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14 Latent Variable Modeling in the LISCOMP Framework: Measurement of Attitudes toward Career Choice

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14.1 Introduction

Schuessler (1982, pp 136-137) points to the usefulness of psychometric models with multiple indicators and multiple causes (MIMIC models) in the study of measurement of social life feelings. The objective of this chapter is to provide an illustration of MIMIC modeling applied to categorical responses.[1] The application concerns the relationship between the personal characteristics and educational backgrounds of college students and their career-choice preferences. The chapter will give a non-technical description of relevant new psychometric techniques; no formulas or greek symbols will be used. Emphasis will be placed on the type of information that can be obtained by such an analysis rather than the technical details. The paper describes several uses of MIMIC modeling. First, the modeling may be viewed as having the usual aim of a structural equation model, describing the influences of background variables on a set of factors. Second, the modeling may be viewed as a more detailed way of doing a factor analysis, allowing for differences in meanswith respect to a set of background variables . In this way, a factor model is stipulated to hold conditionally on a set of background variables , while it may not hold marginally due to population heterogeneity in means. Third, the modeling may be viewed as a way to detect and describe non-invariance of the factor model parameters across groups defined by the background variables . In particular, measurement differences in intercepts can be detected as direct effects from background variables to response variables.

14.2 Psychometric Framework

Drawing on sociological work, Jöreskog & Goldberger (1975) discussed a model with multiple causes and multiple indicators (MIMIC) of a single latent variable. Such a model is a special case of structural equation modeling in which one or more latent variables intervene between a set of observed background variables predicting a set of observed response variables. The latent

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variables are hypothetical constructs which, while not directly observed, have operational implications for the relationships among observed variables. A typical MIMIC model contains both a measurement and structural regression component. The measurement component of the structural model consists of a factor model with multiple indicators for the latent variable constructs, while the regression component of the structural model allows the regression of the latent variables on the background variables . In a MIMIC model, the measurement and regression components are estimated simultaneously.

As discussed in Muthen (1989), the advantage of MIMIC modeling over factor analysis modeling is that the inclusion of a set of relevant background variables provides the analyst with important extra information about the measurements. Such information is useful to the investigation of issues concerning hypotheses of construct validity and detection of population heterogeneity. On the one hand, the inclusion of a set of background variables allows us to study the differential predictive power of the predictors of the factors. On the other hand, the MIMIC approach allows for the detection of noninvariance in measurement intercepts across groups through the inclusion of direct effects from the background variables to the response variables.

Muthen (1989) also points out that common applications of latent variable analysis, which frequently fail to recognize the fact that data may be obtained from several populations with different sets of parameter values, would lead to bias in the parameter estimates for a specific group. By instead using a MIMIC approach that allows direct effects from the predictors to the response variables, the predictors are able to shift the level of the measurement intercepts and avoid this bias. This is analogous to using dummy x variables in conventional regression, where the corresponding coefficient represents a shift in the mean of the y variable conditional on other x's. If such predictors are defined corresponding to group membership, for example, gender, ethnicity, undergraduate major and achievement levels etc., variation of measurement intercepts, and therefore measurement heterogeneity across subpopulations, can then be demonstrated.

When the response variables of an attitude scale can be approximated as continuous-normal variables, MIMIC analysis can be carried out in a conventional structural equation modeling framework, such as Jöreskog and Sörbom's LISREL. In the application below, however, the responses are measured on a trichotomous scale with scale steps of "Not important", "Somewhat important", and "Very important". For several variables the distributions are skewed. Such variables are best treated as ordered categorical variables. Analysis techniques have been proposed for structural modeling of categorical variables using extensions of conventional Pearson product-moment correlations to correlations between latent continuous response variables underlying the categorical manifest variables (see, for example, Muthen, 1984). These types of correlations will be referred to as latent correlations. The associations between background variables and the latent variable responses are captured by further latent correlations, such as polyserials. Conventional structural equation modeling can then be applied to these latent correlations using, for example, LISREL VII together with PRELIS.

The latent correlations do, however, impose the specification of a multivariate normal distribution for the latent response variables and the background variables . This is clearly a limitation when using skewed or dummy background variables or when the response processes are better described as nonnormal. As pointed out in Muthen (1979, 1984, 1989) the restriction of normality is not necessary in MIMIC modeling. Given a set of background variables , the distribution of the latent response variables can instead be viewed as generated by the possibly non-normal background variables and normal residuals. This leads to an analysis based on sample statistics consisting of regression coefficients instead of latent correlations. The appropriate regression coefficients in the case of ordered categorical response variables are the thresholds, slopes, and residual correlations of ordered polytomous regressions of the response variables on the background variables . Muthen (1984) gives the theory for how these regression statistics can be used to fit structural equation models; Muthen (1987) describes how this theory is fit into the LISCOMP program (Analysis of Linear Structural Equations with a Comprehensive Measurement Model) used in the applications below; and Muthen (1989) gives further applications.

The meaning of direct effects in MIMIC-models in the case of trichotomous response variables should be noted. Take for example a dichotomous background variable. A direct effect from such a background variable concerns a path from the background variable to a certain latent response variable specified to underlie a corresponding observed trichotomous variable. This relationship is that of a linear regression, implying that the dichotomous background variable shifts the level of the latent response variable. In line with regression for ordered categorical responses, the response model specifies that there are two threshold parameters for the latent response variable. The three categories of observed response arise depending on the individual's latent response variable value relative to those two thresholds. The inclusion of a direct effect does not change the thresholds, but changes the mean of the latent response variable. Noninvariance of thresholds can be investigated in a simultaneous analysis of multiple groups. The noninvariance of measurement intercepts or thresholds implies that it would be inappropriate to compare group levels with respect to summed scores consisting of such items.

14.3 The Study and the Data

Understanding career-choice preferences among college graduate students can provide valuable information to social scientists in a variety of ways. First, such information could be useful to guide both the educational and vocational counseling of students. Second, information on the career-choice preferences could reveal educational needs of the graduate students. Such information, for instance, could be useful in the prediction of the number of students who might matriculate in a certain graduate program, thus helping the design and planning of the graduate program.

The data for this study comes from the National Longitudinal Study (NLS) which is a large-scale, longitudinal survey supported by the National

Center for Education Statistics (NCES), Office of the Assistant Secretary for Educational Research and Improvement in the U.S. Department of Education. The NLS data base consists of a stratified two-stage probability sample with schools as first-stage sampling units and students as second-stage units. The base year survey started with 19,000 high school seniors in the spring of 1972. Since then five follow-up surveys have been carried out in 1973, 1974, 1976, 1979, and 1986. The sample used in this study consists of respondents who reported that they graduated with a four-year college degree as of 1977. Altogether, there are a total of 2645 students, with 1319 males and 1326 females.

14.4 Analyses

Eleven background variables including eight dichotomous and three continuous variables are used. The three continuous variables SESRAW, SATQUAN, and SATVERB correspond to respondent's socioeconomic status, the SAT (SAT stands for Scholastic Aptitude Test, the standard college entrance test for U.S. colleges) quantitative score, and the SAT verbal score, respectively. Eight dichotomous variables are created to identify respondent's gender, race, father's education and undergraduate major. They are: MALE, BLACK, WHITE, FALTHS (father has less than high school education), SOCSCI (social sciences), SCIENGR (science engineering), HUMANFA (humanities and fine arts), and BUSINESS.

These variables are included as predictors which identify students' characteristics and educational experiences. They are included because, first, we want to examine the differential predictive strength of such predictors in predicting factors that would influence career choice, and, second, we want to investigate whether membership in different groups (corresponding to the dichotomous variables) or relative standing on achievement and socioeconomic status (corresponding to the continuous variables), would change the measurement intercepts of the response variables.

Ten items are considered as the dependent variables. They are taken from the third follow-up in 1976 and concern the job characteristics which would be important in the kind of work respondents plan to be doing for most of their life. The questionnaire is shown in Appendix 1. Even though the same items were asked in other follow-up surveys, answers from the third follow-up are taken because this is the year in which most seniors graduated from college.

14.4.1 Analysis Strategy

We propose the following strategy for a MIMIC analysis as applied to our data. We hypothesize that a particularly important background variable is that of gender. This variable will therefore have a special status in our analyses of measurement invariance across subpopulations. First, exploratory factor analyses will be carried out for each gender separately and together.

Second, a MIMIC model will be analyzed for each gender. Third, a simultaneous analysis will be carried out for the two genders together. Here, a test of measurement invariance will be carried out in two steps, testing first equality of factor loadings and next equality of measurement intercepts as well. If we can establish gender invariance of loadings, the final step then adds gender as a background variable for further investigations of measurement intercept noninvariance through MIMIC analysis of direct effects.

14.4.2 Exploratory Factor Analysis

As a preliminary step, the ten career choice items from the third follow-up are factor analyzed using exploratory factor analysis. Here, no background variables are included so that the analysis is necessarily based on polychoric correlations for the trichotomous items. Such analysis is carried out for the total sample, and for males and females separately with LISCOMP's generalized least squares estimator for polychoric correlations. Results from each of the three separate runs clearly suggest a three-factor solution for the ten items and they all demonstrate the same factor structure. Factor loadings and factor correlations for the total sample is shown in Table 1.

Table 1: Exploratory Factor Analysis Structure for Total Sample

	Career Advancement	Self-Fulfillment	Task Familiarity
Experience	-.045	.082	.519
Relative	-.015	.012	.432
Opening	.519	-.165	.405
Hobby	-.058	.110	.277
Income	.868	-.037	-.018
Security	.804	-.022	.150
Interest	-.100	.787	.144
Freedom	.008	.705	-.023
Promotion	.649	.386	-.155
People	.118	.428	.235
	Factor Correlations:		
Career Advancement	1.000		
Self-Fulfillment	.286	1.000	
Task Familiarity	.272	.236	1.000

In line with the companion paper of Stolzenberg, Muthen, and Muthen (1990), the three factors are interpreted as Career Advancement, Self-

Fulfillment, and Task Familiarity. The Career Advancement factor represents a person's desire for employment that is stable and secure with long-term upward mobility and future earning potential. The Self-Fulfillment factor represents a person's desire for employment where they can have freedom to make their own decisions, associate with sociable and friendly people, and do work that seems important and interesting to them. And finally, the Task Familiarity factor represents a person's desire for employment in a field where he/she has had previous experience, where a friend or relative has had experience, or which is related to a hobby or interest.

Similar factor structures for similar item sets have been found, for example, by Faulbaum (1982) with the labels Extrinsic, Intrinsic, and Social Orientation. See also the Kalleberg's (1977) discussion of Extrinsic and Intrinsic dimensions of work values and Holland's theory of careers (1970, 1972) giving six personality types related to careers, labeled as: Realistic, Investigative, Artistic, Social, Enterprising and Conventional (see also Prediger & Hanson, 1976). Our Career Advancement factor corresponds loosely to Faulbaum's Extrinsic factor and our Self-Fulfillment factor corresponds to a mixture of his Intrinsic and Social factors.

14.4.3 MIMIC Analysis

In the MIMIC model, the exploratory factor analysis part of the career choice variables is specified in a confirmatory factor analysis framework. Here, nine (the number of factors, squared) restrictions on the factor structure corresponding to those of the exploratory analysis are applied. With such restrictions, the factors are allowed to anchor on their most well-defined items. Following this reasoning, the item Income (item E; see Appendix 1) is chosen as the anchor item for the Career Advancement factor, while the item Freedom (H) and the item Experience (A) are the anchor items for the Self-Fulfillment factor and the Task Familiarity factor, respectively. These three items are chosen since they have high loadings on their respective factors and low loadings on other factors as demonstrated in the exploratory factor analysis. While fixing the conditional variances of the three factors given the background variables to unity, we then place the other six restrictions on the factor structure by fixing to zero the loadings from the other two factors to the above three items, E, H and A. All other loadings in the factor structure, including loadings from the factors to their respective anchor items, are then free to be estimated. In the regression part of the model, the three factors are allowed to regress freely on the background variables .

MIMIC models with the above specifications, in which initially no direct effects from the predictors to the response items are included, are analyzed with the whole sample of 2645 college graduates, and also with the 1319 males and 1326 females separately. We use LISCOMP with the weighted least squares estimator for regression-based analysis of ordered trichotomous responses. In each case, we use a model with no direct effects as the base-line model from which the need for including direct effects is detected by model modification techniques. Large first-order derivatives for fixed parameters from the predictors to the response items suggest the need for direct effects.

Such paths are then freed up for estimation. This process continues until either there are no more large derivatives or additional free parameters are not significant. As a guiding principle, we look for at least a five point drop of chi-square value for each degree of freedom lost.

14.5 MIMIC Analysis Results

Table 2 shows the results of model testing from the simultaneous multiple-group analyses while Figure 1 shows the structure of the MIMIC model. Comparing the results of the model with equality constraints on the factor loadings against the base-line model where no equality constraints are imposed, we find that the chi-square difference between the two models is not very large. This indicates that the measurement loadings for the factor model are invariant across gender.

Next, we compare the results from the model with equality constraints on the factor loadings against the model with equality constraints on both the factor loadings and measurement intercepts. The large chi-square difference leads us to reject the latter model which implies that the measurement intercepts are different for the two groups.

Given that factor loading invariance across gender is supported, we may conclude with a single-group MIMIC analysis for the total sample using gender as an additional background variable. The simultaneous multiple-group analysis of males and females was, however, necessary to establish loading invariance, since a single-group MIMIC analysis cannot capture loading non-invariance, only measurement intercept noninvariance. In this analysis, direct effects from gender can be investigated. In this way, the reason for the rejection of measurement intercept invariance, found in the simultaneous analysis, can be conveniently explored in terms of which items contribute to the rejection. If an item is found to have a significant direct effect from gender, this item contributes to the rejection of measurement invariance.

Table 3 summarizes the estimated effects of background variables on career-choice factors and selected job characteristic items for the total sample. The columns in each table correspond to the observed background variables, the first three rows correspond to the three factors, and the last ten rows correspond to the career-choice items. Entries are unstandardized structural regression coefficients. Here, we will be concerned with only sign and significance of the effects. As noted previously, noninvariance of measurement intercepts is captured by direct effects of the background variables on the career-choice items. Dummy variables are coded so that the group in question is contrasted with all others, for example males versus females (two categories in total), blacks versus white and others (three categories), and social science majors versus all other majors (five categories).

Regarding the effect of gender on career choice, males are significantly lower than females on the Task Familiarity factor, all things being equal. It appears that males are less likely than females to consider previous experience, relatives or friends in the same area, or work similar to a hobby when

choosing a job. The two genders do not differ on the Career Advancement or Self-Fulfillment factors.

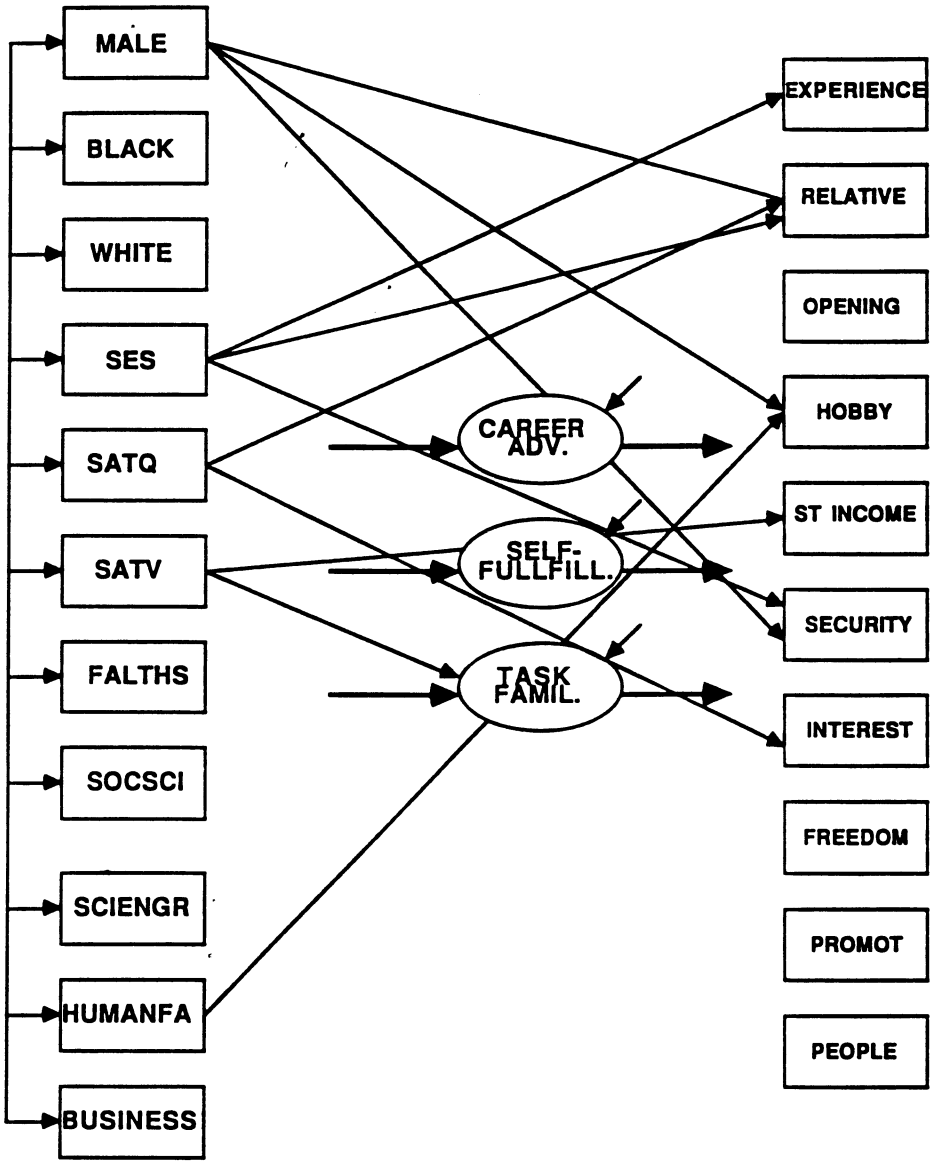

Figure 1: MIMIC Model for Career Attitudes

In examining the direct effects, we need to note which items load on which factors. Looking back at Table 1, we see that the items Opening (C), Income (E), Security (F), and Promotion (I) load on the Career Advancement factor.

Items Interest (G), Freedom (H), and People (J) load on the Self-Fulfillment factor. And items Experience (A), Relative (B), and Hobby (D) load on the Task Familiarity factor.

Table 2: Summary of Multiple-Group Analysis Results

			Difference	
	Chi-square	d.f.	Chi-square	d.f.
Base-line model; no measurement invariance	803.14	176		
			85.01	21
Model with equality constraints on factor loadings	888.15	197		
			155.06	20
Model with equality constraints on factor loadings and measurement intercepts	1043.21	217		

The absence of direct effects in Table 3 shows that the items for the Self-Fulfillment factor are invariant for the two genders. The items for the Career Advancement factor are also invariant, except that there is a tendency for males to have a higher value than females on the item related to job security and permanence. This indicates that males are more concerned than females in having job security and permanence than would be indicated by the factor. Examining the direct effects of the items related to the Task Familiarity factor reveals that males and females may interpret these items differently. Although males are significantly below the female mean on the factor, all things being equal, they are above the female mean on the items related to having a relative or friend in the same line of work and having a job that matches a hobby or interest of theirs.

Blacks are above the rest of the sample on the Career Advancement factor, which would indicate that, all things being equal, they are more interested in secure employment with good future benefits. They are below the rest of the sample on the Task Familiarity factor indicating that they would be less inclined to limit their future work to areas in which they have previous experience, work which a relative or friend does, or work related to a hobby or interest. They are the same as the rest of the sample on the Self-Fulfillment factor. Measurement invariance is seen across all items with respect to ethnicity.

Table 3: Estimated Effects of Background Variables on Factors and Items for Total Sample

	MALE	BLACK	WHITE	SES	SATQ	
Career Advancem.	.04	.74*	.26*	-.02	-.12*	
Self-Fullfillm.	.09	.08	.03	.06	-.09*	
Task Familiar	-.72*	-.44*	-.12	.06	-.14*	
Experience				-.09*		
Relative	.59*			.07*	-.10*	
Opening						
Hobby	.32*					
Income						
Security	.16*			-.06*		
Interest					.14*	
Freedom						
Promot						
People						
	SATV	FALTHS	SOCSCO	SCIENGR	HUMANFA	BUSINE
Career Advancem.	-.14*	-.11	.01	.39*	-.20*	.71*
Self-Fullfillm.	-.03	-.01	.03	-.19	.17	.10
Task Familiar	-.28*	.12	-.52*	-.11	-.21	-.68*
Experience						
Relative						
Opening						
Hobby					.54*	
Income	.06*					
Security						
Interest						
Freedom	.06*					
Promot						
People						

* Significant on 5% level.

Verbal and quantitative scores on the SAT show the same relationship with the three career-choice factors. Having high SAT verbal and quantitative scores has a negative effect on all three of the career-choice factors indicating that all of the factors are less important to such individuals in their career-choice decisions than to the rest of the sample. In examining direct effects however, we see that those high on the SAT quantitative score find work that seems important and interesting more important than the factor would indicate.

Differences are seen in career-choice decisions depending on the college major chosen. Science-Engineering majors score significantly higher than the other majors combined on the Career Advancement factor. Business majors score even higher than the other majors combined on the Career Advancement factor and also well below the others on the Task Familiarity factor. Humanity-Fine Arts majors score lower on the Career Advancement factor, and Social Science majors score lower on the Task Familiarity factor. In examining the direct effects, we see that although Humanity-Fine Arts majors are not different than the others on the Task Familiarity factor, they do indicate additional interest in a job that matches a hobby or interest of theirs.

14.6 Concluding Comments

We have shown in this chapter how MIMIC modeling can be useful in studying invariance of attitude measurements, in this case related to career-choice of college students. It was found that gender, ethnicity, college entrance test scores and undergraduate major all had strong influence on the factor values. In addition, many of these background variables had direct effects on particular items, indicating lack of measurement invariance. For the ten measurement items, strong indications of measurement noninvariance was found for gender with respect to three items (Relative, Hobby, Security) and for Humanity majors with respect to one item (Hobby). Weak indications of measurement noninvariance was found for SES with respect to three items (Experience, Relative, Security), for SATQ with respect to two items (Relative, Interest), and for SATV with respect to two items (Income, Freedom). The three items Relative, Hobby, and Security are therefore identified as having different measurement characteristics with respect to several background variables . The use of these items cannot be relied on for group comparisons by conventional meansof summed scores. In the MIMIC model, however, these differences in measurement characteristics are accounted for and do not present an essential complication of further analyses.

The MIMIC model can then be built on in order to investigate more complex processes such as analyses of higher education, as has been done in Stolzenberg, Muthen, and Muthen (1990). In that paper, the career-interest model discussed above has been extended to include issues of prediction of test-taking for admission into graduate schools, specifically the prediction of taking the GRE, LSAT and GMAT, and enrollment in MBA programs. It is shown that the factors have differential effects on these later actions. This

extended model is interesting also from a methodological point of view in that it incorporates a simultaneous equation system with a mixture of variable types among the dependent variables, including trichotomous, dichotomous, and continuous variables.

The MIMIC structural equation modeling presented above can benefit from further, recent methodological advances. In Muthen (1989, 1990) methods have been made available by which one can investigate population heterogeneity of the college students' career choices in yet another dimension, namely across schools. Such "multilevel structural equation" techniques take into account that the observations have been obtained in a hierarchical fashion with individuals sampled within schools. One might expect that the school environment can induce a certain amount of within-school correlatedness among its students' attitudes. The new techniques provide the proper tools for doing a multilevel analysis where such dependency structures are taken into account and where both individual and school variation is modeled and explored.

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Appendix

Wording and Response Category Percentages of the Items

"How important do you think each of the following factors is in determining the kind of work you plan to be doing for most of your life?"

	Not important 1	Somewhat important 2	Very important 3
A. Previous work experience in the area.			
Male	24.9	39.0	36.2
Female	17.0	34.6	48.3
B. Relative or friend in the same line of work.			
Male	74.4	19.6	6.1
Female	82.0	14.5	3.5
C. Job openings available in the occupation.			
Male	17.6	40.6	41.8
Female	12.2	36.1	51.7
D. Work matches a hobby interest of mine.			
Male	45.6	33.4	21.1
Female	45.8	32.8	21.4
E. Good income to start or within a few year.			
Male	13.7	47.8	38.4
Female	15.5	47.7	36.7
F. Job security and permanence.			
Male	8.4	37.1	54.4
Female	8.0	41.7	50.3
G. Work that seems important and interesting to me.			
Male	0.5	8.8	90.8
Female	0.5	4.8	94.7
H. Freedom to make my own decision.			
Male	2.0	29.6	68.3
Female	2.2	31.6	65.2
I. Opportunity for promotion and advancement in long run.			
Male	8.0	29.0	63.1
Female	9.7	37.3	53.0
J. Meeting and working with sociable, friendly people.			
Male	4.2	32.9	62.9
Female	2.8	26.8	70.4

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