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Medical Specialty Preference Inventory - Revised: Assessing Predictive Validity at the Item and Construct Levels

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The current study examines the predictive validity of the Medical Specialty Preference Inventory (MSPI; Zimny, 1979) employing causal and reflective measurement models and medical specialty residency choice as the outcome. The current version of the MSPI contains 150 items, and provides scores on 38 areas of practice. It also provides preference scores which match a test takers results with six major medical specialties (Family Medicine, Internal Medicine, Obstetrics and Gynecology, Pediatrics, Psychiatry, and Surgery). The present study is situated within a larger program of research and practice aimed at developing a revised Medical Specialty Preference Inventory-Revised (MSPI-R) and new ways of employing the MSPI-R to assist medical students in the U.S. and Canada make residency choices.

Interest assessment has a long history in vocational guidance (Boynton, 1936; Freeston, 1939; Lehman & Witty, 1929, 1930, 1931; Menger, 1932; Merker, 1934) rooted in a trait and factor paradigm of person-environment fit (Parsons, 1909) and supported by a now firmly established science of career personality development (Holland, 1997). There have been many attempts to develop a successful measure of interest within a single profession with few relative successes. Early attempts have used the Strong Vocational Interest Blank to develop physician specialty scales (Campbell, 1966; Gough, 1979) and some have attempted to apply the Holland RIASEC structure with only minimal success. While the SVIB focuses on relating interests of individuals to those of people within a field, the MSPI measures participants' interest in aspects of the actual practice of medicine with much more success (Zimny, 1979, 1980).

The MSPI was developed in 1979 and updated in 2002. The current version contains 150 items, and provides scores on 38 interest factors, or areas of practice. It also provides preference scores aligning with the six major medical specialties (Family Medicine, Internal Medicine, Obstetrics and Gynecology, Pediatrics, Psychiatry, and Surgery) that students and counselors can use to understand the compatibility of one's interest with physician's in those fields. Thirty years of practice and recent research (Glavin, Richard, & Porfeli, 2009) confirm that the six major preference scores derived from the MSPI items predict the selection of these major medical specialties reasonably well.

While the MSPI has been an effective tool, it has its limitations. The MSPI presently offers six medical specialty preference scores (i.e., Family Medicine, Internal Medicine, Obstetrics and Gynecology, Pediatrics, Psychiatry, and Surgery); hence, it only directly predicts a small fraction of the range of medical specially choices currently available. Only about 45% of the active physicians in the U.S. occupy these specialties (American Medical Association, 2009); hence, the scoring procedures yielding the six preference scores do not align with specialties representing the majority of active physicians. Medical students considering their future specialties are likely to express interests in many other specialties for which the MSPI does not provide direct information. For these students and counselors assisting them, they are left to make a great many inferences about how 38 interest factors and 6 preference scores may or may not align with less common medical specialties. Consequently, these medical students will be less likely to utilize this potentially valuable tool as they consider perhaps one of the most important decisions in their professional lives.

Recent research has reduced the burden on students and counselors by reducing the number of interest factors from the original 38 proposed by Zimny to 18 (Sodano & Richard, 2009) and these 18 factors have been used to generate typical interest profiles for 9 medical specialties (Richard, 2009). While the reduction from 32 to 18 factors should reduce the cognitive load discussed previously, the 18 factors and their use to establish medical specialty profiles do not yield a direct indictor of a students' likelihood of entering a given specialty.

Measurement Modeling and Data Analytic Issues in Interest Assessment

When constructing and validating an instrument, modeling the items and the constructs indicated by them is of paramount importance. Within a review centering on the nature of latent constructs in psychological science, Bollen (2002) distinguished between a formative and reflective measurement model. A formative model presumes that the observed variables are causal to the latent construct while a reflective measurement model includes the assumption that the latent construct are causal to the observed indicators (Bollen, 2002; Edwards & Bagozzi, 2000). Borsboom, Mellenbergh, and van Heerden (2003) suggest that the formative model is most commonly employed in the sociological and economics literature (e.g., estimates of SES) where aspects of the context are presumed to influence aspects of the person (e.g., behavior and emotional states) and the reflective model is most commonly used in the psychological literature (e.g., intelligence, values, and the big five personality dimensions) in which observed behaviors are presumed to be manifestations of unobservable psychological factors. To illustrate a formative and reflective conceptualization, work activities that require working with machines and refined motor dexterity may cause a person to become more interested in realistic activities or an interest in realistic work activities may prompt a person to seek out work activities that demand refined motor dexterity and working with machines (See Figure 1). The former is an example of a formative and the latter a reflective conceptualization of a latent construct. Philosophically, the reflective model presumes that a latent variable exists independent of the method employed to observe/assess it while the formative model is based on a constructivist stance suggesting that the latent construct is a product of the human mind and may or may not exist independent from the means of assessment (Borsboom et al., 2003).

Researchers of interest assessment implicitly employ an reflective measurement model because they presume that being more interested in a domain (e.g., Holland's (1997) realistic interest domain) causes a person to like certain activities (e.g., working with machines wood) over others (e.g., counseling students). The latent realistic interest presumably causes increased preferences for realistic activities. Extending to the trait-and-factor tradition, a latent realistic interest type that aligns with a latent realistic work environment translates into what is effectively a latent fit between the person and the environment. This approach is consistent with typical data collection techniques employed in interest assessment development (e.g., Holland, 1997), which essentially involve comparing test takers' inventoried interests with presumed interest types of jobs (i.e., work environments or factors) as a way of inferring compatibility between the two. Since the interest data must be matched to inferred job demands, a latent conceptual structure was needed to bridge them. Holland's hexagon is a successful example of latent conceptual structure explaining the co-variation of various interests, linking interests to job demands, and generally estimating the fit between latent personal traits and latent work demands.

Data analytic techniques like factor analysis are compatible with this approach because they can help discern (via exploratory factor analysis) and/or confirm (via confirmatory factor analysis) (a) the general conceptual components or factors of an instrument, (b) how those components or factors are related, and (c) the extent to which the structure of an instrument is more or less compatible with a target structure. On a technical level, factor analysis assumes that co-variation between items reflects a higher-order construct and, therefore, assigns more weight to items that exhibit stronger covariance with other indicators of a factor. Items exhibiting weak correlations with other items are given little or no weight (i.e., low factor loadings) and are, therefore, often discarded by the researcher.

On the contrary, one may apply a formative measurement model to interest assessment by suggesting that activity preferences (i.e., items) sum to yield the breadth of vocational interests (latent constructs), which in turn predict career choices. Items within an interest assessment are evaluated in terms of their capacity to fully account for the breadth of career interests and perhaps more importantly their ability to predict later career choices. This approach is ideal if, for example, a researcher has assessed participants' interests at an earlier occasion and their actual career choices at a later occasion, which is the case in the present study.

Stepwise discriminant function analysis (DFA) can be used to develop a causal indicators measurement model. This approach is akin to stepwise regression, but accommodates a multinomial outcome. Like stepwise regression and in simple terms, stepwise DFA can be used to identify a subset of *relatively independent* variables that predict a maximal amount of variance in the outcome. Contrary to factor analysis, stepwise DFA generally assigns more weight to interest items that exhibit *weak* inter-correlations with other interest items. This is an important difference as applied to the assessment of an interest inventory because items that would generally have a weak influence in a factor analytic model can have a strong influence in a DFA model and vice versa. Inter-correlations among items improve the fit of a factor model but generally diminish the relative independent contribution of items in a discriminant model

The net of the philosophical and methodological differences between the causal and effect indicators model is that both approaches should be considered and employed if one wishes to fully account for the interpretive and predictive power of an instrument and the items contained therein. Each approach represents two differing but not necessarily incompatible perspectives on measurement assessment. Applied to the MSPI, the 18 areas of practice or factor scores for a particular student can be useful for summarizing students' interests across 150 items, but these summary scores may not be the most powerful discriminators of specialty choice. On the contrary, scores from items identified as being powerful discriminators of specialty choice may not be amenable to interpretation in the way that the 18 medical interest factors (Sodano & Richard, 2009) or Holland's (1997) RIASEC structure aides in understanding how personality characteristics link to work environments.

This study is, therefore, part of a program of research examining the psychometrics of the MSPI. While research on the MSPI and interest assessment in general has employed an effect indictors model to identify an underlying conceptual structure, this study employs a causal indicators measurement model to identify the subset of items that best discriminate medical specialty choices.

Methods

Data for this analysis were obtained from a longitudinal database of medical students in the U.S. and Canada participating in Careers in Medicine, a career planning program supported by the AAMC. The data for the present study were gathered from January 2005 to February 2009. Students completed the MSPI typically in the third year of medical school; hence, the time between the MSPI assessment and 2nd year residency choice was about two to three years.

Sample

The data for this study was obtained from 2339 medical students who completed the MSPI and for whom their second year medical residency selection was available through the Association of American Medical Colleges (AAMC). The sample approximates the age (M = 30.2 years SD = 3.0), sex (54% female), and racial diversity (72 % Caucasian, 15% Asian, 6% African American, and 7% Other or Multiple Races) of medical students in the U.S. and Canada.

The Careers in Medicine program is available on the web via password access to medical students in the U.S. and Canada through the AAMC (http://www.aamc.org/students/cim/). Students obtain passwords to the website free of charge from a school counselor, associate or assistant dean of student affairs or other designate at their medical school. Students who access the site complete a registration process, which includes completing an IRB-approved informed consent form. The students voluntarily access and use the various resources on the website, including the MSPI. Approximately 60% of all medical students register with the Careers in Medicine website with the vast majority of schools actively participating in the program.

Measures

The MSPI is a 150 item interest assessment that underwent a revision in 2002. While 104 were originally used for scoring purposes another 46 were included as pilot items for future MSPI versions. The items reflect a wide range of activities and experiences associated with medicine and the response set for each item ranges from 1 to 7 with higher numbers reflecting greater desirability.

The items have been used to generate two types of scores (Zimny, 1979). First, 104 items are used to calculate 38 areas of practice or interest factor scores. Second, the 38 factors scores are included in a complex formula to generate six specialty scores, which indicate students' preferences for the following 6 medical specialties: Family Medicine, Obstetrics Gynecology, Surgery, Psychiatry, Pediatrics, and Internal Medicine. The reliability of the medical specialty preference scores range from .66-.91, with most in the .80 to .90 range (Zimny, 1979).

Recent research suggests that the MSPI items are better expressed as 18 interest factors employing 88 items (Sodano & Richard, 2009). The 18 interest factors can be used to generate interest profiles for students and these profiles can be compared against the interest profiles of 9 medical specialties (Richard, 2009). Given that this recent work combined with the results presented here will be used to revise the scoring method and reports provided to medical students across the U.S. and Canada, two stepwise DFA models were compared; one included the set of 18 interest factor scores and the other included the entire set of 150 items from the MSPI to determine which best discriminated medical specialty choices.

Second year residency choice data were obtained from the AAMC and was the preferred outcome over first year residence choice because a meaningful fraction of students change their residency choice after the first year. This change can be due to several factors but two of the most common are (a) a natural transition from one specialty to the next (e.g., from a General Internal Medicine residency to Anesthesiology or Dermatology, or from a General Surgery residency to a Neurological Surgery residency) or (b) a recognition that the student is better suited to another specialty. Many fewer students change their residency after the second year; hence, it is deemed to be a more reliable indicator of long-term specialty choice. Of the 24 medical residencies chosen by students in the sample, 16 contained at least 20 students. Given the limitations of DFA as it pertains to the minimum number of participants per group, students selecting these sixteen specialties were retained for subsequent analyses (see Table 1).

Results

Descriptive statistics were computed for the 150 items and the 18 interest factors of the MSPI to ensure normality. Skewness and kurtosis values were within acceptable limits suggesting that the items were approximately normally distributed. Multivariate outliers were identified with the Mahalanobis statistic and about 2% of the sample was excluded from the subsequent analyses. This yielded a total sample size of 2339. Supporting standard practice in DFA (Tabachnick & Fidell, 2007), this yields about 15.6 participants per MSPI item (the minimum is usually 5) and at least 20 participants per specialty (see Table 1). Given that the 150 MSPI items far outnumber the 18 interest factors, the sample size is clearly adequate for the DFA of the interest factors as well.

A series of stepwise DFA's with the set of 150 MSPI items and the set of 18 interest factors as predictors of the 16 most prevalent specialty choices during the second year of residency. The following data analytic steps were chosen because the ultimate aim of this research is to employ the results to generate predicted probabilities of specialty choice for future medical students completing the MSPI. With this goal in mind, we aimed to identify the subset of 150 MSPI items or 18 factors that yielded a maximum percentage of correctly classified medical students into their chosen medical specialty while minimizing the number of MSPI items needed to classify the students (as a way of reducing the possible impact of multicolinearity) and minimizing the difference between the correctly classified and cross-validated (via the U-method) percentages. The later criterion is important because it is a reasonable indicator of the percent of students who would be correctly classified in the population of all students completing the MSPI. The result of this analytic approach is a sub set of MSPI items and factors that best discriminate medical specialty choices.

Table 2 contains model criteria (p-value for entering and removing MSPI items) and fit statistics for models ranging from 26-47 items. The difference between the percent correctly classified and the cross-validated percentage (6th column) and the difference between the percent correctly classified from the model with 47 items against the other models (7th column) were employed to select the final model. After these differences were computed, they were ranked from lowest to highest. The final column in Table 2 presents the average rank of the two difference scores and points to the model including 32 MSPI items as best satisfying the criteria set forth above.

For the model including 32 MSPI items, the average pooled within-group correlation is 0.17 suggesting a typically weak relationship among the predictors, which is consistent with an assumption of DFA. Comparing the hit rate for the 32 item model (57%) against the hit rate associated with random assignment (11.5%) and Morrison's (1969) C_{max} (23%; computed by assigning all students to the most predominant medical specialty, in this case internal medicine) suggests that the 32 item model offers a substantial improvement over chance. Within the 16 medical specialties (see Table 1), internal medicine and dermatology respectively had the highest and lowest hit rates, which represent large improvements over their respective base rates.

The structure matrix suggested that the following items in descending order had the greatest association with the first discriminant function: "take a detailed developmental history" (0.56), "provide counsel to patients about their marital problems" (0.54), "counsel patients about family planning" (0.53), "use a detailed knowledge of anatomy" (-.51), "use a detailed knowledge of the skeletal system" (-.48), and use the services of psychologists (.48). "Suture wounds" had the highest positive loading (0.59) on the second discriminant function followed by "counsel patients about family planning" (.42), "discuss contraception with patients" (.39), "use my hands to obtain information for diagnostic purposes" (0.38), and "deal with children as patients" .37). "Receive referrals from other physicians" had the highest negative loading (-.30) followed by "provide consultation to physicians in a variety of specialties" (-.24), and "use the results of a brain scan" (-21). The first and second discriminant function explained about 41% of the between-group variance in specialty choice.

The 16 specialties were plotted along the first two discriminant functions. This plot of the specialties in combination with the items associated with the functions suggested that the first discriminant function (i.e., x-axis) discriminates medical specialties along interests ranging from biomedical (left) to biopsychosocial-oriented (right) medical care and the second function distinguishes medical specialty interests from consulting medical services to direct patient care. Stepwise DFA was conducted with the 18 MSPI interest factors as predictors of the 16 specialty choices during the second year of residency. The p-value for entering and removing the factors was set at 0.001 and 0.01 respectively. This yielded a model with 16 of the 18 interest factors. The community health and psychosocial medicine factors did not meet the criteria for inclusion in the model. The hit rate for this model was 47.3% and the cross-validated rate was 45.9%. These hit rates were meaningfully lower than those obtained with the stepwise DFA model including the 150 MSPI items. The average pooled-within group correlation was .22 and is therefore larger than the 32 item DFA.

The structure matrix for the interest factor model suggested that the following factors in descending order had the greatest association (loadings > .50) with the first discriminant function: psychological services (-.63), family history (-.62), preventive health

(-.58), anatomy (.57), and operative procedures (.54). Reproductive health and counseling (0.69) and operative procedures (0.48) had the highest and second highest associations respectively with the second discriminant function and these two functions explained 51% of the between-group variance in specialty choice. A plot akin to Figure 2 for these two functions was inspected and found to be quite similar to Figure 2; hence, it is not offered here.

The net of these analyses suggests that the 32 item MSPI item DFA model was superior to the 16 MSPI interest factor DFA model. Sixteen of the items in the 32 item model were not included as indictors of the 18 MSPI interest factors (Sodano & Richard, 2009). The remaining items were indicators of the following interest factors: family history, psychological services, preventative health, reproductive health, comprehensive care, operative procedures, anatomy, emergency-critical care, laboratory tests, systems knowledge, and complex problems. This left seven MSPI interest factors that were not represented within the final set of 32 MSPI items.

Discussion

As in previous research (Glavin et al., 2009; Sodano & Richard, 2009), this study finds the MSPI to be an effective tool for assessing medical interests and predicting medical specialty choice. The results suggest that the MSPI can be used to substantially improve our ability to predict students' residency specialty choice. Specialty choice was predicted with over 50% accuracy with the final 32 item pool, which far exceeds the base rate defined by random assignment or the C_{max} rate. Furthermore, breaking down the hit rates by specialty suggests substantial improvements across all base rates. Comparing the effectiveness of employing items or factors suggests that items are more effective predictors than factors. Interestingly, some items in the final 32 item DFA model were not employed to derive the 18 interest domains (Sodano & Richard, 2009) and some factors in the final 16 factor DFA model were not reflected in the final pool of 32 MSPI items. This finding suggests that factors that help define interest domains within the MPSI may not be effective discriminators of specialty choice and items that discriminate specialty choice may not connect well with an underlying interest domain; hence, the factor analytic and discriminant function approaches are useful complementary tools in measurement development and assessment.

Consistent with the distinction between the formative and reflective measurement model, MSPI items that were powerful discriminators in a DFA were not included in a factor model of the same items and some factors that were deemed to represent a meaningful portion of the overall MSPI conceptual space were not powerful discriminators of specialty choice. These results generally support applying formative and reflective measurement models to the MPSI as both can effectively serve different uses. These results also affirm the utility of the MSPI to predict specialty choice.

The results also suggest how medical specialties may be related to one another based upon the interests of students who eventually enter those residencies. The two discriminant functions or dimensions of interests that best distinguish medical specialties based upon the 32 MPSI items include a dimension ranging from specialty to general medical care and another ranging from biomedical to psychosocially oriented medicine. Locating students on this map may help underscore their general orientation toward these dimensions and how close their interests align with nearby specialties on the map. Future research could continue to explore the relationships between and empirical mapping of medical specialties and how this information can be useful to students exploring medical specialties.

Implications

The analytic approach and results discussed here could be used to revise how MSPI results are reported to students. In addition to providing indicators of medical interests, students could be offered probability plots depicting their probability of entering the 16 most predominant medical specialties based upon their pattern of responding across the 32 MPSI items identified as being predictive of specialty choice. Care should be taken, however, to ensure that this information is delivered in a way that underscores the probabilistic nature of the results in an effort to avoid students giving them too much credence.

The varying hit rates across the specialties suggest that future MSPI development could focus on adding items associated with the practice of dermatology, diagnostic radiology urology, and physical and medical rehabilitation given that these specialties have the lowest hit rates and the least improvement in hit rate relative to the base rate (comparing base and hit rates in Table 1, psychiatry followed by pediatrics had the greatest improvement). New items could be used in place of some of the exiting items that are presently not indictors of the 18 interest domains or within the subset of 32 items used in the present study to predict specialty choice.

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Tables

Table 1

Sample Distribution across Second-Year Residency Choices, Base Rates, and Hit Rates for Final DFA Model.

2nd Year Residency Choice	N	Base Rate	Hit Rate
Anesthesiology	126	5.4	41.1
Emergency Medicine	244	10.4	58
Family Medicine	253	10.8	58.6
Internal Medicine	537	23	64.9
Obstetrics/Gynecology	167	7.1	54.4
Orthopedic Surgery	108	4.6	50.4
Pathology-A&C	63	2.7	41.1
Pediatrics	320	13.7	63.9
Psychiatry	113	4.8	60.8
Diagnostic Radiology	75	3.2	38.8
General Surgery	177	7.6	47.8
Dermatology	21	0.9	25
Neurology	29	1.2	34.3
Otolaryngology	61	2.6	43.5
Physical Med. and Rehab.	21	0.9	36
Urology	24	1	40
Total	2339		

Table X.

Relative Fit of DFAs with Increasingly Stringent Variable Entry and Exit Criteria.

Number of MSPI Items	P-Value Entry/Exit	X^2 (df)*	F-value (df)*	Wilk's Λ*	% Correctly Classified (Cross-Validated)	% Correctly Classified minus Cross-Validated (Rank)	% Correctly Classified in Step 1 minus Current Step (Rank)	Average Rank of Percentage Differences
47	.001/.01	6780.6 (705)	10.6 (705)	0.053	58.4 (54.1)	4.3		
44	.0001/.001	6660.2 (660)	11.1 (660)	0.056	58.1 (53.6)	4.5 (6)	0.3 (1)	3.5
36	.00001/.0001	6295.8 (540)	12.8 (540)	0.066	56.6 (53.2)	3.4 (4)	1.8 (3)	3.5
32	.000001/.00001	6090.8 (480)	13.9 (480)	0.072	57.0 (53.6)	3.4 (4)	1.4 (2)	3
30	.0000001/.000001	6033.4 (465)	14.2 (465)	0.074	56.3 (53.6)	2.7 (3)	2.1 (4)	3.5
29	.00000001/.0000001	5908.6 (435)	14.8 (435)	0.078	55.6 (52.6)	3 (2)	2.8 (5)	3.5
26	.000000001/.00000001	5700.4 (390)	16.0 (390)	0.085	54.9 (52.4)	2.5 (1)	3.5 (6)	3.5

Figure 1

Modeling Interests as a Formative and Reflective Measurement Model.

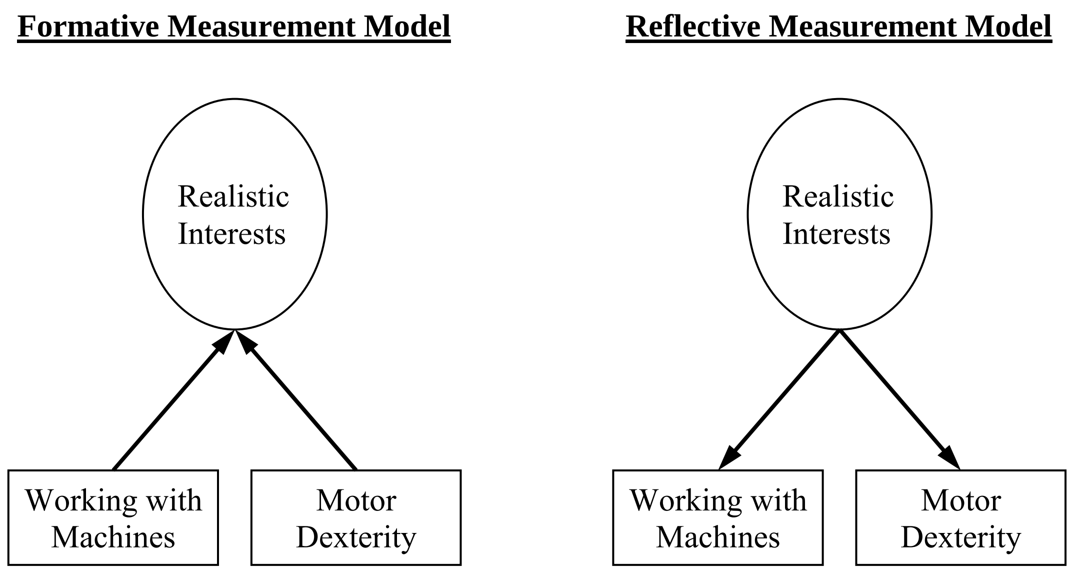

Figure 2

Plot of the First Two Discriminant Functions of the 32 MPSI Item Model.