal learning processes. According to Malmivuori (2001, pp. 59-78), beliefs and perceptions of self constitute the most central cognitive feature or determinant behind students’ personal understandings, interpretations, and self-regulation. Hence, we claim that self-evaluated intelligence, which entails students’ own perceptions of and beliefs about themselves as learners, can serve as an empowering tool in their studies. Self-evaluation has been shown to be less threatening than evaluations completed by the teacher or somebody else (Tirri, 1993). Furthermore, self-evaluation is a viable starting point in the process of learning new things. Self-evaluation can be viewed as a form of evaluation that suits an autonomous, reflective student in continuous growth and development. It is easy to implement because it does not require large investment of personnel or financial resources. In the context of virtual teaching and learning, self-assessment can provide some of the guidance and feedback that students and teachers need in the teaching-studying-learning process.

Next we will describe a detailed example of the psychometric validation process of the Multiple Intelligences Profiling Questionnaire (MIPQ, see e.g., Tirri & Nokelainen, 2008, 2011; Tirri, K., Komulainen, Nokelainen, & Tirri, H., 2002, 2003).

Development of multiple intelligences profiling questionnaire

In this section, we explore the development (e.g., DeVellis, 2003) of a self-evaluation instrument based on Gardner’s Multiple Intelligences theory (1983, 1993) with two empirical samples (*n* = 408).

The first sample (*n* = 256) was drawn from students from five different Finnish universities. The students represent different disciplines, such as teacher education, forestry, and computer science. These participants responded to the original questionnaire that consisted of 70 items operationalized from Gardner’s theory. The participants used a 7-point Likert scale to assess their strengths on ten items for each of the seven intelligence dimensions (1 = Totally disagree … 7 = Totally agree). According to a simulation study by Johnson and Creech (1983), discrete indicators work quite well with continuous variables (such as the seven MI dimensions). They noted that while categorization errors do cause distortions in multiple indicator models, the bias under most of the conditions explored was insufficient to alter substantive interpretations. The complete set of items is listed in the Appendix.

The second sample (n = 152) was drawn from Finnish secondary level vocational students who have participated in international vocational skills competitions (WorldSkills, see Nokelainen, Smith, Rahimi, Stasz, & James, 2012). They represent different skills areas, such as hairdressing, gardening, web design, robotics and caring. These participants responded to the optimized version of the questionnaire that consisted of 28 items. The participants used a 5-point Likert scale to assess their strengths on four items for each of the seven intelligence dimensions (1 = Totally disagree … 5 = Totally agree). These items are marked with an asterisk symbol in the Appendix.

We begin by using the first sample discussing the composition of items and their relationship to the theory. Then we describe the exploratory optimization process that was used to transform the item pool of 70 statements to the final 28-item version. Finally, using both samples, we test the scale's structure with data mining (Bayesian) and confirmatory (SEM) techniques.

Analysis of the item level distributions

The validity of a self-evaluation instrument is affected by the same defects as any rating system. In general for rating systems, in addition to halo effects, which are difficult to avoid, the following three types of error are often associated with rating scales: the error of severity ("a general tendency to rate all individuals too low on all characteristics"), the error of leniency ("an opposite tendency to rate too high"), and the error of central tendency (a "general tendency to avoid all extreme judgments and rate right down the middle of a rating scale") (Kerlinger, 1973, pp. 548-549). The general response tendency in our study shows that the students used all the seven response options in their answers. However, if all the items used were stacked into one single column, the distribution of responses into the seven alternatives in the scale could be described as unimodal, platycurtic and negatively skewed. The means (mean level of all items) between subjects (n = 256) varied heavily (min = 2.77, max = 5.86). A two-way mixed-effect ANOVA showed that the between people variation was about 11 % of the all-item mean variation. This focuses on the fact that response set and/or general self-esteem is strongly present in these measurements. The between measures (p = 70) (within people) variation is also quite notable (min = 2.25, max = 5.50), this share being almost 15 % (see Table 1).

The items with the lowest means (e.g., 19, 51, 6) refer to specific actions, such as writing little songs or instrumental pieces, keeping a diary, or forming mental pictures of objects by touching them. All these activities are so specific that it is not surprising that the students have given low ratings on them. The items with the lowest standard deviations (e.g., 44, 28, 35) are such that they do not discern amongst the student population very well. This can be explained by the nature of the items. Most measure general attitudes or

Table 1:
Item Level Distributions.

		M	SD	g_2	g_1
Items stacked (N=17920)		4.46	1.75	-0.84	-0.38
Item means per subject (n=256)	min	2.77	0.92	-1.54	-1.76
	max	5.86	2.29	2.88	0.94
Item means per item (P=70)	min	2.25	1.11	-1.37	-1.13
	max	5.50	2.42	1.69	1.39
Seven items with highest mean (hi -> lo)		3, 16, 59, 13, 37, 35, 29			
Seven items with lowest mean (lo -> hi)		19, 51, 6, 58, 60, 12, 40			
Seven items with highest stdev (hi -> lo)		29, 24, 46, 59, 63, 64, 53			
Seven items with lowest stdev (lo -> hi)		62, 44, 28, 35, 67, 17, 66			

Note. g_2 = kurtosis, g_1 = skewness. See Appendix for item labels.

talents that are needed in academic life. The items refer to the tendency to look for consistency, models and logical series in things, a realistic idea of a person's strengths and weaknesses, and the ability to teach others something you know yourself. The highest rated items included items related to self-reflection and social skills (e.g., 3, 16, 59). This makes sense because university students need the ability to understand their own feelings and motives in order to plan their academic studies. Furthermore, even in academic studies co-operation and teamwork are necessary elements of successful learning (Table 1).

Correlational analysis

The second phase of item analysis was methodologically multi-staged, starting with the correlations and closing with the results of MIMIC-type modeling (see, e.g., Jöreskog & Goldberger, 1975; Kaplan, 2000; Loehlin, 1998). The question is whether the inter-item covariances (correlations) could be reasonably well-conceptualized using Gardner's seven intelligences (or their derivatives). The analysis began by examining the correlation matrix. There were 2415 correlation coefficients when the diagonal and double-presentations were omitted. Their mean was 0.11 and they ranged from -0.74 to 0.81. Both Pearson product moment and Spearman rank order correlations were calculated, but as they produced similar results, only product moment correlations were used in the analyses.

As the average measure intra-class correlation (identical to all-item alpha) was 0.90 in the previous two-way mixed effect model ANOVA, the measurement area could be treated as only one dimension: the level of self-evaluated intelligence. However, it was possible to find relatively independent components in such a seemingly homogeneous set of items. Some deviating correlations caused problems in the methods that were to be used. The high negative correlation (r = -.74) between items 1 and 70 was especially disturbing and a clear outsider in the distribution. The reason for this was that the wording of item 70 contained two dimensions, the first one ("At school, studies in native language or social studies were easier for me …") relating to linguistic ability and the second one ("… than mathematics, physics and chemistry") relating to logical-mathematical ability. For this reason, the wording of item 70 was changed to "At school, studies in native language were easy for me."

There was also a positive tail, indicated by correlations greater than 0.60. This points to many, but rather specific, components in the matrix. The correlative properties of items with other items also differed notably. The column (and row) means of correlations and their dispersion properties (to the other 69 items) show clearly that there were items that cannot be part of any substantive concept or factor. The same phenomenon could be seen in a condensed way in the initial communality values of the items (squared multiple correlation, SMC), and also in the way they loaded onto the first principal component (see Table 2).

The first two criteria omit the items 12, 11, 6, 60 and 57. The third criterion omits item 1, which refers to the school experiences in math, physics and chemistry. This item is not well formulated and is prone to errors. A person might be very good in mathematics,

Table 2:
The Correlative Properties of Items.

	Share with other items		
	M r^2	min	max
	0.036	0.010	0.077
Seven highest (hi -> lo)	14, 15, 32, 62, 55, 61, 2		
Seven lowest (lo -> hi)	12, 11, 60, 6, 69, 64, 57		
	Share with other items		
	M R^2	min	max
	0.592	0.350	0.834
Seven highest (hi -> lo)	62, 15, 14, 32, 33, 29, 25		
Seven lowest (lo -> hi)	12, 6, 20, 11, 57, 60, 64		
	Principal Component Analysis		
	First PC loading	min	max
	0.342	-0.271	0.673
Seven highest (hi -> lo)	32, 49, 14, 22, 15, 26, 2		
Seven lowest (lo -> hi)	1, 54, 39, 27, 12, 38, 67		

Note. See Appendix for item labels.

physics and chemistry, for example, but still not rank them as his/her favorite subjects. Alternatively, multi-talented people might prefer arts and physical education and rate item 1 low for these reasons. It is clear that the enjoyment of an activity and being good at that activity are quite different. Furthermore, as it was the first item in the questionnaire, this might have had an influence on the rating behavior demonstrated by the students (Table 2).

The analysis, however, commenced with the full set of items. In the process towards the final set of items, useless items were dropped predominantly in phases E2, C2 and C3 (see Table 3). At the end of this process, 28 items remained in the seven-dimension final model. We approached the problem by using exploratory (EFA) and confirmatory (CFA) factor analyses. After coming to the tentative view of a plausible number of dimensions, we then added some background variables to the analysis. In the EFA-approach, this is usually done through correlative means, mainly regression analysis. In the CFA-

Table 3:
The Factor Structure Examination Phases.

E1. Exploratory factor analyses using seven factors with varimax and promax rotation.	B1. Bayesian dependency modeling applied to all variables.	C1. Confirmatory factor analysis according to Gardner's conception and various GFI-estimates.
E2. Each of the seven dimensions analyzed in two dimensions and loading plots.	B2. Bayesian dependency modeling applied to each of the seven dimensions.	C2. Each of the seven dimensions as a congeneric scale.
E3. Reliability estimates to the original seven scales.	B3. Bayesian dependency modeling applied to the selected variables (optimized model).	C3. Estimates of reliability.
E4a. Goal/target rotated exploratory factor analysis using the important items by weights.		C4. The seven component model in MIMIC with background variables.
E4b. The chosen EFA-model with background variables using factor scores.		

approach, the final step is completed using SEM-modeling and manifest variables with estimated latent factor scores. We used a Bayesian approach (e.g., Bernardo & Smith, 2000), namely Bayesian Dependency Modeling (BDM, see Nokelainen, 2008), to find with a data mining approach the most probable model of the statistical dependences among all the variables. Besides revealing the structure of the domain of the data, we interactively studied the dependency model by probing it. The approach is summarized in Table 3.

Modeling of the factor structure

In the following, we apply EFA, CFA, MIMIC and BDM to the data. In each step of the statistical analysis we refer to the corresponding cell of Table 3. The first step in the analysis (C1 in Table 3) is the joining of exploratory factor analysis, confirmatory factor analysis and multiple regression models into a MIMIC model (see, e.g., Bijleveld & van der Kamp, 1998).

The Chi-Square Test of Model Fit resulted a value of 5791.16 (df = 2324, p <.001, $\frac{\chi^2}{df} = 2.49$). The root mean square error of approximation (RMSEA) is designed to evaluate the approximate fit of the model in the population (Kaplan, 2000). The estimate 0.076 (C.I. = 0.074 - 0.079) was within the range of fair fit level (0.05 – 0.08), indicating mediocre fit (for details, see Browne & Cudeck, 1993; Hair et al., 1998). The standardized root mean square residuals (SRMR) help the investigator to examine how well the aspects of the data are captured by the model (Loehlin, 2004). The SRMR value of 0.116 indicated some problems in this aspect, as it was above the cut-off value of .08 (Hu & Bentler, 1995). Incremental fit measures compare the proposed model to a baseline model that all other models should be expected to exceed (Hair et al., 1998). Unfortunately the Tucker-Lewis index (TLI = 0.564), also known as the Non-normed Fit Index (NNFI), was clearly below the recommended level of .90 (Tucker & Lewis, 1973). That was also the case with a similar measure, the comparative fit index (CFI = 0.580). Due to such modest fit indices, further modeling was not possible without having more information from the exploratory analyses. For this reason, the following step was then to proceed to E1 (Table 3).

The scree plot of the eigenvalues (of the principal components extracted from the 70*70 correlation matrix) demonstrated, as expected, that there was a strong first component. We found 18 eigenvalues equal to or greater than 1.0, suggesting an 18-component model. Further examinations with EFA (step E1 in Table 3) using ML (Maximum Likelihood) method with both orthogonal and oblique rotations revealed that some items did not share any common component, and the seven-factor solution did not reflect many of the proposed seven multiple intelligence dimensions.

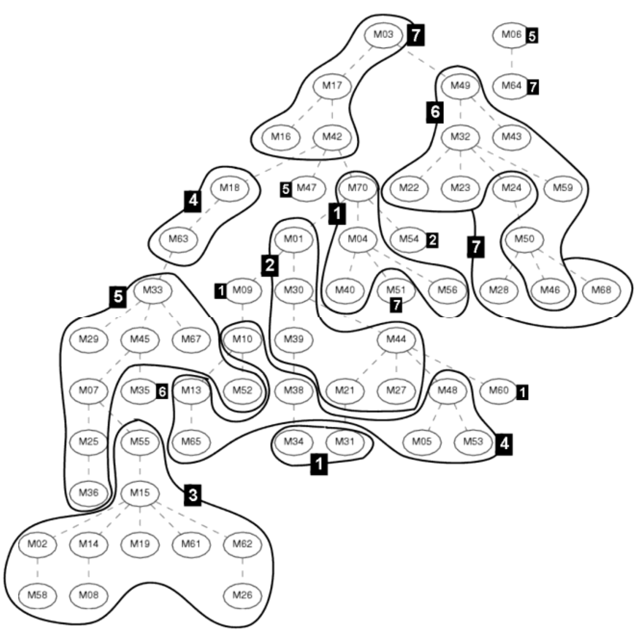
In step B1, we investigated probabilistic dependences among the variables (for variable description see Appendix) with a Bayesian search algorithm (Myllymäki, Silander, Tirri, & Uronen, 2002) in order to find a model with the highest probability. Bayesian Dependency Modeling (BDM) allows the analysis of ordinal indicators, and is able to detect both linear and nonlinear dependencies (Congdon, 2001). BDM produces a Bayesian Network (BN, see, e.g., Heckerman, Geiger, & Chickering, 1995) that is a representation of a probability distribution over the multiple intelligences items.

During the data mining process, 4.027.597 models were evaluated. Table 4 shows a graphical visualization of BN containing two components: (1) observed variables visualized as ellipses and (2) dependences visualized as lines between nodes. Solid lines indicate direct statistical relations and dashed lines indicate dependency where it is not sure if there is a direct or indirect (latent) relation. A variable is considered independent of all other variables if there is no line attached to it.

The first column of Table 4 presents the BN of multiple intelligences variables. The seven intelligences construct quite clear clusters to the network. Each cluster is labeled according to the following list: (1) linguistic, (2) logical-mathematical, (3) musical, (4) spatial, (5) bodily-kinesthetic, (6) interpersonal, and (7) intrapersonal intelligence.

Table 4:
The Initial Bayesian Dependency Model and the Importance Ranking of the Weakest Loading Variables Measuring Self-evaluated Intelligence.

Bayesian Network



Dependency[a]	Probability ratio
M42->M70	1 : 240265
M70->M54	1 : 205727
M25->M36	1 : 162380
M32->M59	1 : 53296
M10->M13	1 : 33827
M70->M04	1 : 31428
M45->M07	1 : 27590
M10->M52	1 : 16768
M30->M39	1 : 12638
M44->M60	1 : 8373
M09->M10	1 : 7246
M01->M09	1 : 6332
M17->M16	1 : 4761
M50->M46	1 : 3585
M44->M48	1 : 892
M18->M63	1 : 719
M14->M08	1 : 483
M06->M64	1 : 238
M42->M18	1 : 186
M45->M35	1 : 116
M49->M43	1 : 106
M44->M21	1 : 79
M63->M33	1 : 71
M50->M68	1 : 34
M21->M31	1 : 33
M04->M56	1 : 33
M30->M44	1 : 32
M50->M28	1 : 25
M42->M47	1 : 18

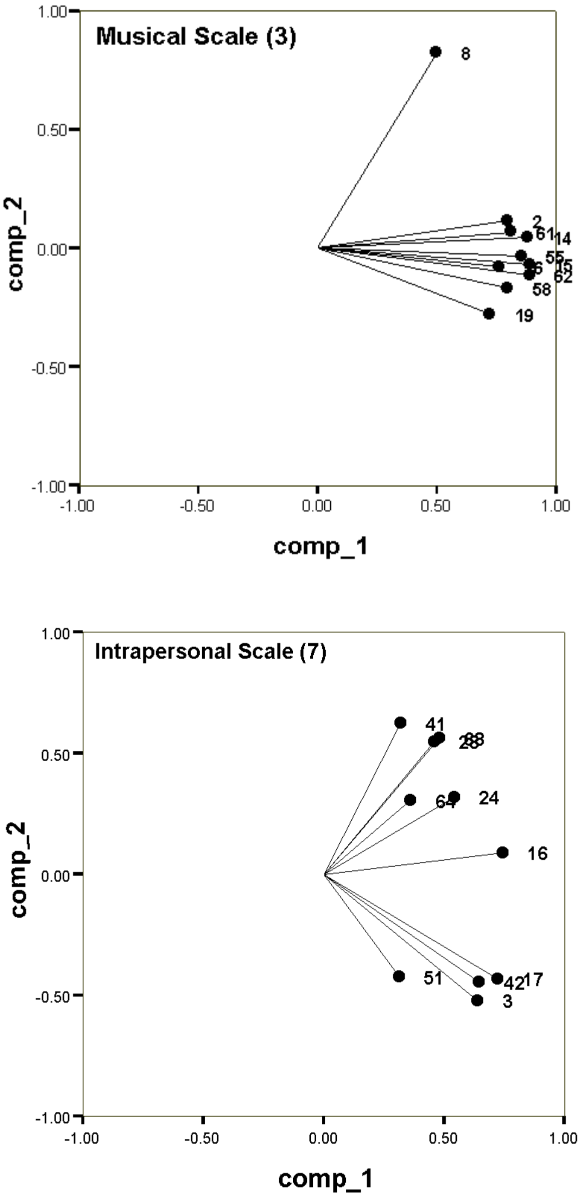
The second and third columns of Table 4 present importance ranking of the variables in the model. The comparison was conducted by slightly changing the final model for each dimension by removing causal relationships between the variables. If the removal made the model less probable, the causal relationship was considered a strong dependency, and if the removal made the model more probable, the causal relationship was considered a weak dependency. In this initial modeling phase only the weakest dependences are listed in decreasing order. Probability ratios indicate how removing an arc affects the probability of the model. If the removal makes the model much worse, that is, less probable, it can be considered an important dependency. If removing the arc does not affect the probability of the model greatly, it can be considered to be a weak dependency. The probability ratios (1 : X) should be read as follows: the final model is X times as probable as the model that is otherwise identical, but in which the dependency has been removed. The conclusion after the Bayesian analysis was almost the same as was found in steps C1 and E1: The factors need to be purified from items, which do not fit to the structure.

Examination of multidimensionality

The purification of the model started with steps E2 and C2 (Table 3). Only two areas were relatively homogeneous, namely musical and interpersonal. We present here the musical scale with all the 10 items, as an example of a homogeneous scale and intrapersonal as an example of a scale that could be split into two components (see Figure 1).

In the case of the musical scale, only one item, 8 (“It is easy for me to repeat correctly a musical theme from TV, or some other tune”), is not among the homogeneous set. Musical talent can be seen as a relatively unidimensional component and thus it has quite a high reliability index. The intrapersonal scale can be better conceived as a two-dimensional concept. The main point is that there are four items that represent factor 1 rather well. There are five items, which belong to factor 2 rather clearly, and item 16 has a substantial loading only on the first principal component. This finding suggests that the number of dimensions should be more than seven.

Bayesian dependency modeling was applied to each of the seven dimensions in order to compare the strengths of dependencies between variables (step B2 in Table 3). Table 5 lists the importance ranking of three dimensions of Gardner’s model. Strongest dependencies are listed first; weaker ones are listed with the figure indicating probability ratio if this dependency is removed from the final model. The results support the preceding conclusion of the homogeneity of musical dimension due to fact that it does not contain any isolated variables (see Table 5).

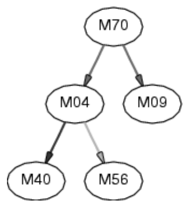


Note. See Appendix for item labels.

Figure 1:
Principal Component Analysis Plots of the Homogeneous Musical (3) and the Two-dimensional Intrapersonal (7) Scale.

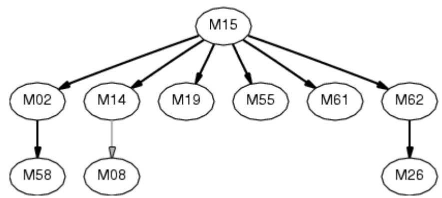
Table 5:
Importance Ranking of the Linguistic, Musical, and Intrapersonal Scales in the Bayesian Dependency Model.

1. Linguistic



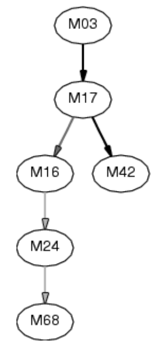
Dependency	Probability ratio
M04 -> M40	1 : Inf.
M70 -> M04	1 : 35920
M70 -> M09	1 : 5265
M12, M31, M34, M60, M69	No importance

3. Musical



Dependency	Probability ratio
M15->M61	1 : Inf.
M15->M14	1 : Inf.
M15->M55	1 : Inf.
M15->M62	1 : Inf.
M15->M02	1 : Inf.
M02->M58	1 : Inf.
M15->M19	1 : Inf.
M62->M26	1 : Inf.
M14 -> M08	1 : 324

7. Intrapersonal



Dependency	Probability ratio
M03->M17	1 : Inf.
M17->M42	1 : Inf.
M17->M16	1 : 4574
M16->M24	1 : 54
M24->M68	1 : 24
M28, M41, M51, M64	No importance

Note. Inf. = Infinitely (extremely) important variable in the BN.

Interpretation of the selected factor structure

The results of the factor structure analysis with the reliability estimates are presented in Table 6 (steps E3 and C3 in Table 3). The estimates of reliability applied in this study were the Cronbach's alpha (α, see Cronbach, 1951; Cronbach, Schonemann, & McKie, 1965) and the Tarkkonen's rho (T, see Tarkkonen, 1987). The Cronbach alpha's basic assumptions allow one-dimensional reliability examination, but the Tarkkonen's reliability index also operates in the context of multi-dimensional models (Vehkalahti, 2000; MacDougall, 2011). Reliabilities, in the reduced 7*4 = 28 items version, form a relatively sufficient set for a screening device for both samples. Tarkkonen's unbiased estimates confirm this conclusion (see Table 6).

The first column of Table 7 presents a BN showing statistical dependencies among the multiple intelligence variables (step B3 in Table 3). This demonstrates that the 28 selected variables form substantially clearer clusters with the first sample, when compared to the initial network model of seventy variables. The clusters are labeled as seen in Table 6. The initial examination of this visualization suggests that variable 65 ("When I read, I form illustrative pictures or designs in my mind") should be removed from the final model. The network model indicates that musical (3) and bodily-kinesthetic (5) dimensions form two separate and isolated homogeneous clusters. Linguistic (1), logical-mathematical (2), spatial (4), interpersonal (6), and intrapersonal (7) intelligences are closely related to each other through statistical dependencies. Closer examination of the probability ratios of dependencies reveals that variables 56 ("Metaphors and vivid verbal expressions help me learn efficiently"), 32 ("I make contact easily with other people"),

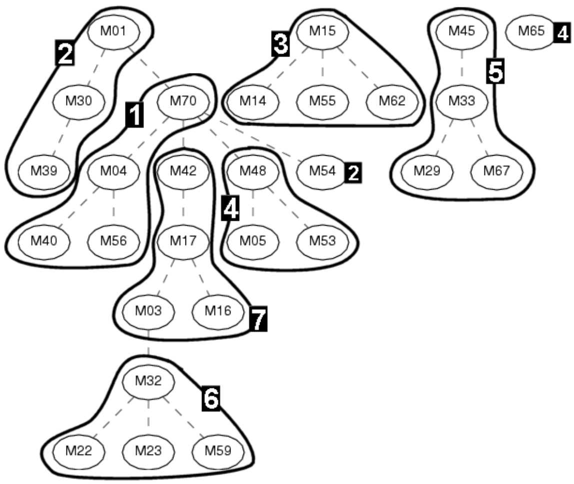
Table 6:
The Results of the Factor Structure Analysis with the Reliability Estimates.

	Original 7-component (70 items)		Optimized 7-component (28 items)			
	University students (*n*=256)		University students (*n*=256)		Vocational students (*n*=152)	
	α	T	α	T	α	T
1. Linguistic	.64	.77	.71	.74	.58	.59
2. Logical-mathematical	.76	.81	.75	.77	.67	.74
3. Musical	.93	.96	.90	.93	.80	.82
4. Spatial	.73	.76	.70	.74	.55	.61
5. Bodily-kinesthetic	.74	.87	.85	.89	.82	.85
6. Interpersonal	.82	.92	.86	.89	.77	.80
7. Intrapersonal	.70	.81	.77	.81	.69	.75

Note. α = Cronbach alpha; T = Tarkkonen rho.

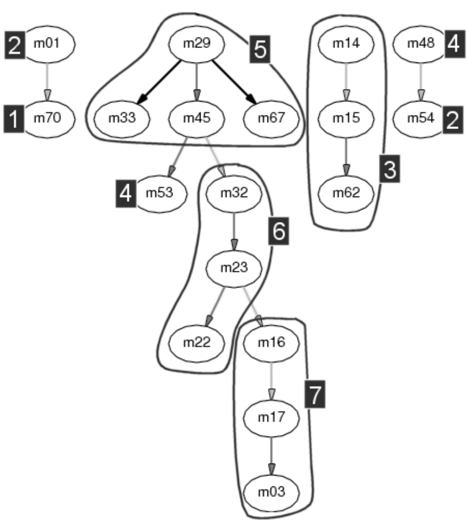
Table 7:
Bayesian Dependency Model and the Importance Ranking of the 28 Selected Variables Measuring Self-evaluated Intelligence.

Bayesian Network	Dependency	Probability ratio
University students (n=256)		



Dependency	Probability ratio
M33->M29	1 : Inf.
M01->M70	1 : Inf.
M15->M14	1 : Inf.
M15->M55	1 : Inf.
M15->M62	1 : Inf.
M33->M67	1 : Inf.
M32->M23	1 : Inf.
M32->M22	1 : Inf.
M17->M03	1 : Inf.
M42->M17	1 : Inf.
M01->M30	1 : Inf.
M45->M33	1 : Inf.
M48->M05	1 : 1.000.000
M04->M40	1 : 1.000.000
M48->M53	1 : 1.000.000
M70->M42	1 : 206003
M70->M54	1 : 177004
M32->M59	1 : 37933
M70->M04	1 : 26949
M30->M39	1 : 10737
M17->M16	1 : 4042
M04->M56	1 : 27
M03->M32	1 : 25
M70->M48	1 : 11
M65	No importance

Vocational students (n=152)



Dependency	Probability ratio
m29->m33	1 : Inf.
m29->m67	1 : Inf.
m15->m62	1 : 519899
m32->m23	1 : 501054
m17->m03	1 : 9472
m45->m53	1 : 5170
m29->m45	1 : 2072
m23->m22	1 : 1614
m45->m32	1 : 32
m01->m70	1 : 8.7
m14->m15	1 : 5.69
m16->m17	1 : 3.71
m23->m16	1 : 2.3
m48->m54	1 : 1.7

Note. Inf. = Infinitely (extremely) important variable in the BN, 1=linguistic, 2=logical-mathematical, 3=musical, 4=spatial, 5=bodily-kinesthetic, 6=interpersonal, and 7=intrapersonal intelligence.

and 48 (“It is easy for me to conceptualize complex and multidimensional patterns”) should also be omitted from the model.

Table 7 shows that the Bayesian network of the second sample (*n* = 152) contains only 18 variables. The network for the second sample shows clear clusters of items measuring the musical, bodily-kinesthetic, interpersonal and intrapersonal dimensions. We believe that this is mostly due to a smaller sample size, which leads to a lack of power in the analysis (Murphy & Myors, 1998).

Modeling of the optimized factor structure

Goal rotation, using one core item per scale in a more influential position in rotation, does not add much to the picture obtained with the full-free, non-constrained EFA. When factor scores are calculated from the ML solution (7 factors, promax rotation), they show, however, a rather good fit to the factor scores. The 28-item seven-component model was factor analyzed in the CFA mode using congeneric thinking: an index had a path from one latent variable only (step E4a in Table 3). In addition, as no error covariances were allowed (the error terms were kept uncorrelated), the model represented several sets of congeneric scores (Jöreskog & Sörbom, 1979, pp. 52-54). The general self-esteem or general self-concept is difficult to model, although there were strong indications of such a dimension in the initial data screening.

The results of CFA indicate that the 28-item optimized model fits the first sample well. The ratio of the chi-square to the degrees of freedom (2.43) and the RMSEA (0.08) are small, indicating good model fit. Earlier research (Tirri & Komulainen, 2002) studied the possibility of a 12-component model with 53 items. The psychometric exploration indicated that the 12-component model would be more valid and appropriate to measure all the different areas of Gardner’s intelligences. However, the optimized seven-component model with 28 items is shorter and more convenient in practice. Furthermore, the seven-component model revealed the same trends as the more detailed 12-component one. Also the corresponding indices for the second sample were satisfactory given that the model consisted of 28 observed variables but only 152 observations (see Table 8).

Some areas in self-evaluated intelligence are explained by the background information of the participants (step E4b in Table 3). Table 9 presents the following background variables – gender (1 = Male, 2 = Female); age (date of birth, from 1950 to 1981); mother tongue (first sample: matriculation examination score, from 1 = lowest to 6 = highest; second sample: self-assessed score, from 1 = lowest to 5 = highest); mathematical skills (first sample: matriculation examination score, from 1 = lowest to 6 = highest; second sample: self-assessed score, from 1 = lowest to 5 = highest); and motivation (self-rated score from 1 = lowest to 5 = highest) – and their zero-order correlations to the multiple intelligences dimensions. The results regarding the first sample (university students, *n* = 256) indicate that gender is a powerful explanation of verbal facility ($r = .49$, $p < .001$) as the females rated their abilities higher than did the males. Furthermore, linguistic ability seems to increase with age ($r = .22$, $p < .001$). These correlations were not present in the

Table 8:
The Goodness-of-fit Values for the 7-component Model.

Statistic	7-component optimized model: University students (*n*=256)	Vocational students (*n*=152)
Chi-Square	799.46	915.35
Df	329	329
p-value	< .001	< .001
Chi-square/df	2.43	2.78
CFI	.864	.662
TLI	.843	.612
RMSEA	.075	.109
CI90	.068 <-> .081	.100 <-> .117
SRMR	.088	.118

results of the second sample (vocational students, n = 152). Both samples showed that good grades in the mother tongue also explained high ratings in this component, university students $r(256) = .34$, $p < .001$ and vocational students $r(152) = .25$, $p < .01$. The female university students were shown to rate themselves significantly higher than did the males in both interpersonal ($r = .29$, $p < .001$) and intrapersonal intelligence ($r = .45$, $p < .001$). Also the female vocational students rated their intrapersonal intelligence significantly higher than males, $r(152) = .23$, $p < .01$. The males in both samples perceived their logical-mathematical skills significantly better than did their female colleagues, $r(256) = -.27$, $p < .001$ and $r(152) = -.27$, $p < .01$. Both samples also indicated that high motivation explained statistically significant skills in the interpersonal, $r(256) = .35$, $p < .001$ and $r(152) = .32$, $p < .01$, and intrapersonal areas, $r(256) = .19$, $p < .001$ and $r(152) = .24$, $p < .01$. Statistically significant correlation was also found from both samples between school success in mathematics and self-assessed logical-mathematical intelligence, $r(256) = .19$, $p < .05$ and $r(152) = .37$, $p < .01$. Both samples also indicated negative correlation between mathematical ability and interpersonal intelligence, $r(256) = -.22$, $p < .001$ and $r(152) = -.14$, *ns*. An interesting finding related to the second sample (vocational students) was that the international vocational skills competition final score correlated statistically significantly with interpersonal, $r(152) = .23$, $p < .01$, and intrapersonal $r(152) = .25$, $p < .01$, intelligences (Table 9).

These analyses will give no definite answer to the basic question of whether the multiple intelligences model can be confirmed in self-evaluated intelligence. This inspection indicates, however, that we may proceed with such an instrument and its development. Concerning our psychometric testing, Gardner’s theory offers a promising background to the revision of self-concept, especially that relating to the academic area.

Table 9:
The Background Variables Explaining the Self-evaluated Intelligence.

7-component model (28 items)	Gender	Age	Mother tongue	Mathematics	Motivation
University students (*n*=256)					
1. Linguistic	.49***	.22***	.34***	-.16**	.14*
2. Logical-mathematical	-.27***	-.03	-.02	.19**	.15
3. Musical	.04	.13*	.07	-.07	.13*
4. Spatial	.09	.08	-.06	-.17**	.09
5. Bodily-kinesthetic	.01	.02	-.15*	-.12	.04
6. Interpersonal	.29***	.20***	.07	-.22***	.35***
7. Intrapersonal	.45***	.16**	.05	-.15*	.19**
Vocational students (*n*=152)					
1. Linguistic	.07	-.01	.25**	-.01	.15
2. Logical-mathematical	-.27**	.01	.07	.37**	.18*
3. Musical	.12	.03	.16*	.02	.13
4. Spatial	-.27**	.05	.11	.19*	.26**
5. Bodily-kinesthetic	-.13	.06	.04	-.12	.07
6. Interpersonal	.09	.10	.03	-.14	.32**
7. Intrapersonal	.23**	.07	.25**	-.05	.24**

* p < .05; ** p < .01; *** p < .001

Concluding remarks: Are we measuring intelligences or sensitivities?

We do not equate all the positive qualities we find in people with intelligences. There are many strengths and skills, in addition to intelligence, that need to be educated. Those qualities that do not meet the original criteria for multiple intelligences proposed by Gardner may be called sensitivities. In our work, we introduce several sensitivity measures that some authors may call intelligences. These sensitivities include spiritual sensitivity, environmental sensitivity, ethical sensitivity, emotional sensitivity and inter-cultural and interreligious sensitivities (Tirri & Nokelainen, 2011).

The existence of spiritual intelligence, for example, has been a widely debated issue and not everybody is ready to label advanced thinking in religious or spiritual domains as intelligence (Tirri, Nokelainen, & Ubani, 2006). This has guided us to use the term 'sensitivity', which is easier to justify than 'intelligence' in these areas of human behavior. Furthermore, environmental sensitivity includes many elements that are very close to the possible naturalist intelligence suggested by Gardner, while emotional sensitivity reflects many aspects of emotional intelligence or social intelligence (Goleman, 1995, 1996).

Ethical sensitivity, on the other hand, is very close to the qualities some authors call moral intelligence (Lennick & Kiel, 2005). According to Moran (2011), assessing a person's sensitivity to opportunities to engage the intelligence allows further investigation of the person/environment interaction. She argues that both educators and students could use such assessments "as supports for developing their awareness and sensitivity to their growing selves and how that self impacts the wider world" (p. 131).

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Appendix

Item selection process

	Original version	Initial version	Final version
1. Linguistic	04, 09, 12, 31, 34, 40, 56, 60, 69, 70	04, 40, 37, 70	04, 40, 56, 70
2. Logical-mathematical	01, 21, 27, 30, 37, 39, 44, 54, 57, 66	01, 30, 39, 44, 27	01, 30, 39, 54
3. Musical	02, 08, 14, 15, 19, 26, 55, 58, 61, 62	02, 14, 15, 19, 55, 61, 62	14, 15, 55, 62
4. Spatial	05, 10, 13, 18, 20, 38, 48, 53, 63, 65	05, 13, 38, 48, 53, 65	05, 48, 53, 65
5. Bodily-kinesthetic	06, 07, 25, 29, 33, 36, 45, 47, 52, 67	07, 25, 29, 33, 45, 67	29, 33, 45, 67
6. Interpersonal	11, 22, 23, 32, 35, 43, 46, 49, 50, 59	23, 32, 49, 50	22, 23, 32, 59
7. Intrapersonal	03, 16, 17, 24, 28, 41, 42, 51, 64, 68	03, 17, 24, 42, 51	03, 16, 17, 42

The Multiple Intelligences Profiling Questionnaire

Items selected for the final version are marked with *

*1. At school I was good at mathematics, physics or chemistry.

2. I am good at singing or playing an instrument.

*3. I often think about my own feelings and sentiments and seek reasons for them.

*4. Writing is a natural way for me to express myself.

*5. At school, geometry and various kinds of assignments involving spatial perception were easier for me than solving equations.

6. I have a talent to form a mental picture of objects by touching them.

7. I am very good at tasks that require good coordination.

8. It is easy for me to repeat correctly a musical theme from TV, or some other tune.

9. I enjoy reading demanding novels or classics.

10. Other people say that I am good with colours.

11. One of my strengths is problem solving together with other people.

12. When walking outside, I am good at finding words on signs and posters and making them rhyme.
13. When I think, I can see clear visual images in my mind.
*14. After hearing a tune once or twice I am able to sing or whistle it quite accurately.
*15. When listening to music, I am able to discern instruments or recognise melodies.
*16. I am able to analyse my own motives and ways of action.
*17. I spend time regularly reflecting on the important issues in life.
18. I am able to see objects or events that I would like to document on camera or video.
19. I can write little songs or instrumental pieces.
20. I usually find my way, even in unfamiliar places.
21. It is easy for me to use abstract concepts.
*22. Even in strange company, I easily find someone to talk to.
*23. I get along easily with different types of people.
24. I have opinions of my own and dare to disagree with others.
25. I have good coordination.
26. I have a good singing voice.
27. I can easily measure, classify, analyse or calculate things.
28. I have a realistic idea of my strengths and weaknesses.
*29. I am handy.
*30. I can work with and solve complex problems.
31. I am good at entertaining myself and others with wordplay and jokes.
*32. I make contact easily with other people.
*33. I can easily do something concrete with my hands (e.g. knitting and woodwork)
34. It is easy for me to play with word games, for example crossword puzzles.
35. I am good at teaching others something I know myself.
36. I have the strength to participate in extreme physical experiences (e.g. shooting the rabbits, parachuting and mountain climbing).
37. I easily notice lapses of logic in other people's everyday speech or actions.
38. I am good at jigsaw puzzles, picture puzzles and various kinds of labyrinth puzzles.
*39. I am good at games and problem solving, which require logical thinking
*40. I have recently written something that I am especially proud of, or for which I have received recognition.
41. I am able to handle criticism directed against me.
*42. I like to read psychological or philosophical literature to increase my self-knowledge.

43. I am the kind of person that neighbours, colleagues or fellow students turn to for advice and instructions.
44. I tend to look for consistency, models and logical series in things.
*45. I am good at showing how to do something in practise.
46. I easily recognise other peoples' motives.
47. It is easy for me to imitate other peoples' gestures, facial expressions and ways of moving.
*48. It is easy for me to conceptualise complex and multidimensional patterns.
49. It is easy for me to understand other peoples' feelings and moods.
50. I consider myself a leader (or have been called one by other people).
51. I keep a diary or note down happenings of my inner life.
52. I often "talk with my hands" and/or otherwise use body language when talking to someone.
*53. I can easily imagine how a landscape looks from a bird's-eye view.
*54. Mental arithmetic is easy for me.
*55. I can easily keep the rhythm when drumming a melody.
*56. Metaphors and vivid verbal expressions help me learn efficiently.
57. I am good at making decisions or predictions from new scientific discoveries.
58. I play a musical instrument or otherwise take part in musical activities.
*59. In negotiations and groupwork, I am able to support the group to find a consensus.
60. I have a talent to use concepts or expressions, which are not very typical in other people's everyday talk.
61. I quickly recognise a song or piece of music.
*62. I notice immediately if a melody is out of tune.
63. I'm good at drawing and designing various kinds of figures.
64. When necessary, I am able to motivate myself, even for unpleasant tasks.
*65. When I read, I form illustrative pictures or designs in my mind.
66. I want to present things as logically as possible and give reasons for them.
*67. I was good at handicrafts at school.
68. I can handle the emotions caused by serious setbacks.
69. In conversation, I often refer to things that I have read or heard about.
*70. At school studies in native language or social studies were easier for me than mathematics, physics and chemistry. (Note new wording: At school, studies in native language were easy for me.)