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RCML History

The **Research Council on Mathematics Learning**, formerly The Research Council for Diagnostic and Prescriptive Mathematics, grew from a seed planted at a 1974 national conference held at Kent State University. A need for an informational sharing structure in diagnostic, prescriptive, and remedial mathematics was identified by James W. Heddens. A group of invited professional educators convened to explore, discuss, and exchange ideas especially in regard to pupils having difficulty in learning mathematics. It was noted that there was considerable fragmentation and repetition of effort in research on learning deficiencies at all levels of student mathematical development. The discussions centered on how individuals could pool their talents, resources, and research efforts to help develop a body of knowledge. The intent was for teams of researchers to work together in collaborative research focused on solving student difficulties encountered in learning mathematics.

Specific areas identified were:

1. Synthesize innovative approaches.
2. Create insightful diagnostic instruments.
3. Create diagnostic techniques.
4. Develop new and interesting materials.
5. Examine research reporting strategies.

As a professional organization, the **Research Council on Mathematics Learning (RCML)** may be thought of as a vehicle to be used by its membership to accomplish specific goals. There is an opportunity for everyone to actively participate in **RCML**. Indeed, such participation is mandatory if **RCML** is to continue to provide a forum for exploration, examination, and professional growth for mathematics educators at all levels.

The Founding Members of the Council are those individuals that presented papers at one of the first three National Remedial Mathematics Conferences held at Kent State University in 1974, 1975, and 1976.

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VALIDATION OF A SHORTENED MEASURE OF STUDENTS' BELIEFS ABOUT PROBLEM SOLVING

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This paper shares shortened versions of three of the Indiana Mathematics Beliefs Scales. Exploratory Factor Analysis (EFA) with principal axis factoring extraction method (common factor extraction) and a promax (oblique) rotation were used to analyze data from a sample of 227 middle school students. The results showed that the scales could be shortened from a total of 18 items to 11 items while retaining adequate internal consistency.

Background

Beliefs may be broadly defined as assumptions or propositions held by individuals that they consider to be true and that may implicitly or explicitly influence actions (Sun & Zhang, 2024; Voss et al., 2013). Research studies that have explored mathematical beliefs often fall into one of five categories of focus: understanding beliefs about the nature and structure of mathematics, understanding how beliefs evolve or change over time, exploring how different beliefs impact behavior and achievement, understanding differences in beliefs across various domains, and testing interventions aimed at changing the beliefs that students have about themselves and the subject (Iannone & Simpson, 2019; Muis, 2004).

Within this research base, numerous studies have found that beliefs may impact students' motivation, comprehension of mathematical texts, and achievement (Iannone & Simpson, 2019; Mcleod, 1992; Schommer et al., 1992; Schunk, 1991). In addition, research has specifically explored the role of beliefs when solving cognitively demanding tasks and problems. For example, Chapman (2015) summarized research across seminal studies on problem solving (PS) - defined herein as the pursuit of a mathematical goal when the solution is not immediately clear (Lester, 2013)—to suggest that beliefs and dispositions played an important role in PS success. This claim was later supported by Rhodes et al. (2023) who conducted a multiple regression of factors influencing PS success and found that beliefs explained unique variance within the model.

In seeking to measure students' beliefs about mathematical PS specifically, Kloosterman and Stage (1992) created the Indiana Mathematics Beliefs Scales (IMBS). The IMBS has six total scales including five original scales and a sixth scale that was adapted from questions from the Fennema-Sherman Usefulness Scale (Fennema & Sherman, 1976). Each scale was constructed to be used independently from the rest (Kloosterman & Stage, 1992). Since their creation, the scales have been widely used and applied in multiple contexts and countries (Iannone & Simpson, 2019). The present study was guided by the following research question:

Can scales 1, 5, and 6 of the IMBS be reduced in length to reduce survey fatigue while retaining adequate internal consistency?

Survey fatigue can be described as over-exposure due to survey length; effort required to respond or repeat administration; this can result in participants feeling overwhelmed and lead to potentially incomplete or lower fidelity data, or even participant withdrawal from studies (Fass-Holmes, 2022).

Methodology

Participants

The participants consisted of 227 middle-school students with 121 in 6th grade and 106 in 7th grade. All participants were drawn from a large, suburban, district that was located on the West Coast of the United States. Participants' ages ranged from 11.5 years old to 14 ($M = 12.43$, $SD = 0.57$) with 116 identifying as male, 111 as female, four as non-binary, and one who preferred not to self-identify gender. Regarding ethnic identity, 24 identified as Black or African American, six as Asian, 79 as Latin(x), one as Native American, 65 as White Non-Latin(x), 30 identified as "Other", 10 as two or more races, and 12 who preferred not to self-identify.

Data Sources

We administered three scales that were selected based on the goals of the cooperating district. Specifically, data were collected on IMBS belief scale 1 (*I can solve time-consuming mathematics problems*), belief scale 5 (*Effort can increase mathematical ability*), and belief scale 6 (*Mathematics is useful in daily life*). Each scale consists of 6 Likert-style items for a total of 18 questions. The scales were designed for use with secondary and college students and evidence of validity for the scales include item structure through item scale correlations and test content through expert review, in addition to reliability calculations (Kloosterman & Stage, 1992; Krupa

et al., 2024). All items were administered using a continuous sliding scale allowing any value between 0 and 100, inclusive, to improve the reliability of the measures (Schraw, 2009).

Analysis

All analyses adhered to methods from Tabachnick and Fidell (2019). All data were tested for requisite statistical assumptions prior to data analysis, including univariate and multivariate normality, collinearity, reproducibility of the correlation matrix, univariate and multivariate outliers, and the Kaiser-Meyer-Olkin (KMO) Test of Sampling Adequacy (Tabachnick & Fidell, 2019). Data were normally distributed at the univariate (all skewness and kurtosis values were less than the absolute value of 2) and multivariate levels (all standardized residuals were less than 2 standard deviations of their respective means), with no collinearity present in the data (all zero-order correlations were < 0.80). Further, outlier analyses revealed no extreme outliers at the univariate (via box-and-whisker plots) or multivariate level (via Mahalanobis Distance).

Descriptive statistics were computed for all measures utilizing IBM SPSS 27 software. Exploratory factor analysis (EFA) with common factor extraction (principal axis factoring [PAF]) and oblique rotations (promax) were employed to examine whether the original scale could be reduced in length. We chose this approach for two reasons. First, our analyses were grounded in theoretical assumptions regarding the relations among these indicators of mathematics anxiety, and hence, justifying the EFA rather than the principal components analysis (PCA), which is atheoretical and purely statistical.

Second, we selected PAF as our extraction method because, unlike PCA, which assumes all communalities to be 1, PAF employs the multiple squared correlation coefficient, R^2 , to determine communalities after extraction. Also, unlike maximum likelihood extraction, which attempts to maximize the variance of the solution and may overestimate the explained variance, PAF is a more conservative solution.

Finally, we employed an oblique rotation because we assumed, based on theoretical considerations, that the factors, if multiple, would, in fact, be correlated. The overall model fit, the standardized factor loadings, and the explained variance each factor contributed to its indicators were analyzed for this purpose for the reduced version of the measure. Our modeling procedure began by including all 18 of the original items. We chose standardized factor loadings ≥ 0.35 because, as a measure of effect, this indicates that $\sim 12\%$ of the item's variability is attributable to the latent variable (Tabachnick & Fidell, 2019).

Results

Descriptive statistics, internal consistency reliability coefficients (Cronbach’s alpha), and the zero-order correlation matrix for the original IMBS scale and for the shortened 11-item scale are presented in Table 1.

Table 1

Descriptive Statistics and Zero-Order Correlation Matrix for the Three IMBS’s for Mathematical PS Beliefs for the Original 18-Item Measure and the Shortened 11-Item Version

Scale	<i>M</i>	<i>SD</i>	α	1	2	3
1. Difficult Problems ([original] 6/[shortened] 5 items)	78.84 ^{a/} 75.53 ^b	17.48 ^{a/} 17.53 ^b	.87 ^{a/} .85 ^b	-	.47*	-.41*
2. Math Utility Value ([original] 6/[shortened] 3 items)	58.52 ^{a/} 32.33 ^b	20.74 ^{a/} 5.72 ^b	.66 ^{a/} .76 ^b	-.41**	-	-.40**
3. Effort ([original] 6/[shortened] 3 items)	38.13 ^{a/} 56.59 ^b	4.18 ^{a/} 22.42 ^b	.69 ^{a/} .77 ^b	.35**	-.35**	-

* $p < .05$ ** $p < .01$ (one-tailed test of significance) *Note.* The correlations above the diagonal are for the original 18-item measure and those below the diagonal are for the shortened 11-item measure. ^a Original 18-item measure ^b Shortened 11-item measure; $N = 227$

Factor Analyses

The EFA results with common factor extraction—PAF—and an oblique rotation (promax) were interpreted next. Inspection of preliminary analyses revealed no difficulties in the data to reproduce a correlation matrix. Finally, the KMO Tests of Sampling Adequacy was appropriate for both original scale ($KMO = .864, \chi^2 (153) = 1702.09, p < .001$) and the 11-item shortened version ($KMO = .886, \chi^2 (91) = 1158.86, p < .001$), thereby permitting the factor analysis to be conducted. As with the original scale, we hypothesized a three-factor solution. This decision was made for theoretical reasons and based on prior research rather than allow a freely estimated solution with eigenvalues greater than 1.

Original Indiana Scale

The EFA with a PAF common extraction and a promax oblique rotation for the original 18-item IMBS yielded a three-factor solution which explained 46.09% of cumulative variance. The correlations among the three factors ranged from $r = .12$ to $r = .64$ in absolute value. Descriptive statistics, communalities after extraction, and standardized factor loadings for this solution are

presented in Table 2. One item in the word problems scale and two items in the effort scale did not load onto any factor, and hence, only 15-items of the 18 were retained.

Table 2

Descriptive Statistics, Communalities, and Standardized Factor Loadings of the Final Model for the Original 18-Item Indiana Scales for Mathematical PS Beliefs

Item	<i>M</i>	<i>SD</i>	Com.	DP	MUV	EF
DP1	81.15	21.45	.73	.90		
DP2	77.62	22.65	.59	.84		
DP3	77.00	22.29	.52	.78		
DP4*	81.53	21.42	.62	.73		
DP5*	80.27	22.65	.50	.71		
DP6*	73.67	25.56	.35	.63		
MUV1*	61.29	8.93	.59		.93	
MUV2*	64.36	12.85	.40		.77	
MUV3*	62.85	8.36	.50		.73	
MUV4	69.67	25.87	.56		.41	
MUV5	70.54	26.29	.73		.41	
EF1	58.80	28.47	.47			.73
EF2	49.30	13.03	.31			.69
EF3	63.12	29.94	.30			.51
EF4	64.44	30.11	.59			.40

Key: Com. = Communality after extraction; DP = Difficult Problems; MUT = Math Utility Value; EF = Effort. * Reverse-coded item

The EFA with a PAF common extraction and a promax oblique rotation for the shortened 11-item IMBS also produced a three-factor solution which explained 52.53% cumulative variance. The correlations among the three factors ranged from $r = .29$ to $r = .51$ in absolute value. Descriptive statistics, communalities after extraction, and standardized factor loadings for this solution are presented in Table 3.

Review of both final EFA solutions yields some intriguing findings. The original 18-item IMBS is not only longer than our shortened version, but, evidently, it also leads to a degraded solution with appreciably lower explained variance. Whereas our proposed shortened 11-item version explains over 52% of variability in the items, the original 18-item version (Kloosterman & Stage, 1992) explains only approximately 46% of the variance in the items. Contrasting the standardized factor loadings for the solutions of the original version and the shortened versions leads us to conclude that factor loadings are generally higher for our proposed shortened scale, especially the lower-bound values, as some of the items in the original longer version not only manifested lower factor loadings at the lower bound, but also lower communalities after extraction. This, along with the more parsimonious measure than its original counterpart, supports our conclusion that our proposed shortened version, S-IMBS, is the better choice, especially when combined with other measures in a longer survey.

Table 3

Descriptive Statistics, Communalities, and Standardized Factor Loadings of the Final Model for the Shortened 11-Item Indiana Scales for Mathematical PS Beliefs

Item	<i>M</i>	<i>SD</i>	Com.	DP	MUV	EF
DP1	58.48	28.40	.46	.73		
DP2	63.02	26.72	.51	.66		
DP3*	67.64	31.01	.98	.69		
DP4*	66.33	28.88	.57	.68		
DP5*	80.10	22.69	.52	.41		
MUV1*	64.38	22.68	.70		.81	
MUV2*	61.41	28.84	.50		.77	
MUV3*	63.08	28.38	.61		.76	
EF1	77.18	22.52	.65			.83
EF2	81.09	21.40	.71			.68
EF3	81.31	21.36	.66			.64

Key: Com. = Communality after extraction; DP = Difficult Problems; MUV = Math Utility Value; EF = Effort. * Reverse-coded items

Discussion, Limitations and Avenues for Future Research

The present study provides evidence that Belief Scales 1, 5, and 6 can be shortened from the original 18 items to 11 items while maintaining adequate internal consistency. Moreover, the study adds to the evidence of validity supporting IMBS. Researchers should place a greater focus on ensuring that self-report measures are as short as possible, yet reliable and valid, to increase the odds that participants will yield accurate, complete data and avoid survey fatigue when completing measures. We have met this challenge by shortening a tool that measures an important psychological phenomenon, math PS beliefs.

Despite these findings, the study is still limited by the sample of students which were all drawn from a single district. Thus, future research should consider replicating the study across contexts. Moreover, as this study only focused on three of the six scales from the original IMBS, future research should explore whether the remaining three scales can also be shortened.

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