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This study examines the construct validity of Cohen, Oxford, and Chi's (2001) *Learning Style Survey* in an applied setting with a sample of 854 military personnel. The participants were randomly split into three cross-validation samples. Confirmatory factor analysis (CFA) results provide initial empirical evidence of construct validity for Visual, Auditory, and Tactile/Kinesthetic scales. Limitations and directions for future research are discussed.

Training is an incredibly important function in both private sector firms and government organizations. U.S. organizations spend approximately $51.4 billion training their employees (Dolezalek, 2004). The U.S. government's estimated training budget for 2005 was $5.24 billion (GPO Access, 2004). Recently there has been an increased interest in foreign language proficiency and training, in both military (e.g., U.S. Department of Defense [DoD], 2005, 2006) and business settings (Lynch, 2006). Noe (2005) indicates that approximately 20 to 30 percent of organizations have a budget allocated for foreign language training. The large amount of time and money that is invested in employee foreign language training is a reflection of the importance placed on this type of training. In order to ensure that these resources are effective, it is important to identify variables that can contribute to or predict learning in foreign language training environments. Once identified, these variables can be used to modify the training or learning environment in order to maximize trainee learning (e.g., providing additional training for the instructor or customized learning strategies for students). The learning style of the student is one

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variable that is often measured and used for pre-training feedback in foreign language instruction. However, although frequently used, little empirical psychometric research exists with regard to learning styles instruments. Therefore, our research evaluates the construct validity of a learning styles instrument that will be used as part of a foreign language training effectiveness framework.

Training Effectiveness

Training effectiveness encompasses many variables, including trainee characteristics, training characteristics, contextual factors, and training criteria (Cannon-Bowers, Salas, Tannenbaum, & Mathieu, 1995). The interaction between the characteristics of the trainee and the training situation can be used to address important questions about effectiveness (e.g., Is the training equally effective for all trainees?). Over a decade ago, Tannenbaum and Yukl (1992) indicated the need for more research relating individual differences to training effectiveness. Since then, research investigating the role of individual characteristics in training performance has increased dramatically (e.g., Colquitt, LePine, & Noe, 2000; Facteau, Dobbins, Russell, Ladd, & Kudisch, 1995; Martocchio & Judge, 1997) with many positive implications for practice, as well as substantial theoretical contributions to understanding the training process (Salas & Canon-Bowers, 2001).

Noe and Colquitt (2002) suggested a number of individual differences or trainee characteristics that might be expected to impact training outcomes, such as cognitive ability, basic skills, motivation, and personality. Researchers have frequently examined the influence of cognitive ability on training effectiveness (e.g., Fox, Taylor, & Caylor, 1969; Mobley, Hand, Baker, & Meglino, 1979; Neel & Dunn, 1959; Tubiana & Ben-Shakbar, 1982; Bell & Kozlowski, 2002; Cannon-Bowers et al., 1995; Livens, Harris, Van Keer, & Bisqueret, 2003; Olea & Ree, 1994; Ree & Earles, 1991). For example, Cannon-Bowers et al. (1995) found that cognitive ability was strongly and positively related to academic training performance. Whereas cognitive ability has been the most widely researched trainee characteristic, other individual differences that affect training outcomes, such as personality (e.g., Martoccho & Judge, 1997) and goal orientation (e.g., Fisher & Ford, 1998; Phillips & Gully, 1997), have been studied less frequently.

The original call for research by Tannenbaum and Yukl (1992) is still relevant today – more research is needed to identify which individual differences are most important in various training situations. As Noe and Colquitt (2002) point out, “organizations interested in making their training programs more effective would do well to assess these [individual and work environment] characteristics as part of the needs assessment process and design appropriate interventions to support training efforts” (p. 75). Studying these characteristics should result in more effective selection or assignment of trainees, optimized instructional design, and learner-centered strategies to improve cognitive, behavioral, and affective learning outcomes.

Learning Styles

The learning style of the student is one individual difference that has received attention in foreign language instruction. The National Task Force of Learning Style and Brain Behavior (cited in Bennett, 1990) defines the construct as:

> that consistent pattern of behavior and performance by which an individual approaches educational experiences. It is the composite of characteristic cognitive, affective, and physiological behaviors that serve as relatively stable indicators

> of how a learner perceives, interacts with, and responds to the learning environment. It is farmed in a deep structure of neural organization and personality which molds and is molded by human development and the cultural experiences of home, school, and society. (p. 94).

In a review of 17 studies, Hayes and Allinson (1993) concluded that learning style orientation can moderate the effectiveness of instructional methods on trainee learning. According to Sternberg and Grigorenko (1997), learning style orientation can be thought of as bridging the gap between personality and cognition, and it has been described as the "way in which each learner begins to concentrate on, process, and retain new and difficult information" (Dunn, Griggs, Olsen, Beasley, & Gorman, 1995, p. 353).

Learning style inventories/surveys measure various types of learning styles. Our research utilized one widely used learning style instrument developed by Cohen, Oxford, and Chi (2001). There are several styles it measures, including, among others, how individuals use their physical senses (i.e., sight, sound, and touch). Individuals who have a visual learning style learn best through visual means (e.g., books, video, charts, and pictures). Individuals who are more auditory in preference prefer listening and speaking activities (e.g., discussions, lectures, audiotapes, and role-plays). Individuals with a tactile/kinesthetic preference benefit from doing projects, working with objects, and moving around (e.g., games, building models, and conducting experiments).

Other learning styles measured by the Cohen et al. (2001) instrument include closure-oriented vs. open, global vs. particular, synthesizing vs. analytic, extraverted vs. introverted. Closure-oriented individuals focus carefully on most or all learning tasks, strive to meet deadlines, plan ahead for assignments, and want explicit direction. In contrast, individuals who are open in orientation enjoy discovery learning (in which they pick up information naturally) and prefer to relax and enjoy their learning without concern for deadlines or rules. Individuals with global style preference enjoy getting the gist or main idea and are comfortable communicating even if they don't know all the words or concepts, whereas individuals who are more particular in preference focus on details and remember specific information about a topic well. Synthesizing individuals summarize material well, enjoy guessing meanings and predicting outcomes, and notice similarities more quickly, whereas analytic individuals can pull ideas apart and do well on logical analysis and contrast tasks, and tend to focus on grammar rules. The extraverted/ introverted distinction involves how individuals expose themselves to learning situations (Jackson & Lawty-Jones, 1996; Peeke, Steward, & Ruddock, 1998). Individuals who are more extraverted enjoy a wide range of social, interactive learning tasks (e.g., games, conversations, discussions, debates, role-plays, and simulations). Introverted individuals like to do more independent work (studying or reading by themselves or learning with a computer) or enjoy working with one other person they know well.

There are additional learning styles that are measured by other inventories. For instance, some inventories measure how individuals handle possibilities (i.e., random-intuitive vs. concrete-sequential; Furnham, 1996; Peeke, Steward, & Ruddock, 1998). Random-intuitive individuals are future-oriented, prefer what can be over what is, like to speculate about possibilities, enjoy abstract thinking, and tend to disfavor step-by-step instruction.

Concrete-sequential individuals are tend to be present-oriented, prefer one-step-at-a-time activities, and want to know where they are going in their learning at every moment. Some of the other factors measured by learning style inventories include how individuals deal with language rules (i.e., deductive vs. inductive; Oxford, 1995), how they deal with multiple inputs (i.e., field-independent vs. field-dependent; Oxford, 1995), how they deal with response time (i.e., impulsive vs. reflective; Furnham, 1996; Jackson & Lawty-Jones, 1996), and how literally they take reality (i.e., metaphoric vs. literal; Furnham, 1996).

It has been suggested that a student's learning style impacts training effectiveness by interacting with various instructional methods used by instructors to affect learning outcomes. For example, a student with a visual learning style may perform well with an instructor, who lectures, while a tactile/kinesthetic learner may do poorly with this instructional method (Oxford, 1995). Consequently, it is important for organizations to take a more formative approach to training by assessing student learning style and using this information to tailor training to meet individual student needs. Additionally, the concept of learning styles should be used to inform instructional design and instructor training.

There is an abundance of literature related to learning styles for students of a second language (Ehrman, 1996; Leaver & Oxford, 2001; Oxford, 1995; Oxford & Anderson, 1995). Although many learning style inventories have been developed and are widely used in industry, government, and education, there is a dearth of research investigating the validity of these instruments. The purpose of this study was to investigate the construct validity of the instrument developed by Cohen, et al. (2001). Specifically, we focused on three of the most commonly measured learning styles – visual, auditory, and tactile/ kinesthetic.

Method

Participants

Participants in this study were 854 military personnel. These data were collected as part of a larger study designed to evaluate the effectiveness of language training in a large military organization.

Measures

Participants were asked to complete a pre-training questionnaire containing parts of Cohen et al.'s (2001) *Learning Style Survey*. The instrument consists of eleven parts, each dealing with a different type of approach to learning. Five of these parts were used in the larger study, including how individuals use their physical senses, how they expose themselves to learning situations, and how they deal with ambiguity and with deadlines. For the purpose of this investigation, however, we focused on the learning styles most commonly measured, that is, those dealing with the physical senses – visual, auditory, and tactile/ kinesthetic. Each of these three scales consisted of 10 items and respondents were asked to respond on a 5-point Likert scale ranging from 1 (*never*) to 5 (*always*). Visual learning style consists of items such as "When I listen, I visualize pictures, numbers, or words in my head." Auditory learning style consists of items such as "I need oral directions for a task." Tactile/ kinesthetic style consists of items such as "Manipulating objects helps me to remember what someone says."

Procedure

As part of an ongoing language training effectiveness study, military personnel in language training at various locations were asked to complete a comprehensive pre-training assessment of individual differences. The constructs included demographic characteristics, motivation, goal orientation, personality, learning preferences, and learning styles. Scanable questionnaires were used to collect the data. For all locations except one, the questionnaires had to be mailed to the member of the unit responsible for language training. This person received, administered, and returned the questionnaires. The project was officially sanctioned by the organization, and an official letter from the study sponsor as well as administration instructions accompanied the questionnaires. For the remaining location, the data were collected by the researchers during three large-group administration sessions at a military academic facility.

Analytic Procedure

Upon receipt of the completed questionnaires, the data were processed. Following the practice in other studies (e.g., Chen, Faraone, Biederman, & Tsuang, 1994), the sample was randomly split into three different groups for cross-validation purposes. A one-factor a-priori CFA was performed on each group for each scale. Next, tetrad analysis was performed for each scale in each group. Thereafter, a one-factor CFA based on the tetrad analysis was performed for each of the three scales, and cross-validated on the other two groups. Finally, a three-factor CFA based on the tetrad analysis was performed, and cross-validated on the other two groups.

Results

To address our initial single-factor a-priori models, confirmatory factor analyses (CFAs) were performed for each model using Mplus 3.13 software (Muthén & Muthén, 1998-2005). Criteria specified by Hu and Bentler (1999), Millsap (2002), and Vandenburg and Lance (2000) were examined to assess the overall fit of the measurement models. The ratio of chi-square to degrees of freedom (χ^2/df) was computed, with ratios of less than 2.0 indicating a good fit. However, since absolute indices can be adversely effected by sample size (Loehlin, 1992), two other relative indices, the comparative fit index (CFI) and the Tucker and Lewis index (TLI) were computed to provide a more robust evaluation of model fit (Tanaka, 1987; Tucker & Lewis, 1973). For CFI and TLI, coefficients closer to unity indicate a good fit, with acceptable levels of fit being above 0.90 (Marsh, Balla, & McDonald, 1988). For root mean square error approximation (RMSEA), good fit is indicated by values less than 0.05; values from 0.05 to 0.10 are indicative of moderate fit and values greater than 0.10 are taken to be evidence of a poorly fitting model (Browne & Cudeck, 1993). For standardized root-mean-square residual (SRMR), values less than .10 are indicative of acceptable model fit (Kline, 1998).

A priori one-factor CFA results for Visual, Auditory, and Tactile/Kinesthetic scales across the three groups are summarized in Table 2. These results indicate that Tactile/Kinesthetic scale has relatively better fit than the other two scales. None of the scales, however, had chi-square to degrees of freedom ratios lower than two. In addition, CFIs and TLIs ranged from .40 to .92, with Tactile/Kinesthetic scale exhibiting the higher values. Finally, RMSEA was at or below .10 only for Tactile/ Kinesthetic scale, and SRMR ranged from .05 to .10. Overall, the evidence suggests that Tactile/Kinesthetic scale exhibits moderate fit. Visual and Auditory scales, however, do not have quite as good fit.

In order to improve model fit, tetrad analysis was performed on each scale across the three groups. One of the uses of tetrad analysis is for determining the best combination of items that measure the underlying construct. In other words, the analysis indicates which items should be dropped and which ones should be retained for further analyses (Bollen, 1990; Bollen & Ting, 1993).

Tetrad analysis was performed using Tetrad II software (Scheines, Spirtes, Gymour, & Meek, 1994). Tetrad analysis indicated the items that needed to be dropped from each scale in order to improve model fit. Tables 3 summarizes the items that were dropped for each scale across the three groups based on tetrad analysis. For example, for the Visual scale in Group 1, Items 2, 6, 7, and 9 were dropped based on tetrad analysis. The results indicate that only two items have to be dropped from the Tactile/Kinesthetic scale for each group, as opposed to two to four items for the other two scales. Thus, tetrad analysis results confirm the observation based on a-priori CFA models that Tactile/Kinesthetic scale has relatively better fit than the other two scales.

Tables 4 through 6 summarize the results of one-factor CFAs based on tetrad analysis and cross-validated on the other two groups for Visual, Auditory, and Tactile/ Kinesthetic, respectively. There are three models for each scale, and each model has three parts. For example, Model 1a represents the CFA model specified based on tetrad analysis on Group 1 and validated on Group 1. Model 1b, on the other hand, represents the CFA model specified based on tetrad analysis on Group 1 and cross-validated on Group 2.

For the Visual scale (see Table 4), Model 3a has the best overall fit. However, when the cross-validations are taken into account, Model 1a, Model 1b, and Model 1c (i.e., CFAs specified based on tetrad analysis on Group 1) have the best fit. The RMSEA ranged from .05 to .08, CFI and TLI ranged from .70 to .93, the chi-square to degrees of freedom ratio ranged from 1.91 to 3.28, and SRMR was between .04 and .06.

For the Auditory scale (see Table 5), the best-fitting models were based on tetrad analysis on Group 3 (i.e., Model 3a, Model 3b, and Model 3c). For these models, the RMSEA ranged from .04 to .07, CFI and TLI ranged from .83 to .97, the chi-square to degrees of freedom ratio ranged from 1.62 to 2.72, and SRMR was between .04 and .06.

The best-fitting models for the Tactile/ Kinesthetic scale (see Table 6) were based on tetrad analysis on Group 2 (i.e., Model 2a, Model 2b, and Model 2c). For these models, the RMSEA ranged from .03 to .05, CFI and TLI ranged from .93 to .98, the chi-square to degrees of freedom ratio ranged from 1.37 to 1.89, and SRMR was between .03 and .04.

To investigate the fit of a 3-factor model, the set of items for each scale was based on results from the one-factor revised CFAs. For example, the set of items for the Visual scale were based on tetrad analysis on Group 1, and the set of items for the Auditory scale were based on tetrad analysis on Group 3. Once the appropriate set of items was selected for each scale, the 3-factor CFA was performed on each of the three groups. Table 7 compares the results for the 3-factor a-priori CFAs and the 3-factor CFAs based on tetrad analysis. It should be noted that none of the items were dropped for the a-priori 3-factor CFAs (i.e., it consisted of ten items for each scale). The results indicate that the revised models had better fit than the a-priori models. Although for the a-priori models, the CFI and TLI ranged from .77 to .83, the RMSEA, SRMR, and the chi-square to degrees of freedom ratio were all within acceptable ranges. Thus, it seems reasonable to conclude that tetrad analysis was effective in improving the fit of the models.

Discussion

The purpose of the present study was to investigate the construct validity of three of the most commonly measured learning styles from Cohen et al.'s (2001) learning style instrument. Establishing the construct validity of this instrument is important because it has not been previously demonstrated in the literature, and the literature indicates that learning styles may have an important influence on training effectiveness. If training designers and instructors are able to understand how student learning styles impact training outcomes and effectiveness, training curriculums can be designed to meet the needs of students with a variety of learning styles.

The results of a-priori one-factor CFAs suggested that Tactile/Kinesthetic scale moderate fit, and it was better than for the other two scales. As expected one-factor CFAs based on tetrad analysis had better fit compared to the a-priori one-factor CFAs. In addition, Tactile/Kinesthetic scale once again had better fit than the other two scales.

Based on the revised CFA results, the best-fitting set of models for each scale were used to select a set of items for investigating the fit of three-factor CFAs. Once selected, three-factor CFAs were performed on each group, and these results were compared with a-priori one-factor CFAs performed on each group. The results of the revised three-factor CFAs indicate that there was acceptable fit.

Our study provides initial empirical evidence of construct validity of three factors on Cohen et al.'s (2001) *Learning Style Survey*. Although further research on other samples is needed before any conclusive statements can be made, our study does provide a good starting point for the inclusion of learning style as an individual difference variable in future military research on training effectiveness.

Limitations

There are several limitations in this study that are noteworthy. The first limitation is related to generalizability. The adult learner/military sample used to validate the *Learning Style Survey* may not be reflective of the general population. Another limitation is that the *Learning Style Survey* was administered as part of a larger questionnaire. The items related to learning styles were presented towards the end of the survey and therefore, rater fatigue may have affected responses.

Future Directions

This study suggests many important avenues for future research. It is important that this instrument be validated on other groups. This instrument was validated on adult learners in a military environment. Future research should explore the extent to which the instrument exhibits construct validity in other samples.

It is also important for future research to assess the criterion-related validity of the *Learning Style Survey*. Although there is theoretical support for the relationship between learning styles and training effectiveness, there is a need for research to support this relationship. In addition, future research should also investigate the incremental validity of learning styles over cognitive ability and personality in predicting important training outcomes.

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Table 1

Items for Each of the Three Constructs from Style Analysis Survey

Items
Visual
1. I remember something better if I write it down.
2. I take detailed notes during lectures.
3. When I listen, I visualize pictures, numbers, or words in my head.
3. I prefer to learn with TV or video rather than other media.
3. I use color-coding to help me as I learn or work.
3. I need written directions for tasks.
3. I have to look at people to understand what they say.
3. I understand lectures better when instructors write on the board.
3. Charts, diagrams, and maps help me understand what someone
10. I remember peoples' faces but not their names.
Auditory
11. I remember things better if I discuss them with someone.
12. I prefer to learn by listening to a lecture rather than reading.
13. I need oral directions for a task.
14. Background sound helps me think.
15. I like to listen to music when I study or work.
16. I can understand what people say even when I cannot see them.
17. I remember peoples' names but not their faces.
18. I easily remember jokes that I hear.
19. I can identify people by their voices (e.g., on the phone).
20. When I turn on the TV, I listen to the sound more than I watch
Tactile/Kinesthetic
21. I'd rather start to do things, rather than pay attention to
22. I need frequent breaks when I work or study.
23. I need to eat something when I read or study.
24. If I have a choice between sitting and standing, I'd rather stand.
25. I get nervous when I sit still too long.
26. I think better when I move around (e.g., pacing or tapping my
27. I play with or bite on my pens during lectures.
28. Manipulating objects helps me to remember what someone says.
29. I move my hands when I speak.
30. I draw a lot of pictures (doodles) in my notebook during lectures.

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Table 2

Comparison of Model Fit Statistics for a-priori CFAs

Model	X^2	Df	X^2/Df	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR
Visual								
Group 1	172.105	35	4.92	.73	.65	.11	[.09 - .12]	.08
Group 2	276.630	35	7.90	.53	.40	.14	[.12 - .16]	.10
Group 3	175.879	35	5.03	.67	.58	.11	[.10 - .13]	.08
Auditory								
Group 1	155.893	35	4.45	.64	.53	.10	[.09 - .12]	.09
Group 2	167.809	35	4.79	.58	.46	.11	[.09 - .12]	.09
Group 3	189.232	35	5.41	.63	.53	.12	[.10 - .14]	.10
Tactile/Kinesthetic								
Group 1	95.678	35	2.73	.90	.88	.07	[.06 - .09]	.06
Group 2	92.386	35	2.64	.92	.90	.07	[.05 - .09]	.05
Group 3	144.910	35	4.14	.83	.78	.10	[.08 - .12]	.07

Note. G = Group; GFI = goodness of fit index; NFI = normed fit index; TLI = Tucker-Lewis index (also known as the non-normed fit index); RMSEA = root mean square error of approximation. Summary consists of cross-validation of each group on the other two groups.

Table 3

Summary of Items that were Dropped from Model Specification Based on Tetrad Analysis

Model	*Dropped Items*
Visual	
Group 1	2, 6, 7, 9
Group 2	1, 6, 8, 9
Group 3	2, 4, 5, 7
Auditory	
Group 1	13, 16
Group 2	11, 14, 18, 20
Group 3	11, 13, 19
Tactile/Kinesthetic	
Group 1	23, 24
Group 2	22, 27
Group 3	22, 26

Table 4

Comparison of Model Fit Statistics for CFAs Based on Tetrad Analysis for Visual Learning Style

Model	X^2	Df	X^2/Df	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR
Model 1_a: G1 validated on G1	19.221	9	2.14	.93	.89	.06	[.02 - .10]	.04
Model 1_b: G1 cross-validated on G2	29.499	9	3.28	.82	.70	.08	[.05 - .11]	.06
Model 1_c: G1 cross-validated on G3	17.153	9	1.91	.92	.86	.05	[.01 - .09]	.04
Model 2_a: G2 validated on G2	17.971	9	2.00	.94	.89	.05	[.01 - .09]	.04
Model 2_b: G2 cross-validated on G1	37.908	9	4.21	.76	.59	.10	[.07 - .13]	.07
Model 2_c: G2 cross-validated on G3	17.834	9	1.98	.92	.86	.06	[.01 - .09]	.04
Model 3_a: G3 validated on G3	5.211	9	0.58	1.00	1.00	.00	[.00 - .04]	.02
Model 3_b: G3 cross-validated on G1	46.801	9	5.20	.86	.76	.11	[.08 - .14]	.07
Model 3_c: G3 cross-validated on G2	28.970	9	3.22	.87	.79	.08	[.05 - .13]	.05

Note. G = Group; GFI = goodness of fit index; NFI = normed fit index; TLI = Tucker-Lewis index (also known as the non-normed fit index); RMSEA = root mean square error of approximation. Summary consists of cross-validation of each group on the other two groups.

Table 5

Comparison of Model Fit Statistics for CFAs Based on Tetrad Analysis for Auditory Learning Style

Model	X^2	Df	X^2/Df	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR
Model 1_a: G1 validated on G1	59.312	20	2.97	.82	.75	.08	[.06 - .10]	.07
Model 1_b: G1 cross-validated on G2	105.663	20	5.28	.68	.56	.11	[.09 - .13]	.09
Model 1_c: G1 cross-validated on G3	107.020	20	5.35	.75	.65	.12	[.10 - .14]	.09
Model 2_a: G2 validated on G2	15.962	9	1.77	.82	.71	.05	[.00 - .08]	.04
Model 2_b: G2 cross-validated on G1	33.305	9	3.70	.77	.62	.09	[.06 - .12]	.07
Model 2_c: G2 cross-validated on G3	30.275	9	3.36	.72	.53	.09	[.05 - .12]	.07
Model 3_a: G3 validated on G3	22.622	14	1.62	.97	.95	.04	[.00 - .08]	.05
Model 3_b: G3 cross-validated on G1	38.030	14	2.72	.88	.83	.07	[.04 - .10]	.06
Model 3_c: G3 cross-validated on G2	29.334	14	2.10	.92	.89	.06	[.03 - .09]	.04

Note. G = Group; GFI = goodness of fit index; NFI = normed fit index; TLI = Tucker-Lewis index (also known as the non-normed fit index); RMSEA = root mean square error of approximation. Summary consists of cross-validation of each group on the other two groups.

Table 6

Comparison of Model Fit Statistics for CFAs Based on Tetrad Analysis for Tactile/Kinesthetic Learning Style

Model	X^2	Df	X^2/Df	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR
Model 1_a: G1 validated on G1	29.834	20	1.49	.98	.97	.04	[.00 - .07]	.03
Model 1_b: G1 cross-validated on G2	32.416	20	1.62	.98	.97	.04	[.01 - .07]	.03
Model 1_c: G1 cross-validated on G3	69.408	20	3.47	.91	.87	.09	[.06 - .11]	.05
Model 2_a: G2 validated on G2	27.467	20	1.37	.98	.98	.03	[.00 - .06]	.03
Model 2_b: G2 cross-validated on G1	29.772	20	1.49	.98	.97	.04	[.00 - .07]	.04
Model 2_c: G2 cross-validated on G3	37.716	20	1.89	.95	.93	.05	[.02 - .08]	.04
Model 3_a: G3 validated on G3	33.949	20	1.70	.96	.95	.05	[.02 - .07]	.04
Model 3_b: G3 cross-validated on G1	23.233	20	1.16	.99	.99	.02	[.00 - .05]	.03
Model 3_c: G3 cross-validated on G2	41.488	20	2.07	.95	.93	.06	[.03 - .08]	.04

Note. G = Group; GFI = goodness of fit index; NFI = normed fit index; TLI = Tucker-Lewis index (also known as the non-normed fit index); RMSEA = root mean square error of approximation. Summary consists of cross-validation of each group on the other two groups.

Table 7

Comparison of Model Fit Statistics for 3-factor A-priori CFAs and CFAs Based on Tetrad Analysis

Model	X^2	Df	X^2/Df	CFI	TLI	RMSEA	RMSEA 90% CI	SRMR
Group 1: A-priori	988.934	402	2.46	.67	.64	.07	[.04 - .06]	.08
Group 2: A-priori	1167.821	402	2.91	.58	.55	.08	[.07 - .08]	.09
Group 3: A-priori	988.934	402	2.46	.67	.64	.07	[.06 - .07]	.08
Group 1: Revised	343.499	186	1.85	.83	.81	.05	[.04 - .06]	.06
Group 2: Revised	359.016	186	1.93	.80	.77	.05	[.04 - .06]	.06
Group 3: Revised	356.371	186	1.92	.81	.78	.05	[.05 - .06]	.07

Note. G = Group; GFI = goodness of fit index; NFI = normed fit index; TLI = Tucker-Lewis index (also known as the non-normed fit index); RMSEA = root mean square error of approximation. Summary consists of cross-validation of each group on the other two groups.

ABOUT SWA CONSULTING INC.

SWA Consulting Inc. (formerly Surface, Ward, and Associates) provides analytics and evidence-based solutions for clients using the principles and methods of industrial/organizational (I/O) psychology. Since 1997, SWA has advised and assisted corporate, non-profit and governmental clients on:

- Training and development
- Performance measurement and management
- Organizational effectiveness
- Test development and validation
- Program/training evaluation
- Work/job analysis
- Needs assessment
- Selection system design
- Study and analysis related to human capital issues
- Metric development and data collection
- Advanced data analysis

One specific practice area is analytics, research, and consulting on foreign language and culture in work contexts. In this area, SWA has conducted numerous projects, including language assessment validation and psychometric research; evaluations of language training, training tools, and job aids; language and culture focused needs assessments and job analysis; and advanced analysis of language research data.

Based in Raleigh, NC, and led by Drs. Eric A. Surface and Stephen J. Ward, SWA now employs close to twenty I/O professionals at the masters and PhD levels. SWA professionals are committed to providing clients the best data and analysis with which to make solid data-driven decisions. Taking a scientist-practitioner perspective, SWA professionals conduct model-based, evidence-driven research and consulting to provide the best answers and solutions to enhance our clients' mission and business objectives. SWA has competencies in measurement, data collection, analytics, data modeling, systematic reviews, validation, and evaluation.

For more information about SWA, our projects, and our capabilities, please visit our website (www.swa-consulting.com) or contact Dr. Eric A. Surface (esurface@swa-consulting.com) or Dr. Stephen J. Ward (sward@swa-consulting.com).