PERSONNEL PSYCHOLOGY
1999, 52

THE MEASUREMENT OF WORK: HIERACHICAL REPRESENTATION OF THE MULTIMETHOD JOB DESIGN QUESTIONNAIRE

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To study the changing nature of work, researchers need measures of work that are valid and comprehensive. One potentially useful measure of work is the Multimethod Job Design Questionnaire (MJDQ; Campion, 1988), which was developed to assess 4 general approaches to work design (i.e., motivational, mechanistic, biological, perceptual-motor). Although the MJDQ holds promise as a general measure of work, little information is available regarding its psychometric properties. This study examines the MJDQ, using alternative hierarchical factor structures to represent work at varying levels of abstraction. Little support was found for the 4-factor structure corresponding to the work design approaches underling the MJDQ or for various hierarchical factor structures that simultaneously depicted general and specific aspects of work. However, a 10-factor first-order model received good support and may provide a useful basis for scoring and interpreting the MJDQ in future research.

In recent years, the nature of work has changed dramatically. Traditional employment arrangements have been replaced by outsourcing, temporary work, and individualized career paths (Hall, 1996). Work activities have been reshaped by new technology and a shift from manual labor to knowledge and service work (Adler, 1992; Howard, 1995). These forces have combined to create a postindustrial work environment in which the experience of work has fundamentally changed. These changes provide the impetus for a new generation of research into the meaning, determinants, and consequences of work.

To study the changing nature of work, researchers need measures of work that are valid, comprehensive, and applicable across contexts. Numerous approaches to the measurement of work have been developed

The authors thank Bonnie N. Pollack, Larry J. Williams, and three anonymous reviewers for their comments on this article.

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(Campion & Thayer, 1985). Some of these approaches focus on specific task activities (e.g., Fleishman & Quaintance, 1984; McCormick, 1979), others examine the motivational properties of jobs (e.g., Hackman & Oldham, 1980; Sims, Szilagyi, & Keller, 1976), and others assess the ergonomic and biological requirements of work (Grandjean, 1980; Tichauer, 1978). Each of these approaches has strong disciplinary roots and has proven useful for research and practice. However, by drawing from a particular discipline, each approach risks overlooking aspects of work considered important from other perspectives. This risk becomes increasingly problematic as work evolves in new and potentially unanticipated directions. Moreover, some approaches offer prescriptions viewed from other approaches as irrelevant or even detrimental (Campion & Thayer, 1985). For these reasons, researchers need measures of work that integrate multiple approaches and apply across a variety of work situations.

One potentially useful measure of work is the Multimethod Job Design Questionnaire (MJDQ; Campion, 1988; Campion & Thayer, 1985). The MJDQ integrates four general approaches to the conceptualization and measurement of work: (a) *motivational*, which comprises job enrichment, job enlargement, intrinsic work motivation, and sociotechnical systems (Cherns, 1976; Hackman & Oldham, 1980; Steers & Mowday, 1977); (b) *mechanistic*, which draws from classic industrial engineering and scientific management (Barnes, 1980; Maynard, 1971; Salvendy, 1978; Taylor, 1911) and emphasizes task specialization, skill simplification, and repetition; (c) *biological*, which encompasses biomechanics, work physiology, and ergonomics (Astrand & Rodahl, 1977; Grandjean, 1980; Tichauer, 1978) and focuses on physical task requirements and environmental factors (e.g., noise, temperature); and (d) *perceptual-motor*, which derives from human factors engineering, perceptual and cognitive skills, and information processing (Fogel, 1967; McCormick, 1979; Welford, 1976) and deals with designing jobs that accommodate the mental and physical limitations of workers. Studies using the MJDQ have found that scores representing these four approaches exhibit meaningful relationships with work-related outcomes (e.g., satisfaction, efficiency, comfort, reliability; Campion, 1988, 1989; Campion & Berger, 1990; Campion & McClelland, 1991, 1993; Campion & Thayer, 1985; Wong & Campion, 1991).

Although the MJDQ holds promise as a comprehensive, general measure of work, information regarding its psychometric properties is limited. Studies have reported reliability estimates for the MJDQ scales and correlations between the scales and relevant outcomes, thereby providing evidence for criterion validity (Nunnally, 1978). However, no study has formally tested the 4-factor structure presumed to underlie the MJDQ. Moreover, each approach encompassed by the MJDQ may itself contain multiple dimensions. For example, within the motivational approach, researchers have delineated at least five core job dimensions (Harvey, Billings, & Nilan, 1985; Idaszak, Bottom, & Drasgow, 1988; Kulik, Oldham, & Langner, 1988; Sims et al., 1976). Hence, the MJDQ may be best represented by a hierarchical factor structure in which the four approaches identified by Campion and Thayer (1985) constitute second-order factors, each of which encompasses a number of first-order factors.

The purpose of this study is to rigorously evaluate the psychometric properties of the MJDQ. We examine reliabilities of the MJDQ scales, discriminant validity among the MJDQ factors, and alternative factor structures for the MJDQ at various hierarchical levels. This study contributes to research on the measurement of work by providing the first comprehensive evaluation of the factor structure of the MJDQ. This measure deserves particular attention, as it is perhaps the most general and integrative measure of work available. This study also contributes to research on the meaning of work by empirically evaluating hierarchical factor models that characterize work at varying levels of abstraction. These analyses help determine whether specific work attributes can be organized into general conceptualizations of work such as those underlying the MJDQ.

Development of the MJDQ

Conceptual Origins of the MJDQ

As stated earlier, the MJDQ was intended to integrate approaches to work design from various disciplines. These approaches were identified through a comprehensive review of the organizational psychology, industrial engineering, human factors, and sociotechnical literatures (Campion & Thayer, 1985). This review yielded 700 job design rules, which were consolidated into 70 categories based on homogeneity of content. For each category, a principle was written that summarized the content of its associated rules. These principles were then organized into four categories, representing motivational, mechanistic, biological, and perceptual-motor approaches to work design.

Original Version of the MJDQ

To measure the motivational, mechanistic, biological, and perceptual-motor work design approaches, Campion and Thayer (1985) developed

16, 13, 18, and 23 items, respectively. Using these 70 items, two job analysts scored 30 jobs, producing interrater reliabilities (bivariate correlations) for the four MJDQ scales ranging from .89 to .93. The MJDQ was then used by a sample of supervisors to rate the content of 112 jobs in wood products operations. Internal consistency reliabilities for the four scales ranged from .82 to .89, and correlations among the scales ranged from −.69 for the motivational and mechanistic scales to .47 for the biological and perceptual-motor scales.

Evidence for the criterion validity of the 70-item MJDQ has also been reported. Campion and Thayer (1985) found that, as hypothesized, satisfaction, efficiency, comfort, and reliability were positively related to the motivational, mechanistic, biological, and perceptual-motor measures, respectively. However, contrary to predictions, the perceptual-motor measure exhibited a slightly higher correlation with efficiency than with reliability. In a later study using these data, Campion (1989) constructed job ability requirement estimates using the *Dictionary of Occupational Titles* (U.S. Department of Labor, 1977) and found that cognitive skill requirements (e.g., quantitative, verbal, spatial, and general learning ability) were positively related to the motivational scale and negatively related to the mechanistic and perceptual-motor scales. Measures of physical skill requirements (e.g., dexterity, strength, and coordination) tended to exhibit positive relationships with the motivational scale and negative relationships with the mechanistic, biological, and perceptual-motor scales.

Revised Version of the MJDQ

Campion (1988) revised the MJDQ by eliminating redundant items, dropping items relevant to only certain jobs (e.g., manufacturing), and revising the instructions to permit self-rating of jobs by incumbents. The resulting instrument contained 48 items, with 18, 8, 10, and 12 items for the motivational, mechanistic, biological, and perceptual-motor approaches, respectively. The revised MJDQ was used by three job analysts to score 30 jobs, yielding average interrater reliabilities ranging from .78 to .95. Self-report data from 1,024 employees in 92 jobs produced internal consistency reliabilities for the motivational, biological, and perceptual-motor scales ranging from .85 to .87, whereas the reliability of the mechanistic scale was .64. Correlations among the scales were smaller in magnitude than those reported by Campion and Thayer (1985), ranging from −.15 for the biological and mechanistic scales to .39 for the mechanistic and perceptual-motor scales. When data were aggregated to the job level, these correlations increased in absolute magnitude but followed the same pattern.

Data from Campion (1988) have also been used to examine the criterion validity of the revised MJDQ. Campion (1988) reported correlations between the revised MJDQ scales and satisfaction, efficiency, comfort, and reliability that paralleled results for the original MJDQ. Using data collected by Campion (1988, 1989) and Campion and Berger (1990) reported that cognitive skill requirements were positively related to the motivational scale and negatively related to the mechanistic and perceptual-motor scales, again replicating results based on the original MJDQ. However, for the revised MJDQ, cognitive skill requirements were also positively related to the biological scale. Relationships with physical skill requirements were similar for the original and revised MJDQ, although relationships with required dexterity were in opposite directions for the two versions of the MJDQ.

Subsequent studies using the revised MJDQ have produced interrater reliabilities ranging from .46 to .94 and internal consistency reliabilities ranging from .49 to .94, with the mechanistic scale again exhibiting the lowest internal consistency reliability (Campion, Kosiak, & Langford, 1988; Campion & McClelland, 1991, 1993; Wong & Campion, 1991). In two quasi-experimental studies, Campion and McClelland (1991, 1993) reported reliabilities that were often higher than those found in other studies, perhaps because these investigators modified several MJDQ items to suit the particular characteristics of their sample. Scale intercorrelations reported in these studies ranged from −.72 for the motivational and mechanistic scales to .88 for the mechanistic and perceptual-motor scales. Like Campion (1988), these studies obtained scale intercorrelations that were larger in absolute magnitude for data at the job level than at the incumbent level. However, scale intercorrelations at the job level reported by Campion and McClelland (1991) were notably larger than those found by Campion (1988) and, for the mechanistic and perceptual-motor scales, raise concerns regarding discriminant validity.

Further evidence for criterion validity corroborated previously reported findings. Cognitive skill requirements were positively related to the motivational scale and negatively related to the mechanistic and perceptual-motor scales (Campion & McClelland, 1991, 1993; Wong & Campion, 1991). Similar relationships were observed between these scales and measures of mental overload and training requirements (Campion & McClelland, 1991, 1993). In addition, affective measures such as job satisfaction exhibited positive relationships with the motivational scale and, to a lesser extent, the biological and perceptual-motor scales, and negative relationships with the mechanistic scale (Campion & McClelland, 1991, 1993; Wong & Campion, 1991). Finally, Campion et al. (1988) also found that the total score from the Job Diagnostic Survey (JDS; Hackman & Oldham, 1980) was more highly correlated with the motivational scale than with the other three MJDQ scales, providing some evidence for convergent validity.

Summary

Overall, evidence regarding the psychometric properties of the MJDQ has been variable but generally favorable. Support has been strongest for the motivational scale, which has yielded high interrater and internal consistency reliabilities and stable relationships with conceptually relevant outcomes. Evidence for the mechanistic, biological, and perceptual-motor scales has been less consistent, with interrater and internal consistency reliabilities ranging from the .40s to the .90s and relationships with outcomes that varied in sign and magnitude across studies. The weakest support was found for the mechanistic scale, which produced internal consistency reliabilities below .60 in several studies.

Although the evidence summarized above provides useful information regarding the MJDQ, this evidence is incomplete, as several important properties of the MJDQ have not been assessed. First, the fit of the 4-factor model implied by the MJDQ has not been evaluated. As a result, it is unclear whether the relationships among the 48 MJDQ items are adequately explained by the four work design approaches identified by Campion and Thayer (1985). Second, the loadings of the MJDQ items on their intended factors have not been reported. Although the overall magnitudes of these loadings can be inferred from the internal consistency reliabilities of the MJDQ scales, it remains unclear which items best represent each factor. If a factor is represented by only a few items, then the prevailing interpretation of the associated MJDQ scale may be incorrect. Third, correlations among the four MJDQ factors have not been formally tested for discriminant validity. In two studies (Campion, 1988; Campion & McClelland, 1991), the disattenuated correlation between the mechanistic and perceptual-motor scales exceeded .98, suggesting that these scales may represent the same factor. Finally, the dimensionality of the items contained within each MJDQ scale has not been examined. Although the MJDQ treats each work design approach as a single dimension, research indicates that these approaches may contain multiple dimensions (e.g., Harvey et al., 1985; Harvey, Friedman, Hakel, & Cornelius, 1988; Idaszak et al., 1988; Kulik et al., 1988; Sims et al., 1976). If so, it may be more appropriate to represent the MJDQ using a second-order factor model in which the MJDQ items load on a set of specific work design factors, which in turn load on factors representing the four approaches identified by Campion and Thayer (1985).

The Present Study

This study provides a comprehensive examination of the factor structure of the MJDQ. Our analyses follow a 3-stage sequence, progressing from strictly confirmatory to quasi-confirmatory to exploratory factor models. First, we conduct a confirmatory factor analysis of the 4-factor model corresponding to the four work design approaches underlying the MJDQ. Second, we examine hierarchical factor models that use the four work design approaches as second-order factors and use items from each approach to create first-order factors, based on exploratory factor analysis conducted separately for items from each approach. These models retain the general structure of the four work design approaches but allow specific work design dimensions to emerge within each approach. Third, we conduct exploratory factor analyses of all MJDQ items, calculate correlations among the obtained factors, and conduct exploratory factor analyses of these correlations to identify second-order factors. These analyses combine items from different work design approaches and can uncover second-order factor structures that differ from that suggested by the MJDQ. To reduce risk of capitalizing on chance sampling variability, we cross-validate all exploratory factor structures using confirmatory factor analysis (Cudeck & Browne, 1983). In sum, this investigation progresses from confirmatory analyses of the simple 4-factor structure implied by the MJDQ to exploratory analyses of complex hierarchical factor structures that provide alternative representations of the MJDQ. As we show, the factor model that best fits the MJDQ deviates substantially from the 4-factor model currently used to score and interpret the MJDQ.

Method

Sample

Data were collected from employees at a large university in the southern United States. Job descriptions for all nonfaculty positions at the university were reviewed to identify a subset of jobs that represented a broad range of skill and task requirements. Efforts were made to include jobs that would vary on each job design approach. For example, some jobs involved working in cold or noisy conditions, other jobs required physical strength, and other jobs entailed extensive information processing. In total, 35 job titles were chosen. These jobs fell into six categories: (a) clerical (e.g., clerks, typists, secretaries); (b) technical (computer programmer, systems programmer, laboratory technician); (c) scientific (e.g., chemists, biologist); (d) skilled labor (e.g., mechanic, carpenter); (e) unskilled labor (e.g., maintenance support worker, laborer); and (f) custodial (custodial worker).

Of the 1,795 surveys distributed, 754 were returned, yielding a response rate of 42%. Response rates by job category were 53% for clerical, 25% for technical, 50% for scientific, 17% for unskilled labor, 66% for skilled labor, and 16% for custodial. A comparison of respondents and nonrespondents on age, sick leave, and annual leave indicated no significance differences; $F(1, 1626) = .09$; $F(1, 1626) = 1.29$; $F(1, 1626) = .58$, respectively. The mean age of the respondents was 40.88 (SD = 10.86), and over 97% of the respondents were employed full-time. Organization tenure for the respondents averaged 8.78 years (SD = 7.43) and ranged from less than 1 year to 40 years. Nearly all respondents (98%) had a high school degree, 77% had some college education or a technical degree, and 35% had an undergraduate or graduate degree.

Of the 754 surveys returned, 352 had missing data on at least one MJDQ item. Hence, listwise deletion of cases with missing data would have yielded a sample size of 402. Although listwise deletion is widely used, other procedures for handling missing data are available that retain statistical power and provide more accurate estimates of population parameters (Little & Rubin, 1987; Roth, 1994). One simple but effective procedure is regression imputation, in which values for missing data are estimated based on scores from related variables without missing data. Regression imputation is particularly appropriate when variables with and without missing data are highly correlated and the sample size is large (Roth, 1994).

For each item, missing data were imputed using items from the same work design approach. Two criteria were used to determine whether to impute a missing score. First, the respondent must have provided complete data on at least 80% of the items within the relevant work design approach (Roth, 1994). For example, to impute a score for a biological item, a respondent must have had complete data on at least 8 of the 10 biological items. Second, at least 80% of respondents within a job title must have responded to the item. These criteria increased the likelihood that imputed scores would be derived from items and respondents relevant to the score in question. Using these criteria, the imputation procedure yielded 602 usable cases. This sample size provided a ratio of cases-to-parameters of at least 5.90 to 1 for all confirmatory factor analyses, thereby exceeding the 5:1 ratio suggested by Bentler and Chou (1987).

Measures

The self-report version of the revised MJDQ was used (Campion, 1988). As noted previously, this version of the MJDQ contains 48 items (18 motivational, 8 mechanistic, 10 biological, 12 perceptual-motor). Respondents were asked to indicate the extent to which each statement described their job, using a 7-point scale ranging from 1 = *not at all* to 7 = *exactly*. A separate response option was provided for items that did not apply to the respondent's job.

Analysis

To provide continuity with prior research, we calculated internal consistency reliabilities and intercorrelations for the four MJDQ scales. We then analyzed the three sets of factor models corresponding to the 3-stage sequence outlined earlier. First, we tested the 4-factor model implied by the MJDQ, using confirmatory factor analysis with maximum likelihood estimation as implemented by LISREL 8 (Jöreskog & Sörbom, 1993). Overall model fit was evaluated by examining the root mean squared error of approximation (RMSEA; Steiger, 1990) and the comparative fit index (CFI; Bentler, 1990). The RMSEA is an estimate of the discrepancy between the original and reproduced covariance matrices in the population. Browne and Cudeck (1993) suggested that a RMSEA of .05 indicates close fit and a value of .08 represents reasonable errors of approximation in the population. The CFI indicates the relative improvement in fit of the target model over a null model in which all observed variables are uncorrelated (Bentler, 1990). The CFI is independent of sample size (Gerbing & Anderson, 1993) and has an expected value of 1.00 when the target model is true in the population. Although standards for indices such as the CFI are difficult to establish (Marsh, Balla, & McDonald, 1988), a value of .90 or higher has been suggested as indicating adequate fit (Bentler & Bonett, 1980). In addition to assessing overall model fit, we tested item loadings, standardized residuals, and modification indices indicating the potential improvement in model fit if an item loaded on more than one factor. These additional tests provided specific information regarding the sources of model misfit.

Second, we tested hierarchical factor models that used the four work design approaches as second-order factors and assigned items within each approach to first-order factors. For each work design approach, first-order factors were identified through exploratory factor analysis of items from that approach, using principal axis factoring and oblimin rotation (Kim & Mueller, 1985). The number of first-order factors retained for each approach was determined by the scree test (Cattell &

Vogelmann, 1977) and substantive interpretability. The resulting second-order factor models were estimated with confirmatory factor analysis, which provided comprehensive information regarding model fit and permitted detailed comparisons of alternative models. As before, model fit was assessed using the RMSEA, CFI, standardized residuals, and modification indices.

Third, we constructed hierarchical factor models by combining all 48 MJDQ items, conducting exploratory factor analyses to identify first-order factors, and then factoring the correlations among the first-order factors to derive second-order factors. Both sets of analyses used principal axis factoring with oblimin rotation and employed the scree test and substantive interpretability to determine the number of factors to retain.[1] The resulting second-order factor models were then estimated with confirmatory factor analysis to evaluate model fit, to compare alternative models, and to assess the relative fit of models with and without second-order factor structures, using chi-square difference tests (Bagozzi & Edwards, 1998). Model fit was again evaluated using the RMSEA, CFI, standardized residuals, and modification indices.

To reduce the likelihood of capitalizing on sampling variability, all exploratory factor analyses were performed using data from two random stratified subsamples ($n = 302$, $n = 285$), in which the strata were gender and job title (the subsamples do not sum to the full sample size of 602 due to missing data on the variables used for stratification). For each analysis, the model that best suited each subsample was identified, and a common factor model was identified that contained items that loaded on the same factors in both subsamples. Thus, each exploratory factor analysis yielded three models, one obtained from each subsample and a third indicated by both subsamples. These models were then tested in both subsamples using confirmatory factor analysis. The model that produced admissible parameter estimates in both subsamples and yielded the best overall fit was chosen and reestimated using data from the full sample. Hence, our exploratory factor analyses followed the double cross-validation procedure suggested by Campbell (1976) for empirical measurement development and employed confirmatory factor analysis to choose from among competing factor models based on which model best survived cross-validation (Cudeck & Browne, 1983).

[1] When principal axis factoring is used, communalities are inserted along the diagonal of the input correlation matrix, which corrects correlations among first-order factors for measurement error (Kim & Mueller, 1985). When these factor correlations are subsequently analyzed, there is no need to again correct them for measurement error. Therefore, when the correlations among the first-order MJDQ factors were factor analyzed, unities were retained along the diagonals of the input correlation matrix. If communalities had been inserted along the diagonal, correlations among the first-order MJDQ factors would have been corrected for measurement error twice.

TABLE 1

Means, Standard Deviations, Correlations, and Internal Consistency Reliabilities for the MJDQ Scales

	M	*SD*	1	2	3	4
1. Motivational	4.86	0.99	(.89)			
2. Mechanistic	3.86	0.73	−.02	(.39)		
3. Biological	4.73	1.01	.26	.09	(.71)	
4. Perceptual-motor	4.22	0.92	.16	.32	.47	(.77)

Note: $N = 602$. Correlations that exceed .08 in absolute magnitude are statistically significant ($p < .05$). Internal consistency reliabilities (Cronbach's alpha) are reported along the diagonal.

Results

Internal Consistency Reliabilities and Scale Intercorrelations

Descriptive statistics, internal consistency reliabilities, and intercorrelations for the four MJDQ scales are reported in Table 1. All four scales yielded good dispersion and showed no evidence of floor or ceiling effects. Reliabilities for the motivational, biological, and perceptual-motor scales ranged from .71 to .89, whereas the reliability for the mechanistic scale reached only .39. Correlations among the scales ranged from −.02 for the motivational and mechanistic scales to .47 for the biological and perceptual-motor scales. These results are consistent with prior studies of the psychometric properties of the MJDQ using data at the job incumbent level (Campion, 1988; Campion et al., 1988; Campion & McClelland, 1991, 1993).

Original Four-Factor Model

Results from the confirmatory analysis of the 4-factor model implied by the MJDQ are summarized in Table 2. The RMSEA of .084 exceeded the upper threshold of .08 suggested by Browne and Cudeck (1993), and the CFI reached .59, indicating very poor fit. Although most item loadings differed significantly from zero, many were low in absolute magnitude, with over one-third failing to reach .30. In addition, several item loadings were negative for the mechanistic factor, providing one explanation for the low internal consistency reliability obtained for this scale. Based on these loadings, factor reliabilities (Jöreskog, 1971) ranged from .17 for the mechanistic factor to .89 for the motivational factor, with reliabilities for the biological and perceptual-motor factors reaching .61 and .68, respectively. Hence, only the reliability of the motivational factor exceeded the criterion of .70 suggested by Nunnally (1978).

TABLE 2

Results from Confirmatory Factor Analysis of Four-Factor MJDQ Model

	Motivational	Mechanistic	Biological	Perceptual-Motor
Motivational items				
1. The job allows freedom, independence, or discretion in work scheduling, sequence, methods, procedures, quality control, or other decision making.	.51	–	–	–
2. The work I do provides me with direct feedback about the effectiveness (e.g., quality and quantity) of my performance.	.61	–	–	–
3. My managers and coworkers provide me with feedback about the effectiveness (e.g., quality and quantity) of my job performance.	.59	–	–	–
4. My job provides the opportunity for social interaction such as team work or coworker assistance.	.49	–	–	–
5. The job duties, requirements, and goals are clear and specific.	.52	(.42)	(.11)	(.33)
6. I have a variety of duties, tasks, and activities on my job.	.55	(−.13)	–	(−.16)
7. The job requires completion of a whole and identifiable piece of work. It gives you a chance to do an entire piece of work from beginning to end.	.43	–	–	–
8. My job requires a high level of knowledge and skills.	.68	(−.45)	–	(−.31)
9. My job requires a variety of knowledge and skills.	.69	(−.33)	–	(−.30)
10. My job is significant and important compared with other jobs at the University.	.62	(−.12)	–	–
11. My job provides the opportunity for learning and growth in competence and proficiency.	.79	(−.10)	–	–
12. My job provides opportunities for advancement to higher level jobs.	.49	(.30)	–	(.17)
13. My job gives me a feeling of achievement and accomplishment.	.83	(.09)	–	–
14. My job gives me the opportunity to participate in decisions that affect my job.	.72	(.10)	–	(.09)
15. The job has access to relevant communication channels and information flows.	.26	–	(.13)	–
16. My job offers adequate pay compared with the job requirements and with pay in similar jobs.	.30	(.39)	–	(.31)
17. The job provides acknowledgment and recognition from others.	.67	(.16)	–	(.16)
18. My job offers job security as long as I do a good job.	.21	(.18)	(.11)	(.13)

TABLE 2 (continued)

	Motivational	Mechanistic	Biological	Perceptual-Motor
Mechanistic items				
19. The job is highly specialized in terms of purpose, tasks, or activities.	(−.28)	−.48	–	(.33)
20. The tools, procedures, materials, and so forth, used on this job are highly specialized in terms of purpose.	(−.17)	−.38	–	(.38)
21. The tasks I do on my job are simple and uncomplicated.	(−.17)	.73	–	–
22. My job requires me to do only one task or activity at a time.	(−.14)	.47	–	(−.47)
23. My job requires little skill and training time.	–	.71	–	–
24. I perform the same task or activity repeatedly on my job.	–	.50	–	–
25. I have little spare time between activities on my job.	–	−.24	–	(.26)
26. Many of the activities of this job are automated or assisted by automation.	–	−.18	(−.15)	–
Biological items				
27. My job requires very little muscular strength.	–	–	.85	–
28. My job requires very little lifting, or the objects I lift are of very light weight.	(−.08)	–	.89	–
29. The task performed on this job require fairly little muscular endurance.	–	–	.52	–
30. The chair on my job is comfortable and provides good back support.	(.24)	(−.14)	.32	–
31. The work place allows for all size differences between people in terms of clearance, reach, eye height, leg room, and so forth.	(.41)	(−.16)	.08	–
32. The job allows the wrists to remain straight without excessive movement.	(.30)	(−.17)	.16	–
33. My work area is free from excessive noise.	(.23)	–	.19	–
34. My work area is comfortable in terms of temperature.	(.22)	–	.15	–
35. My job offers adequate time for work breaks given the demands of my job.	(.16)	(.15)	.12	(.24)
36. My job does not require me to work excessive overtime.	–	(.20)	.23	(.19)

TABLE 2 (continued)

	Motivational	Mechanistic	Biological	Perceptual-Motor
Perceptual-motor items				
37. My work area lighting is adequate and free from glare.	(.27)	(−.31)	(.19)	.06
38. The displays, gauges, meters, and computerized equipment on this job are easy to read and understand.	(.29)	(−.36)	(.17)	.11
39. On my job, the computer programs I use are easy to learn and use.	(.23)	–	(.27)	.15
40. The other equipment (all types) used on this job are easy to learn and use.	(.22)	–	(.21)	.28
41. The printed materials I use on the job are easy to read and interpret.	(.34)	(−.18)	(.16)	.24
42. My work area is laid out so that I can see and hear everything I need to perform the job.	(.39)	(−.38)	(.15)	.18
43. The amount of information I must attend to in order to perform this job is fairly minimal.	(.09)	–	–	.77
44. The amount of information I must put out on this job, in terms of both action and communicate, is fairly minimal.	–	–	–	.69
45. The amount of information I must process, in terms of thinking and problem solving, is fairly minimal.	(−.11)	–	–	.88
46. The amount of information I must remember on my job is fairly minimal.	(−.08)	-	(−.13)	.81
47. There is relatively little stress on my job.	(.19)	–	–	.45
48. The chances of boredom on this job are fairly small.	(.37)	(−.53)	–	−.29

Note: $N = 602$. Table entries are standardized loadings. Entries not in parenthesis are loadings from the 4-factor model; entries in parenthesis indicate the expected value of the loading if the corresponding parameter were freed (these values are reported only for loadings that yielded a modification index larger than 5.28).

Factor correlations ranged from –.53 for the motivational and mechanistic factors to .72 for the mechanistic and perceptual-motor factors. Because these correlations are corrected for measurement error (Jöreskog & Sörbom, 1993), they are larger in absolute magnitude than the corresponding correlations among the MJDQ scales. For all factor correlations, 95% confidence intervals excluded –1.0 and 1.0, thereby satisfying a necessary condition for discriminant validity (Bagozzi & Phillips, 1982).

Sources of misfit were identified from two supplemental analyses. First, modification indices for item loadings were examined to determine whether model fit would improve if an item were allowed to load on two or more factors. Modification indices are distributed approximately as a chi-square with one degree of freedom (Sörbom, 1975). For tests corresponding to each item, Type I error was controlled by dividing the nominal alpha of .05 by the number of tests performed (i.e., three), yielding a critical chi-square of 5.73. For modification indices that exceeded this criterion, Table 2 shows the expected value of the associated item loading. These values revealed that many items apparently represented more than one factor, and several items yield expected secondary loadings that were larger in absolute magnitude than their primary loading. For example, items representing autonomy, task identity, and feedback were uniquely associated with the motivational factor. However, items describing skill level and skill variety not only represented the motivational factor, but also signified the opposite of the mechanistic factor, which emphasizes work that is simple and repetitive. Items referring to rewards received from work, such as pay, recognition, and job security, represented the motivational factor as well as the mechanistic and perceptual-motor factors. Items that described work conditions (e.g., reading materials, lighting, computer display, work area) were assigned to the biological and perceptual-motor factors but exhibited weak relationships with all four factors.

Second, standardized residuals were examined to identify item covariances not accounted for by the model. For tests pertaining to each item, Type I error was again controlled by dividing the nominal alpha of .05 by the number of tests performed (i.e., 47), yielding a critical t-value of 3.29. Across all items, the median number of standardized residuals that exceeded the critical t-value was 16, with a range from 2 to 33. In many cases, high standardized residuals were found for items from different scales. For example, items from the biological and perceptual-motor scales that described good working conditions yielded large positive residuals with items from the motivational scale that referred to job enrichment. In effect, the model underestimated the degree to which enriched jobs were accompanied by good working conditions. In other cases, high standardized residuals were obtained for items from the same scale. For instance, several subsets of items from the motivational scale represented specific aspects of motivating jobs (e.g., variety, feedback, rewards). Covariances among items within these subsets were underestimated by assigning all motivational items to one general factor. Similarly, the biological and perceptual-motor scales contained item subsets with specific content (e.g., ergonomics, working conditions, equipment features) that produced large positive residuals within each subset. These item subsets foreshadowed the possibility that items assigned to each MJDQ scale represent multiple factors, thereby suggesting a hierarchical factor model.

Hierarchical Four-Factor Model

Using data from the random stratified subsamples, exploratory factor analyses of items assigned to each MJDQ scale indicated that each scale comprised multiple factors. Results from the first subsample yielded four, two, four, and two factors for the motivational, mechanistic, biological, and perceptual-motor scales, respectively, whereas results from the second sample produced four, two, four, and three factors for these scales. Results common to both subsamples indicated four, two, four, and two factors for the four MJDQ scales.

The preceding results were used to construct three hierarchical factor models, corresponding to results from the first subsample, results from the second subsample, and results common to both subsamples. These models were then estimated using data from both subsamples. The overall fit of these models is summarized in Table 3. For both subsamples, all three models yielded notable improvements in fit over the original 4-factor model. RMSEA values ranged from .068 to .071, well below the value of .084 from the original model. Likewise, CFI values for the hierarchical models ranged from .77 to .79, exceeding the value of .59 from the original model. However, in an absolute sense, the fit of the hierarchical models was modest, in that all RMSEA values exceeded the criterion of .05 indicating close fit, and none of the CFI values reached .90. Moreover, the fit of the models did not vary greatly, making it difficult to determine which model was superior. Further inspection of results from both subsamples showed that, for the model from the first subsample, the perceptual-motor factor exhibited correlations with the mechanistic and biological factors that did not differ significantly from unity, thereby failing to satisfy a necessary condition for discriminant validity. Similarly, for the common model, the correlation between the perceptual-motor factor and the mechanistic factor did not differ significantly from unity. These problems did not emerge

TABLE 3

Fit of Four-Factor Second-Order Models

	k	p	χ^2	df	CFI	RMSEA
Data from Subsample 1						
Model from Subsample 1	42	12	1923.60	802	.77	.070
Model from Subsample 2	44	13	2038.83	883	.78	.068
Model common to both subsamples	39	12	1615.54	684	.78	.069
Data from Subsample 2						
Model from Subsample 1	42	12	2024.54	802	.77	.071
Model from Subsample 2	44	13	2108.08	883	.78	.068
Model common to both subsamples	39	12	1685.73	684	.79	.070

Note: N = 286 for Subsample 1; N = 302 for Subsample 2. The number of items included in each model is indicated by k; the number of first-order factors in each model is indicated by p (all models included four second-order factors).

in the model from the second subsample. Therefore, the model from the second subsample was deemed superior. This model indiciated the following first-order factors within each work design approach: (a) *motivational*: skill, feedback, rewards, enrichment; (b) *mechanistic*: task simplicity, work specialization; (c) *biological*: ergonomic design, physical ease, work scheduling, work conditions; and (d) *perceptual-motor*: cognitive simplicity, equipment interface, visibility.

The model from the second subsample was reestimated using data from the full sample. The RMSEA for the model was .065, and the CFI reached .79, indicating modest fit. All item loadings differed significantly from zero (p <.05), and nearly 90% exceeded .50 in magnitude. Using these loadings, factor reliabilities ranged from .51 for the biological work scheduling factor to .85 for the motivational skill factor, with a median reliability of .75. All first-order factor loadings differed significantly from zero and, with two exceptions, all loadings exceeded .60 in absolute magnitude. Loadings for the two first-order factors under the mechanistic factor (i.e., task simplicity and work specialization) were opposite in sign, suggesting that in our sample specialized work tended to be complex rather than simple.[2] Correlations among the second-order factors ranged from −.70 for the motivational and mechanistic factors to .87 for the biological and perceptual-motor factors. Although these correlations were large in absolute magnitude, their 95% confidence intervals excluded −1.0 and 1.0, respectively, satisfying a necessary condition for discriminant validity.

[2]Tables listing all item loadings and first-order factor loadings for this model may be obtained from the first author.

Modification indices were again examined to identify sources of misfit. For tests regarding each item, Type I error was controlled by dividing the nominal alpha of .05 by the number of tests performed (i.e., 12), yielding a critical chi-square of 8.21. Likewise, for tests concerning each first-order factor, the nominal alpha of .05 was divided by the number of tests performed (i.e., three) for a critical chi-square of 5.73. Most items yielded significant modification indices for loadings on at least one secondary factor, but the expected absolute magnitudes of these loadings were generally small. Exceptions included item 16 (adequate pay) on the motivational rewards factor and items 47 and 48 (low stress and low boredom, respectively) on the perceptual-motor cognitive simplicity factor, each of which yielded expected secondary loadings that approached or exceeded their primary loadings. All but two first-order factors produced significant modification indices for loadings on other second-order factors, and the expected absolute magnitude at least one of these secondary loadings was larger than the primary loading for the biological physical ease factor, the biological work scheduling factor, the perceptual-motor cognitive simplicity factor, and the perceptual-motor visibility factor.

Standardized residuals were again examined to further investigate sources of misfit. As before, Type I error was controlled by dividing the nominal alpha of .05 by the number of tests performed for each item (i.e., 43), yielding a critical t-value of 3.26. The median number of standardized residuals that exceeded the critical t-value was 9, with a range from 2 to 28. Hence, the hierarchical 4-factor model yielded substantially fewer significant residuals than the original 4-factor model. The most notable reduction in residuals involved items assigned to the same work design approach. By separating items for each approach into specific first-order factors, the model better reproduced covariances among distinct item subsets within each approach. However, items assigned to different work design approaches again produced many significant residuals. For example, items assigned to the perceptual-motor cognitive simplicity factor exhibited large positive residuals with items on the mechanistic task simplicity factor and large negative residuals with items on the motivational skill and feedback factors.

The preceding findings suggested that the second-order factor structure corresponding to the four work design approaches did not adequately account for the covariances among the 13 first-order factors. This speculation was supported by estimating a model that replaced the second-order factor structure with unrestricted covariances among the first-order factors, thereby yielding a simple first-order 13-factor model. This model produced a RMSEA of .056 and a CFI of .85, both of which indicated better fit than the second-order model. A chi-square difference test showed that the first-order model produced a significant improvement in fit relative to the second-order model ($\Delta\chi^2$ (59) = 702.73, p <.001). These results indicate that the second-order structure corresponding to the four work design approaches may not be viable. However, the results do not preclude alternative hierarchical factor structures, as considered in the following analyses.

Hierarchical Exploratory Model

Using data from the random stratified subsamples, exploratory factor analyses of all 48 MJDQ items yielded a 46-item 11-factor solution in the first subsample and a 43-item 10-factor solution in the second subsample. Results common to both subsamples indicated a 35-item 10-factor solution. These results were used to construct three first-order factor models, which were estimated in both subsamples. Factor correlation matrices from these analyses were then used as input to exploratory factor analyses. For both subsamples, these analyses suggested three second-order factors that accounted for all but two of the first-order factors. Rather than discarding these first-order factors and their associated items, the factors were assigned to their own second-order factors, yielding a total of five second-order factors for both subsamples. Results common to both subsamples also indicated three second-order factors that accounted for all but two first-order factors. As before, these first-order factors each were assigned to their own second-order factors, producing five second-order factors. For each second-order factor with a single first-order factor, the residual variance of the first-order factor was set to zero to achieve model identification. This constraint rendered each of these second-order factors conceptually identical to its assigned first-order factor.

The three first-order factor models and corresponding second-order factor models derived from the preceding analyses were estimated using data from both subsamples, yielding a total of six models for each subsample. Results from these analyses are summarized in Table 4. For the first-order models, RMSEA values ranged from .057 to .063 and CFI values ranged from .81 to .88. Fit was notably better for the common model than for the models from either subsample, and RMSEA and CFI values for the common model approached the suggested criteria of .05 and .90, respectively, indicating reasonably good fit. For the second-order models, RMSEA values ranged from .062 to .069 and CFI values ranged from .76 to .85. Compared to the first-order models, the second-order models yielded somewhat worse fit, although the values of the fit indices followed a similar pattern, with the common model again yielding the

TABLE 4

Fit of Respecified First-Order and Second-Order Factor Models

	k	p	χ^2	df	CFI	RMSEA
	First-order models					
Data from Subsample 1						
Model from Subsample 1	46	11	1800.31	934	.84	.057
Model from Subsample 2	43	10	1748.84	815	.81	.063
Model common to both subsamples	35	10	969.56	515	.88	.056
Data from Subsample 2						
Model from Subsample 1	46	11	2014.28	934	.81	.062
Model from Subsample 2	43	10	1753.09	815	.83	.062
Model common to both subsamples	35	10	1011.91	515	.88	.057
	Second-order models					
Data from Subsample 1						
Model from Subsample 1	46	11	2041.88	970	.80	.062
Model from Subsample 2	43	10	1989.29	841	.76	.069
Model common to both subsamples	35	10	1131.96	542	.85	.062
Data from Subsample 2						
Model from Subsample 1	46	11	2246.10	970	.78	.066
Model from Subsample 2	43	10	1942.75	841	.80	.066
Model common to both subsamples	35	10	1181.52	542	.85	.063

Note: N = 286 for Subsample 1; N = 302 for Subsample 2. The number of items included in each model is indicated by k; the number of first-order factors in each model is indicated by p (all models included five second-order factors).

best fit of the three models. Chi-square difference tests indicated that, for both subsamples, the first-order models yielded significantly better fit than their corresponding second-order models (all $p < .001$). Moreover, of the second-order models, the common model and the model from the second subsample yielded a negative residual variance for one first-order factor, signifying an inadmissible solution. Of the first-order models, the common model yielded the best fit. Therefore, this model was chosen for further examination using data from the full sample.

Results from the first-order common model using data from the full sample are reported in Table 5. The model yielded a RMSEA of .054 and a CFI of .89, close to the criteria of .05 and .90, respectively. Thus, the model fit the data reasonably well. For all but one factor, all items loading on each factor came from a single work design approach. The sole exception was item 22, a mechanistic item that described doing work one task at a time that grouped with a subset of the perceptual-motor items dealing with cognitively simple work. All item loadings were significantly different from zero ($p < .05$), and loadings ranged in magnitude from .30 to .93, with nearly 95% exceeding .50 (see Table 6). Factor reliabilities ranged from .49 for the workload factor to .86 for the cognitive simplicity factor, with all but two reliabilities exceeding the

TABLE 5

Loadings From Respecified First-Order Factor Model

	Feedback	Cognitive simplicity	Physical ease	Work conditions	Specialization	Ergonomics	Task simplicity	Work scheduling	Rewards	Skill
Feedback items										
2.	.73	–	–	–	–	–	–	–	(–.36)	–
3.	.71	–	–	–	(.10)	–	–	–	–	–
4.	.53	–	–	(–.14)	–	–	–	–	–	–
5.	.67	(.29)	–	(.28)	–	(.29)	(.35)	(.34)	–	(–.24)
Skill items										
6.	(.19)	–	–	–	(–.12)	(.13)	–	–	–	.60
8.	(–.13)	–	–	–	(.13)	–	(–.16)	–	–	.83
9.	–	–	–	–	(–.12)	–	(.17)	–	–	.84
11.	(.40)	(.13)	–	(.24)	–	(.19)	–	(.31)	(.56)	.75
15.	–	–	(.15)	–	–	(.17)	–	(.18)	–	.30
Rewards items										
12.	–	(.14)	–	–	–	–	(.27)	–	.55	(–.18)
13.	–	–	–	–	–	(–.11)	(–.14)	(–.13)	.89	(.30)
14.	–	–	–	–	–	–	–	–	.75	–
16.	–	(.31)	–	(.16)	(–.15)	(.18)	(.33)	(.29)	.36	(–.34)
Specialization items										
19.	–	–	–	–	.93	–	–	–	–	–
20.	–	–	–	–	.67	–	–	–	–	–
Task simplicity items										
21.	(.18)	(.22)	–	(.14)	(–.13)	(.23)	.76	(.20)	(.16)	–
23.	–	(.13)	–	–	–	–	.74	–	(.13)	–
24.	–	–	–	–	(.12)	–	.53	–	–	–

TABLE 5 (continued)

	Feedback	Cognitive simplicity	Physical ease	Work conditions	Specialization	Ergonomics	Task simplicity	Work scheduling	Rewards	Skill
Physical ease items										
27.	–	–	.87	–	–	–	–	–	–	–
28.	–	–	.88	–	–	–	–	–	–	–
29.	–	–	.51	–	–	–	–	–	–	–
Work conditions items										
33.	–	–	–	.67	–	–	–	–	–	–
34.	–	–	–	.60	–	–	–	–	–	–
37.	–	–	–	.56	–	(.18)	–	–	–	–
Work scheduling items										
35.	(.21)	–	–	–	–	–	–	.64	(.17)	(.17)
36.	(–.15)	–	–	–	–	–	(.15)	.50	(–.17)	–
Ergonomics items										
38.	–	–	–	–	(.16)	.66	(–.14)	–	–	(.12)
39.	–	–	(.13)	–	–	.67	–	–	–	–
40.	–	(.15)	–	–	–	.61	(.17)	–	–	(–.11)
41.	–	–	–	–	–	.71	–	–	–	–
Cognitive simplicity items										
22.	–	.53	–	–	–	–	(.13)	–	–	–
43.	(.16)	.77	–	–	–	–	–	–	(.16)	(.16)
44.	–	.70	–	–	–	–	–	–	–	–
45.	–	.86	(.10)	–	–	(.10)	(.16)	(.12)	–	(–.11)
46.	–	.83	–	–	–	–	–	–	–	–

Note: N = 602. Table entries are standardized loadings. Entries not in parenthesis are loadings from the respecified 10-factor model; entries in parenthesis indicate the expected value of the loading if the corresponding parameter were freed (these values are reported only for loadings that yielded a modification index larger than 7.69).

criterion of .70 suggested by Nunnally (1978). Correlations among the factors ranged from –.63 for the task simplicity and skill factors to .75 for the skill and rewards factors. The 95% confidence intervals for all correlations excluded –1.0 and 1.0, thus satisfying a necessary condition for discriminant validity.

Modification indices for item loadings were examined, and Type I error was controlled by dividing the nominal alpha of .05 by the number of tests performed (i.e., 9), producing a critical chi-square of 7.69. For modification indices that exceeded this value, Table 5 displays the expected value of the associated loading. Of the 35 items, 24 yielded significant modification indices for loadings on one or more secondary factors. In most cases, the expected magnitudes of these secondary loadings were small. An exception was item 16, the adequate pay item on the rewards factor, which had a primary loading of .36 but produced seven significant modification indices with secondary loadings ranging in expected value from –.34 to .33. Similarly, the learning item on the skill factor (item 11) had a primary loading of .75 but yielded six significant modification indices with secondary loadings ranging from .13 to .56 in expected value. In contrast, the items on the physical ease and work specialization factors yielded no significant modification indices, and the items on the physical environment factor produced a single significant modification index. Overall, these results indicate that most items represented their assigned factor reasonably well.

Standardized residuals were inspected, with Type I error controlled by dividing the nominal alpha of .05 by the number of tests performed for each item (i.e., 34) for a critical *t*-value of 3.20. Across all 35 items, the median number of standardized residuals that exceeded the critical t-value was 4, and the range was 0 to 11. Thus, the model produced far fewer significant residuals than the preceding models. The largest within-factor residuals were found for the skill factor, which contained item subsets that may be considered conceptually distinct (i.e., skill variety vs. skill level). The largest between-factor residuals were found for the skill and rewards factors, primarily due to underestimated covariances between the learning item on the skill factor and the advancement, achievement, and participation items on the rewards factor.

Overall, our analyses indicate that the MJDQ is best represented by a 35-item, 10-factor first-order model. Information from scales based on this model is summarized in Table 6, which shows means, standard deviations, internal consistency reliabilities, and intercorrelations of the 10 scales. All scales exhibited good dispersion and showed little evidence of floor or ceiling effects. One exception was the cognitive simplicity scale, which produced a mean only slightly larger than one standard deviation from the theoretical scale minimum. This finding is not surprising, as many respondents in our sample were engaged in work that was fairly technical and complex. Eight scales yielded reliabilities greater than .70, and the work conditions scale produced a marginal reliability of .67. However, the work scheduling scale exhibited a reliability of .49, raising questions regarding the utility of this scale. Correlations among the scales ranged from −.43 for task simplicity and skill to .57 for skill and rewards. All disattenuated scale correlations were less than .75 in absolute magnitude, providing evidence for discriminant validity.

Discussion

This study presents the first comprehensive examination of the factor structure of the MJDQ. Our results provide little support for the 4-factor structure implied by the work design approaches underlying the MJDQ (Campion, 1988; Campion & Thayer, 1985). A confirmatory factor analysis of this structure yielded very poor fit, primarily due to the presence of conceptually distinct items within each of the four MJDQ factors. Separating these items into subsets yielded a second-order factor model, with 13 first-order factors assigned to four second-order factors corresponding to the four work design approaches. Although this model fit the data much better than the original 4-factor model, its fit was modest in an absolute sense, due in part to the overly restrictive constraints imposed by the second-order factor structure on the correlations among the first-order factors. A third model was derived, consisting of 10 first-order factors that comprised 35 of the original 48 MJDQ items. This model fit the data reasonably well and produced factors that achieved discriminant validity and, with two exceptions, yielded adequate reliabilities. Attempts to explain the covariances among these first-order factors with a second-order factor structure were unsuccessful, as indicated by significant deterioration in model fit. Thus, our analyses indicate that the MJDQ is best represented by a first-order model with 10 factors, each of which represents a distinct aspect of work.

One explanation for the poor fit of the original 4-factor model is suggested by the procedures used to develop the MJDQ. According to Campion and Thayer (1985), each work design approach underlying the MJDQ was intended to capture a set of distinct principles, and each of these principles was described by a single MJDQ item. Hence, the items for each work design approach were not designed to reflect a common factor, but instead were intended to represent distinct facets of a work design approach. This interpretation is reinforced by Campion (1988, p. 469), who stated that the revised MJDQ was derived in part by "eliminating redundancy" among the original MJDQ items. This statement indicates that item homogeneity was purposely minimized during the development of the MJDQ. Unless items can be grouped into conceptually homogeneous subsets, it is unlikely that a stable, meaningful factor structure will emerge (Nunnally, 1978). Moreover, items that represent different facets of a broader concept are unlikely to covary, as such items share no common cause (Bollen & Lennox, 1991; MacCallum & Browne, 1993). For these reasons, it is perhaps not surprising that the MJDQ failed to yield a factor model that conformed to the four work design approaches.

It is noteworthy that, in the 10-factor model derived for the MJDQ, the items loading on each factor came almost exclusively from one of the four original work design approaches. Given this pattern, it may seem plausible that these 10 first-order factors would load on four second-order factors that correspond to four work design approaches. However, this hierarchical structure did not emerge from exploratory factor analyses of the correlations among the first-order factors. We formally tested this structure by imposing four second-order factors corresponding to the MJDQ work design approaches on the 10 factor first-order model. Results indicated a significant worsening of fit relative to the simple first-order model ($\Delta\chi^2(29) = 404.03, p < .001$). Hence, our findings indicate that the four work design approaches underlying the MJDQ do not represent factors that explain covariances among the MJDQ items or their associated first-order factors. Rather, the MJDQ work design approaches constitute a classification scheme that may be used to organize measures of specific aspects of work, such as the 10 MJDQ scales derived in this study.

Based on our results, we advise researchers to score the MJDQ according to the 10-factor model summarized in Tables 5 and 6. This model provides a more fine-grained assessment of work than the original MJDQ scoring procedure. At the same time, the 10 scores from this model may be grouped according to the four MJDQ work design approaches. In particular, the feedback, skill, and rewards scales fall within the motivational approach, the specialization and task simplicity scales signify the mechanistic approach, the physical ease, work conditions, and work scheduling scales represent the biological approach, and the ergonomic design and cognitive simplicity scales correspond to the perceptual-motor approach. Scores from these scales may be used collectively to generate a multidimensional representation of each work design approach. Accordingly, the effects of each work design approach on outcomes should be examined not as simple bivariate relationships, but rather as multivariate relationships in which scales from each approach are treated as joint predictors of outcomes. Such studies will help reveal the precise nature of the trade-offs among the four work design approaches identified in prior research (Campion & Thayer, 1985).

We acknowledge two shortcomings of the 10-factor MJDQ model advocated here. First, the reliabilities of the work conditions and work scheduling scales were marginal at best. Therefore, these scales may need to be revised or replaced in future research. Second, the 10 MJDQ scales do not fully represent the dimensions relevant to each work design approach. For example, the motivational approach includes not only the feedback, skill, and rewards dimensions derived here, but also dimensions such as autonomy, task identity, and task significance (Hackman & Oldham, 1980). These dimensions are each represented by an omitted MJDQ motivational item (i.e., items 1, 7, and 10, respectively). However, because these items are the sole indicators of these dimensions, they cannot be used to represent factors or form scales. To measure these dimensions within the MJDQ framework, researchers may develop additional items for autonomy, task identity, and feedback or may draw from existing measures of these dimensions (Hackman & Oldman, 1980; Sims et al., 1976). Likewise, additional dimensions relevant to the mechanistic, biological, and perceptual-motor approaches may be measured by developing new scales based on the MJDQ items or by adapting scales from measures such as the Position Analysis Questionnaire (McCormick, Jeanneret, & Mecham, 1972), the Job Element Inventory (Cornelius, Hakel, & Sackett, 1979), and Functional Job Analysis (Fine, 1995). The number of dimensions measured under each approach will depend on the degree of precision desired by the researcher.

Although the MJDQ did not support a hierarchical factor structure, it may be possible to develop measures of work that yield hierarchical structures. Such measures may be developed by defining work constructs at varying depths (Bagozzi & Edwards, 1998), ranging from specific, concrete aspects of work to general, abstract work dimensions. Multiple items representing each specific work construct should be developed, ensuring that items for each construct are sufficiently homogeneous to designate a single content domain (Gerbing & Anderson, 1988; Nunnally, 1978). Specific work constructs may then be collected into conceptually homogeneous subsets, and constructs within each subset may serve as indicators of general work dimensions. Measures that strive for conceptual homogeneity at each level are more likely to yield hierarchical factor structures than measures that classify distinct facets of work, such as the MJDQ. We emphasize, however, that the prospect of developing hierarchical measures of work does not diminish the utility of measures like the MJDQ that are organized around classification schemes. Rather, researchers may consider two types of hierarchical work measures, one that provides higher-order factor structures that explain covariances among distinct but related work dimensions, and another that furnishes classification schemes that organize distinct aspects of work.

Either type of hierarchical measure may be appropriate, depending on whether the researcher desires the integrative coherence of a higher-order factor structure or the clean distinctions of a classification scheme.

Although this study contributes to research on the measurement and meaning of work, it has several limitations. First, we analyzed data at the incumbent level rather than the job level. Our findings should not be generalized to the job level, as incumbent-level and job-level applications of the MJDQ have indicated different psychometric properties (Campion, 1988). Second, although our data were not multivariate normal, we used maximum likelihood estimation. As a result, standard errors and chi-square values may have been inflated (Satorra, 1990). Unfortunately, our sample was not sufficiently large to use estimation methods that are robust to deviations from multivariate normality (Browne, 1984). Third, by focusing on the internal structure of the MJDQ, we did not examine relationships of the original and respecified MJDQ with outcome variables such as those used in previous studies (Campion, 1988; Campion & Berger, 1990; Campion & McClelland, 1991, 1993; Campion & Thayer, 1985; Wong & Campion, 1991). These relationships merit attention in future research.

A final limitation concerns the sample used in this study. Our sample differed from samples used in previous studies of the MJDQ, and our findings partly reflect idiosyncrasies of our data. As a result, it is unclear whether our results will generalize to other samples and settings. We attempted to counteract this limitation by following a double cross-validation procedure, creating two random stratified subsamples and restricting our conclusions to results that emerged in both subsamples (Campbell, 1976). Nonetheless, both subsamples were drawn from the same population, and the generalizability of our findings awaits further research using samples from different populations (Murphy, 1983).

Summary and Conclusion

The changing nature of work raises numerous intriguing research questions. To investigate these questions, researchers need valid, comprehensive measures of work. This study indicates that the MJDQ may be respecified as a 10-factor measure that encompasses a variety of cognitive, social, and physical aspects of work. Moreover, these 10 factors may be meaningfully classified according to the four work design approaches underlying the MJDQ. Thus, researchers should consider the respecified MJDQ as a potentially viable measure of work. Future studies using the respecified MJDQ should further scrutinize its psychometric properties and examine relationships between the 10 MJDQ scales and outcomes such as satisfaction, efficiency, comfort, and reliability

(Campion, 1988; Campion & Thayer, 1985). This research may help clarify the nature of the trade-offs between the four work design approaches identified by Campion and Thayer (1985). Future research should also develop measures of additional dimensions within the four work design approaches underlying the MJDQ, as the respecified MJDQ did not provide measures of several dimensions relevant to these approaches. Future research may also benefit from hierarchical measures that assess work at varying levels of abstraction, ranging from specific aspects of work to general work dimensions. Collectively, these measures will help researchers investigate important questions regarding the meaning and changing nature of work.

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