Technical Report 1378

Adaptive Vocational Interest Diagnostic: Development and Initial Validation

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October 2019

United States Army Research Institute for the Behavioral and Social Sciences

U.S. Army Research Institute
for the Behavioral and Social Sciences

Department of the Army
Deputy Chief of Staff, G1

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Research accomplished under contract
for the Department of the Army by

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REPORT DOCUMENTATION PAGE

1. REPORT DATE *(DD-MM-YYYY)* October 2019	**2. REPORT TYPE** Final	**3. DATES COVERED** *(From – To)* March 2015 – December 2018
4. TITLE AND SUBTITLE Adaptive Vocational Interest Diagnostic: Development and Initial Validation		**5a. CONTRACT/GRANT NUMBER** W911NF-15-C-0038 **5b. PROGRAM ELEMENT NUMBER** 633007
6. AUTHOR(S) Christopher D. Nye, James Rounds, Cristina D. Kirkendall, Fritz Drasgow, Oleksandr S. Chernyshenko, and Stephen Stark		**5c. PROJECT NUMBER** A782 **5d. TASK NUMBER** 329a **5e. WORK UNIT NUMBER**
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Drasgow Consulting Group 3508 N. Highcross Rd. Urbana, IL 61802		**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) U.S. Army Research Institute for the Behavioral and Social Sciences 6000 6th Street (Bldg. 1464 / Mail Stop: 5610) Fort Belvoir, Virginia 22060-5610		**10. SPONSOR/MONITOR'S ACRONYM(S)** ARI **11. SPONSORING/MONITORING** Technical Report 1378

12. DISTRIBUTION AVAILABILITY STATEMENT
Distribution Statement A: Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES
ARI Research POC: Dr. Cristina Kirkendall, Selection and Assignment Research Unit

14. ABSTRACT

Recent research has demonstrated the validity of vocational interests for predicting both work and academic outcomes. As a result of these findings, a number of public and private organizations are now considering the use of vocational interest measures to help individuals make important employment and career decisions. This report describes the development of a new vocational interest measure known as the Adaptive Vocational Interest Diagnostic (AVID) for the U.S. Army. This measure was specifically developed to help Soldiers identify military occupational specialties (MOS) that match their interests and to predict their satisfaction and performance in those MOS. First, a review of the literature and analyses of existing military interest data were used to identify important interest dimensions that are relevant to U.S. Army MOS. Next, large pools of statements were developed to assess 20 basic interest dimensions and these statements were pretested on large samples of Army Soldiers to estimate item response theory (IRT) and social desirability parameters. Finally, a static version of the AVID was developed and used to collect initial validation evidence. The results of the initial validation indicated that the AVID can be useful for predicting important military outcomes and for differentiating between MOS.

15. SUBJECT TERMS
Enlisted Personnel Manpower Vocational Interest Measures MOS Assignment

SECURITY CLASSIFICATION OF:			**19. LIMITATION OF ABSTRACT**	**20. NUMBER OF PAGES**	**21. RESPONSIBLE PERSON**
16. REPORT	**17. ABSTRACT**	**18. THIS PAGE**			
Unclassified	Unclassified	Unclassified	Unlimited Unclassified	69	Tonia S. Heffner 703-545-4408

Standard Form 298 (Rev. 8-98)

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ACKNOWLEDGMENTS

The authors are especially thankful to Dr. Tonia Heffner for her insights and unwavering support. The authors are also thankful to the U.S. Army Center for Initial Military Training and U.S. Army Forces Command for supporting development of the AVID, and the Soldiers who gave their time and attention to accomplish this task.

ADAPTIVE VOCATIONAL INTEREST DIAGNOSTIC: DEVELOPMENT AND INITIAL VALIDATION

EXECUTIVE SUMMARY

Research Requirement:

There is a long history of research on vocational interests in the applied psychological literature. More recently, a growing body of research has shown that interests can be strong predictors of both work and academic performance. These findings have resulted in increased efforts to use vocational interest assessments in both public and private organizations. Given this renewed attention, high quality assessments are necessary to realize the benefits of vocational interests in the workplace. However, existing interest measures have a number of disadvantages for use in high-stakes organizational settings. For example, existing measures can be inefficient to administer, are not constructed to measure all levels of a latent interest dimension well, and are susceptible to faking and other response biases. Recent advances in psychometric and vocational interest theories can help to address these limitations and improve the assessment of vocational interests. This report describes the development of a new measure of vocational interests known as the Adaptive Vocational Interest Diagnostic (AVID). This assessment was developed specifically for military applications and to help Soldiers identify military occupational specialties (MOS) that match their interests and in which they will be satisfied and successful.

To address issues with existing measures, the AVID was developed by both Drasgow Consulting Group (DCG) and the U.S. Army Research Institute for the Behavior and Social Sciences (ARI) to take advantage of recent psychometric advances and developments in the theory of vocational interests. Specifically, the AVID was developed to 1) assess both global and narrow interest factors, 2) incorporate an item response theory (IRT) model (i.e., an ideal point model) that correctly characterizes the relations between latent interests and observed responses, 3) be resistant to faking and other response biases, and 4) utilize computer adaptive technology to measure accurately and efficiently across a broad range of trait continua. Given these characteristics, the AVID is expected to predict Soldiers’ attitudes and behavior in organizational settings and to be useful for MOS assignment.

Procedure:

The development of the AVID consisted of several steps. First, a literature review was conducted and existing Army interest data were analyzed to identify basic interest dimensions that would be useful for differentiating military occupations. Using the results of these analyses, we identified 20 basic interest dimensions to be developed for the AVID. Next, large statement pools consisting of approximately 50-60 statements were developed for each of these 20 basic interest dimensions and pretested on a large sample of Soldiers in the U.S. Army. These pretest data were then used to estimate IRT parameters and create both static and computer adaptive forms of the AVID using the pairwise preference format.

Finally, initial validation evidence for the AVID was collected in two large samples of Soldiers. To examine the validity of the AVID, we calculated regression-weighted composites of the basic interest scales for predicting attitudes and behaviors assessed using the Army life Questionnaire (ALQ). In addition, we also examined the validity of the match between individuals and their MOS using polynomial regression models. These models were estimated in the full samples and in the five largest MOS in these datasets including Infantry (11B; *n* = 343), Military Police (31B; *n* = 287), Combat Medics (68W; *n* = 273), Motor Transport Operators (88M; *n* = 529), and Wheeled Vehicle Mechanics (91B; *n* = 457).

Findings:

Using the pretest data, initial construct validity evidence was obtained for all 20 AVID dimensions. Results indicated that the AVID basic interests were correlated with the Department of Labor's O*NET Interest Profiler in theoretically meaningful ways. In addition, the initial criterion-related validity evidence demonstrated that the AVID scales can also predict important attitudes and behaviors in Active-Duty Soldiers. Regression weighted composites of these scales had multiple R's ranging from .14 to .47 in Sample 1 and from .17 to .52 in Sample 2, depending on the criterion. The AVID also predicted an overall performance criterion composite. Moreover, results indicated that the validity of the AVID was highest when the fit between individuals and their MOS were considered. This was done by estimating a series of regression models that included both individual and MOS interest scores. Finally, results also showed that the AVID dimensions that were the best predictors of overall performance differed across the five largest MOS in these samples. These results suggest that the AVID scales will not only be useful for predicting important military outcomes but can also be useful for improving MOS assignment.

Utilization and Dissemination of Findings:

The AVID was developed specifically for use in the U.S. Army to help facilitate the assignment process. The results presented in this report suggest that the AVID is a promising predictor of Soldiers' attitudes and behaviors in their MOS. Importantly, the AVID also predicted an overall performance variable, indicating that this assessment may be useful for identifying individuals with high potential for success in a particular MOS. Because the AVID dimensions appear to be useful for differentiating individuals who may be successful in one (or multiple) MOS but not others, these results also indicate that the AVID can be used for MOS assignment. Therefore, these results provide preliminary evidence of the potential utility of the AVID in the U.S. Army.

ADAPTIVE VOCATIONAL INTEREST DIAGNOSTIC: DEVELOPMENT AND INITIAL VALIDATION

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ADAPTIVE VOCATIONAL INTEREST DIAGNOSTIC: DEVELOPMENT AND INITIAL VALIDATION

CHAPTER 1: INTRODUCTION

There is a long history of research on vocational interests in the applied psychological literature and early researchers suggested that the study of interests could substantially improve our understanding of individual behavior. In fact, as recounted by E. K. Strong (1943, p. vii), early researchers suggested that “the developments with regard to the diagnostic meaning of interests would prove to be one of the great, if not the greatest, contributions to applied psychology.” Subsequent research expanded on this prediction and suggested that individuals will be more satisfied and successful in their jobs when they are doing work in which they are interested (Holland, 1959, 1997). In part, this prediction was fulfilled by research finding that individuals whose interests match the activities performed in their jobs tend to be more satisfied with their work (Morris, 2003; Bizot & Goldman, 1993).

More recently, a growing body of research has shown that interests can be strong predictors of both work and academic performance. For example, Van Iddekinge, Roth, Putka, and Lanivich (2011) showed that interests were moderately correlated with a number of job performance outcomes. In addition, they also showed that regression-weighted composites of interest scales could predict these same outcomes even better than individual scales. Nye, Su, Rounds, and Drasgow (2017) conducted a more comprehensive meta-analysis of the relationship between interests and work performance that summarized over 60 years of research, 92 studies, and 1,858 correlations. Again, they found that the match between individuals’ interests and job activities (called congruence in the vocational interest literature) was the best predictor of performance outcomes including task performance, organizational citizenship behavior, turnover, and training performance with correlations ranging from .19 to .40. Similar research showed that interest congruence can also predict performance in academic settings (Nye, Su, Rounds, and Drasgow, 2012). As a result of positive empirical findings such as these, many private organizations are starting to consider using vocational interests for employee selection (Rounds, 2013).

Given the resurgence in interest in this topic (Rounds & Su, 2014), high quality assessments will be necessary to realize the benefits of vocational interests in the workplace. However, existing interest measures have a number of disadvantages for use in high-stakes organizational settings. For example, existing measures can be inefficient to administer, are not constructed to measure all levels of a latent interest dimension well, and are susceptible to faking and other response biases. Recent advances in psychometric and vocational interest theories can help to address these limitations and improve the assessment of vocational interests in the workplace. Therefore, a new assessment that incorporates recent research findings may be useful for helping individuals to identify jobs that match their interests and for helping organizations to identify applicants who might be the best fit for a position. This applies to the military as well. The U.S. Army has over 140 initial entry military occupational specialties (MOS) and a measure of vocational interests could help Soldiers to identify the jobs in which they are likely to be successful and satisfied. Nevertheless, because existing interest measures were not developed to differentiate between military jobs, a new interest measure is needed to assess the types of activities performed by Soldiers in their MOS. To address these issues, Drasgow Consulting Group (DCG) and the U.S. Army Research Institute for the Behavioral and Social Sciences (ARI) developed the Adaptive Vocational Interest Diagnostic (AVID) for use in high-stakes military contexts. Before describing the development of the AVID, we first discuss the importance of interest congruence for predicting work outcomes and then discuss the need for a new measure that can assess interests and be used for matching individuals to their MOS.

INTEREST CONGRUENCE

The vast majority of interest assessments are based on Holland's (1959, 1997) model of vocational interests. Holland suggested that vocational interests could be represented well by six primary interest types: individuals with **Realistic** interests like to work with things, gadgets, or in the outdoors; individuals with **Investigative** interests prefer activities involving the physical, social, or medical sciences; individuals with **Artistic** interests enjoy activities that allow creative expression (e.g., art, photography, dance, music); individuals with **Social** interests enjoy activities that involve interacting with and helping other people; individuals with **Enterprising** interests enjoy leadership roles and activities that involve persuading other people; and individuals with **Conventional** interests prefer activities performed in well-structured environments. These six interest types are collectively known by their acronym as the RIASEC types.

Holland (1997) also proposed that work environments could be categorized using the same six RIASEC types. A number of different approaches have been used to operationalize the RIASEC profile of the environment. For example, one approach is to create an interest profile using job analysis information about the activities performed on the job (Holland et al., 1972; McCormick, Jeanneret, & Meacham, 1972; cf. Rounds, Shubsachs, Dawis, & Lofquist, 1978). However, this approach is limited in that job analysis information may not always be available. Therefore, another approach to estimating the interest profile of an occupation is to use the interest scores of job incumbents (Campbell & Holland, 1972; Donnay & Borgen, 1996; Holland, 1997). Again, this approach may be limited in that some individuals in an occupation may not be interested in the type of work they perform and incumbent samples are often not representative of ill-defined occupations (Nye, Perlus, & Rounds, 2018). Finally, the most direct approach to estimating the interest profile of the environment is to measure it directly by asking employees, supervisors, or other subject matter experts (SMEs) to rate the extent to which activities related to each interest type are performed on the job. This approach is not only the most direct but also the most efficient method of calculating occupational interest profiles.

Because both individuals and environment can be categorized using the same six interest types, Holland (1959, 1997) proposed that the match between the two would be particularly important for predicting work and academic outcomes. In the interest literature, a distinction can be made between the level (i.e., strength) of one's interests and the shape of his or her interest profile. Exploring interest levels involves measuring vocational interests and correlating scores on a scale with some criterion of interest. In contrast, an interest profile reflects the individual's relative standing on each of the various interest types and the validity of the profile is examined by correlating congruence indices (which quantify the match between the interest profiles of individuals and their occupations) with the criterion. Although, Holland's theory (1997) of vocational interests emphasized the congruence between an individual and his or her environment, most studies focus on interest levels and correlate scores with performance criteria. However, Nye et al. (2012) showed that correlations of performance with congruence indices were .16 larger, on average, than correlations with scores on a particular interest scale. In other words, the match between individuals' interest profiles and the profiles of their jobs is a better predictor of performance and attrition than interest scores alone. This finding is important because it has implications for the assignment of individuals in the U.S. Army.

In the interest literature, several approaches have been used to quantify the match between individuals and occupations. The most popular approaches to quantifying interest fit have involved calculating congruence indices based on Holland's model of interests (Brown & Gore, 1994). Although these indices are widely used and have demonstrated validity in past research (Nye et al., 2012, 2017), they also have a number of limitations. For example, traditional congruence indices place constraints on the relationships between the interest profiles of the individual and the environment and the outcomes that they are supposed to predict. These constraints can limit the validity of traditional congruence indices (Nye et al., 2018). In addition, calculating congruence results in a single numeric value that excludes information about an individual's actual standing on each interest dimension and the sources of any incongruence between individuals and their jobs. This issue is problematic because it ignores situations in which an individual may be only slightly less interested in some activities performed in a job. These and other limitations of congruence indices have been written about extensively (e.g., Edwards, 1993).

To address the problems with congruence indices, some have suggested using polynomial regression to calculate interest congruence (Edwards, 1993; Nye, Prasad, Bradburn, & Elizondo, 2018). With this approach, congruence is calculated by estimating a regression model that includes the individual interest scores, the environment interest scores, quadratic regression terms, and interaction terms in a model predicting an outcome of interest. After the regression weights for this model are estimated, they can then be used to calculate a composite score for each individual using their own interest scores and the scores for a particular occupation. This composite score is their index of fit (i.e., higher scores indicate better fit) and can be correlated with work outcomes to estimate the validity of interest congruence. Nye et al. (2018) demonstrated that the validity of the polynomial regression approach was approximately three to four times higher than many other widely used indices. Therefore, we examined a similar approach for the AVID.

THE NEED FOR A NEW INTEREST ASSESSMENT

The development of modern interest inventories can be traced back to a seminar in 1919 conducted by C. S. Yoakum at the Carnegie Institute of Technology. From this seminar came a pool of 1,000 items that could be used in paper-and-pencil questionnaires. Since that time, a number of different interest measures have been developed. Despite the positive validity evidence that has been obtained using these measures, existing interest assessments have several characteristics that limit their potential utility for making important personnel decisions. First, currently used scales were not constructed to measure well across all levels of the trait continuum. Specifically, because classical test theory methods were used to evaluate and choose items during the scale development process, only those items having a positive standing on the underlying trait continuum were retained while neutral items were discarded (Chernyshenko, Stark, Drasgow, & Roberts, 2007; Stark, Chernyshenko, & Drasgow, 2003; Stark, Chernyshenko, Drasgow, & Williams, 2006). The exclusion of neutral items is problematic because it affects the rank-order of high and low scoring individuals who are often of primary interest in selection and assignment contexts. Second, traditional paper and pencil interest measures are inefficient and cumbersome to administer and maintain. They have rigid administration prescriptions in the sense that all items must be administered to every individual in a prespecified order. This process increases testing time and decreases test security through repeated item exposure. Finally, in high-stakes testing situations, single statement items can be faked easily; i.e., test takers can discern the correct or socially desirable answers and, thus, deliberately increase or decrease their scores. Intentional distortion has been found to undermine the utility of personality measures for personnel selection and assignment (White & Young, 1998). In the interest literature, past research has shown that individuals can inflate their scores on an interest assessment when instructed to do so (Abrahams, Neumann, & Githens, 1971; Garry, 1953, Hough et al., 2001). Therefore, faking may be a potential concern for interest inventories as well. Similarly, response biases (e.g., acquiescence) can also be a concern and can affect the validity of the measure.

Due to these limitations, the AVID was developed to take advantage of recent psychometric advances and developments in the theory of vocational interests. To address the limitations of previous interest measures, the AVID was developed to 1) assess both global and narrow interest factors, 2) incorporate a measurement model (i.e., an ideal point model) that correctly characterizes the relation between latent interests and observed responses, 3) be resistant to faking and other response biases, and 4) utilize computer adaptive technology to measure accurately and efficiently across a broad range of trait continua. We discuss each of these characteristics next.

First, the AVID was designed to assess both global and narrow interest dimensions. Although Holland's RIASEC model is widely used, one criticism of this traditional framework for measuring interests is that it may not reflect the changing nature of work (e.g., Day & Rounds, 1997). Specifically, the RIASEC types were developed to describe broad occupational preferences and are generally associated with specific occupations. Although this framework was useful for describing interests and job assignments at a time when employees stayed in a job or at a company for their entire career, these broad interest types are less useful for understanding the current workforce which is characterized by frequent job/occupation changes and increased overall mobility. In addition, other research has questioned whether the six RIASEC types are sufficient to capture the full range of differences across occupations (e.g., Campbell, 1992; Jackson, 1977; Rounds, 1995). This potential weakness is particularly important in the Army because many MOS primarily involve activities related to the Realistic interest type. Therefore, it would be difficult to differentiate between Army MOS using assessments based on the RIASEC model because many MOS would have similar interest profiles. As a result, some have suggested assessing basic interests as an alternative to the broader occupational themes represented by the RIASEC model (Jackson, 1977; Liao, Armstrong, & Rounds, 2008). Basic interests are more homogeneous dimensions of interest that group together work activities that may be relevant to a number of occupations. These narrow interest dimensions are analogous to trait facets in personality research and assessing basic interests can provide both the content specificity and the flexibility required to more accurately select and assign individuals into a broad range of occupations. Several interest inventories, like the Strong Interest Inventory (Donnay, Morris, Schaubhut, & Thompson, 2005), do assess basic interests. However, there is not a generally accepted structure of narrow interest dimensions that is specific to the military. As such, it is possible that existing basic interest measures are not assessing the full range of interest dimensions that are relevant for modern military occupations.

Second, the AVID was also developed to take advantage of modern test theory and recent findings related to the psychometric properties of interest items. For example, recent research has indicated that an ideal point IRT model provides the best representation of the response process for interest items (Tay, Drasgow, Rounds, & Williams, 2009). An ideal point model suggests that the choice to endorse or not endorse a statement is described by a proximity relation, wherein one tends to endorse an item only if he/she is located near the item on the latent continuum. Being too far above or below the item therefore decreases the probability of endorsement. However, past efforts to create interest assessments have tended to use dominance models that do not measure well across all levels of the trait continuum and can influence selection and assignment decisions as a result (Chernyshenko, Stark, Drasgow, & Roberts, 2007; Stark, Chernyshenko, Drasgow, & Williams, 2006). In addition, past research has shown that incorrectly applying a dominance model to ideal point data can also influence correlations between variables and the potential utility of selection decisions (Carter, Dalal, Boyce, O'Connell, Kung, & Delgado, 2014; Dalal & Carter, 2015). As a result, the AVID was developed using the framework of ideal point models.

Third, the AVID was developed to be resistant to faking and other responses biases by using a forced-choice response format. The format of the AVID was modeled after another non-cognitive measure known as the Tailored Adaptive Personality Assessment System (TAPAS; Drasgow, Stark, Chernyshenko, Nye, Hulin, & White, 2012). The TAPAS is a personality assessment that was developed for use in the Army to make MOS selection and assignment decisions and has been administered to nearly one million applicants since 2009. To facilitate its use in high-stakes settings, the TAPAS was designed to be administered in a forced choice format in which statements assessing different personality dimensions but matched on their extremity and social desirability are administered in pairs. Respondents are then asked to select the statement that is "most like you." This format appears to work as past research has demonstrated the validity of the TAPAS (Nye et al., 2012) and found little evidence of faking in high-stakes settings (Drasgow et al., 2012).

Like the TAPAS, the AVID items consist of pairs of statements representing different interest dimensions that are matched on their extremity and social desirability. Although two-alternative forced-choice vocational interest items are unlikely to deter faking good when occupational titles are used (e.g., an individual wanting to be a computer technician can easily select "computer technician" when it is paired with "truck driver"), the AVID uses statements of work activities. A respondent's task is to choose the statement in each pair that is "more interesting to me." By forcing respondents to choose between two equally desirable options, this forced-choice format makes faking more difficult and potentially limits responses biases. In the past, such a response format produced only ipsative scores, which were largely unsuitable for personnel selection and assignment. However, this issue was addressed by using the multidimensional pairwise preference (MDPP) model (Stark, Chernyshenko, & Drasgow, 2005), which overcame this major limitation and is capable of successfully recovering normative scores regardless of how many interest dimensions are assessed. Again, this model is also used for TAPAS scoring and has shown promise in previous research (Drasgow et al., 2012; Nye et al., 2012). Therefore, this model was used for the AVID.

Finally, the use of a formal IRT model to score the AVID paves the way for computer adaptive testing (CAT), which increases measurement accuracy and decreases testing time. Therefore, the AVID was developed to be administered in either static or computer adaptive formats. The adaptive algorithm selects pairs of statements that are specifically chosen based on a respondent's previous answers and matched to estimates of his or her standing on the latent interest dimensions. One advantage of CAT is that the assessment can be updated and administered more efficiently than a paper-and-pencil form. In addition, the adaptive process allows for a reduced number of items to be administered with some research indicating that test length can be cut by 50% with no loss of measurement precision (Stark, Chernyshenko, Drasgow, & White, 2012). Given this benefit and other advantages of the AVID measurement approach, we expected the AVID to demonstrate validity in high-stakes testing situations and help Soldiers to identify MOS in which they will be successful and satisfied.

PURPOSE OF THE CURRENT RESEARCH

In sum, research in the civilian world shows that placing people into jobs that are good matches to their vocational interests increases job satisfaction, reduces attrition, and improves performance. We expect that placing Soldiers into military occupational specialties (MOS) that match their interests would have similar effects. Consequently, this report describes the development of the AVID and initial efforts to evaluate the utility of this measure for predicting attitudes and performance in U.S. Army Soldiers.

First, we will discuss efforts to identify a comprehensive set of basic interests that would be useful for differentiating Army MOS. This work focused on examining existing data and reviewing the literature on basic interest assessments. Next, we discuss the development of statement pools for the AVID dimensions. Because adaptive testing requires a large number of statements that can be matched to respondents' estimated levels of the latent traits, statement pools consisting of approximately 50-60 statements for each AVID dimension need to be developed and pretested before they can be administered in the forced choice computer adaptive format used for the AVID. Finally, we also discuss initial efforts to validate the AVID in several of the largest MOS in the U.S. Army.

CHAPTER 2: IDENTIFYING A COMPREHENSIVE SET OF BASIC INTEREST DIMENSIONS

BACKGROUND

The first step in developing the AVID was to conduct a review of the interest literature to identify a comprehensive set of nonredundant basic interests that are expected to be important for MOS assignment decisions. As noted in the previous chapter, traditional measures of the RIASEC interest types are designed to assess a wide range of activities that reflect broad occupational themes. Although these dimensions have demonstrated validity for predicting performance on the job (e.g., Nye et al., 2012), they may be too broad and may lack the precision necessary to differentiate individual interest in a broad range of occupations. In contrast, basic interest measures are comprised of more homogeneous dimensions of interest that group together work activities and may be relevant to a number of occupations. Unfortunately, a comprehensive set of basic interests has not yet been identified in the literature. Therefore, we used two approaches to identify the basic interests that may be useful for MOS assignment in the Army:

1. We re-examined data from the Army Vocational Interest Career Examination (AVOICE; Hough, Barge, & Kamp, 2001) collected during Project A to identify the structure of basic interest dimensions that may be of particular interest in military settings.
2. We conducted a review of existing interest measures to identify additional basic interests that may not have been included in the AVOICE but yet still may be useful for MOS assignment.

Using these two approaches, we were able to identify a more comprehensive list of basic interest dimensions for development. Below we describe these approaches in more detail and discuss our findings regarding potentially useful basic interest dimensions for the Army.

METHODS

We first analyzed existing AVOICE data from the Army's Project A Longitudinal Validation. The AVOICE was based on another interest measure known as the Vocational Interest Career Examination (VOICE; Alley & Matthews, 1982), which was developed by the U.S. Air Force. Although based on this previous measure, the AVOICE was modified to reflect occupations in the Army and included four sections that assessed interest in 1) specific jobs, 2) work activities and environments, 3) leisure activities, and 4) desired learning experiences. In addition, a fifth section asked about Soldiers' confidence in their chosen career fields and also included several items assessing basic interest dimensions (i.e., single-item measures). In total, the AVOICE included 182 items and 22 scales that could be aggregated into RIASEC scores.

The data for these analyses consisted of 45,002 responses to the 182 interest items included in the AVOICE. These data were analyzed using Goldberg's (2006) proposed method for exploring the hierarchical structure of a set of personality variables. With this approach, exploratory factor analyses are used to extract successively higher numbers of factors. First one factor is extracted, then two factors, three factors, and so forth until none of the items have their highest loading on each new factor that is extracted.

For our analyses, we used principal axis factoring with varimax rotation. With this method of extraction, each factor maximizes the amount of variance accounted for in the items. So, for example, the first factor accounts for the most variance in the items. The second factor extracted is the next largest factor that accounts for the highest proportion of the remaining variance after accounting for the first factor. The last factor extracted in each set of analyses will account for the least amount of variance in the items. Therefore, the order of extraction is informative.

Goldberg (2006) also suggested examining the correlations between the factor scores for each successive model. These correlations will illustrate the relationships between the factors at each stage of the analyses and will help to demonstrate the hierarchical structure of the data.

Next, we also conducted a literature review to identify potentially important basic interest factors that might not be represented well in the AVOICE. Although past interest measures, including the AVOICE, have been developed to assess basic interests, none of these measures have assessed a comprehensive set of dimensions. However, a number of basic interests have been assessed across all of these measures. Therefore, we believe that we can identify a more comprehensive set of dimensions by comparing across scales. Moreover, the frequency with which these basic interest dimensions have been assessed can provide a rough indication of their perceived importance. The more frequently a particular dimension has been assessed, the more important it is believed to be. Consequently, the purpose of this literature review was to identify a broad range of potential basic interest scales that could be developed to enhance assignment decisions in the U.S. Army.

RESULTS

AVOICE Hierarchical Analyses. The results of the hierarchical analyses of the AVOICE data are shown in Figure 2.1. Again, the path coefficients between each factor indicate the correlations between the factor scores for each successive set of analyses. Based on these results, it appears that the 22 AVOICE scales assessed 10 basic interest dimensions. These dimensions are illustrated in the bottom row of Figure 2.1. The labels for these dimensions were selected based on the content of each factor and representative items are provided in Table 2.1. Several of the basic interests assessed by the AVOICE are lower-order dimensions of the Realistic interest type (i.e., Electronics, Construction, Mechanical, Combat, Protective Services) described in Holland’s (1959, 1997) RIASEC model. Many military jobs include Realistic activities and, therefore, it is not surprising that these interests would be represented well in the AVOICE.

The rank order of each factor in terms of the amount of variance accounted for is also shown in Figure 2.1. For example, the Combat factor (1/10) was the first factor extracted in the 10-factor solution. In other words, this factor accounts for the most variance in the items when

10 factors are extracted. This finding is not surprising given that the AVOICE was developed for the Army context and includes a number of combat-related items. In contrast, the Visual Arts dimension accounted for the least amount of variance. Again, this finding was expected given the nature of Army jobs and the content of the AVOICE.

Figure 2.1. **Hierarchical Structure of the AVOICE**

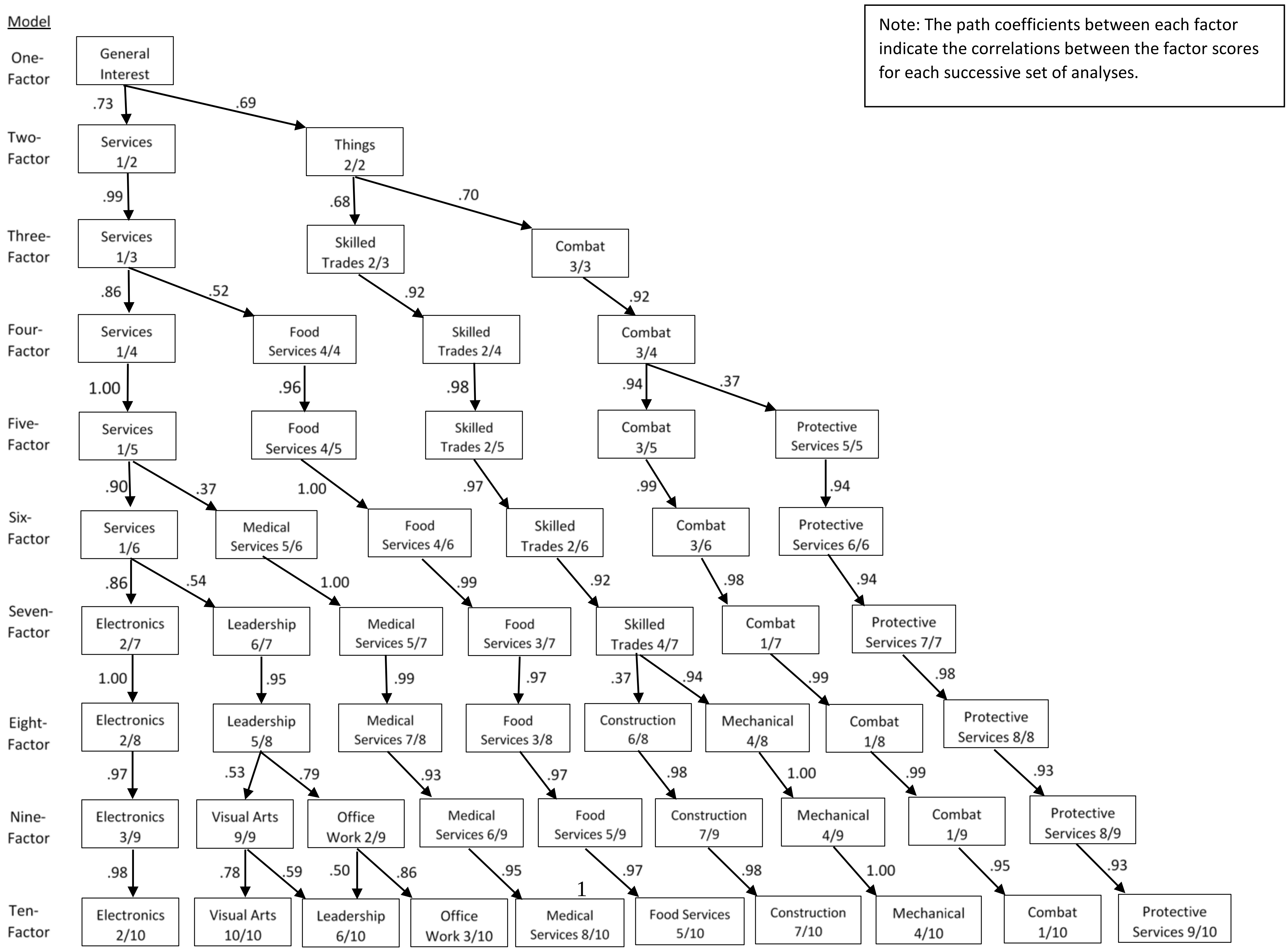

Table 2.1. ***Example Items for the 10 Basic Interests Assessed by the AVOICE***

AVOICE Basic Interests	Representative Items for Each Basic Interest (factor loadings in parentheses)
Combat	• Use cover, concealment, or camouflage (.62) • Zero in a tank's main gun (.57) • Identify a target and adjust a cannon's firing to hit it (.61)
Electronics	• Technician (Electronics) (.65) • Perform maintenance on a computer (.65) • Design a circuit board (.66)
Office Work	• Make out invoices (.60) • Check a list of supplies received against those ordered (.65) • Help prepare the payroll for a business (.61)
Mechanical	• How different types of engines work (.71) • Adjust a carburetor (.81) • Rebuild or overhaul an engine (.80)
Food Services	• Wash, peel, dice vegetables (.60) • Clear tables in a restaurant (.64) • Serve food in a cafeteria (.75)
Leadership	• Inspire others with a speech (.61) • Organize and lead a study group (.61) • Mold a group of co-workers into an efficient team (.56)
Construction	• Pour concrete for highway construction (.62) • Construction worker (.61) • Work with a hammer, trowel, or other hand tools (.56)
Medical Services	• Take blood samples from people (.74) • Give injections to people for immunizations (.73) • Perform emergency medical operations (.64)
Protective Services	• Highway patrol officer (.71) • Arrest a traffic violator (.63) • Police officer (.75)
Visual Arts	• Photographer (.50) • Television camera operator (.47) • Operate a movie camera (.44)

Note: The AVOICE includes different sections that ask respondents to indicate how much they like various jobs, work tasks, leisure activities, or learning experiences, respectively. The example items presented above are taken from each of these sections and, therefore, the question stem differed slightly for some of these questions.

Review of Existing Basic Interest Measures. Given the 10 dimensions assessed by the AVOICE, we next conducted the literature review to determine what basic interest dimensions, if any, were not represented well by the AVOICE. Our review identified 26 different interest measures (including the AVOICE) that included 214 basic interest scales. However, there was also significant overlap among many of these scales. Therefore, we categorized the 214 scales into a reduced set of basic interest dimensions. To accomplish this task, two experts on the assessment of vocational interests (Nye and Rounds) examined any available descriptions provided for each scale (i.e., either from empirical studies or technical reports) and created a rational categorization based on their perceived content similarities. The dimensions that resulted from this categorization are described in Tables 2.2 and 2.3. Table 2.2 describes the basic interest dimensions that ARI and DCG believed could be useful for MOS assignment and could be developed using the proposed framework for the AVID. Table 2.3 provides some additional basic interest dimensions that we identified in our review but that may be less relevant for the Army.

As shown in Table 2.2, a number of the scales that we identified in our review and that are relevant to the Army are lower-order dimensions of Holland's (1997) Realistic interest type. In contrast, we only identified one lower-order dimension of Holland's Artistic interest type that seemed relevant to the Army (i.e., Writing). These findings are similar to what we found in the AVOICE analyses. In addition, although a number of the dimensions described in Table 2.2 were also assessed in the AVOICE, we also identified several new basic interests that appear related to Army jobs. For example, the AVOICE did not assess a unique dimension related to information technology. However, activities related to this basic interest dimension are becoming increasingly important in the Army and several of the interest measures we identified in our review included an information technology scale. We also identified a number of scales that may be particularly relevant for some MOS or special assignments but not others. The Teaching dimension may be relevant for Instructors or Drill Sergeants and the Sales dimension may be relevant for Recruiters but neither of these dimensions are likely to be relevant to Infantry. Instead, the Infantry MOS is likely to be related to a number of other dimensions in Table 2.2 (e.g., Combat). Therefore, the basic interests identified in our review may be useful for selection and assignment into a broad range of MOS. In addition, compared to the AVOICE data, the dimensions described in Table 2.2 represent a more comprehensive list of basic interest dimensions that can be assessed. Given these results, we developed pools of statements to assess the 20 basic interest dimensions described in Table 2.2. In the next chapter, we describe the process for developing and evaluating these statement pools.

Table 2.2. ***Potential AVID Dimensions Identified in the Literature Review***

Basic Interests	Activities Associated with Each Dimension	Frequency	RIASEC Type
Writing	Writing in detail factual reports, memos, textbooks, scientific, legal, historical or technical essays for business and record-keeping purposes. This interest may be satisfied by a number of jobs that involve significant writing tasks.	13	Artistic
Teaching	Instructing people inside and outside of school (e.g., teachers and instructors in school, churches, clinics, and welfare agencies). May also include training, coaching athletics, or providing child care.	15	Social
Personal Service	Performing everyday tasks for others (e.g., household worker; hospitality services in airplanes and hotels; or hair and beauty services, etc.).	12	
Construction	Designing and/or building things or maintaining structures with one's hands or using tools and materials. Includes jobs like construction worker, mason, or welder.	14	Realistic
Protection	Guarding, ensuring safety, and enforcing rules and laws. Includes jobs like law enforcement officer, park ranger, firefighter, or in leadership and management positions in protective service organizations.	9	
Combat	Operating weapons and equipment in ground combat operations; performing reconnaissance operations; attacking enemy positions and defending friendly posts. Includes jobs in infantry, field artillery, and special forces.	4	
Physical Activity	Engaging in physical activity, exercise, sports, and games. Includes jobs like physical trainer, athletic coach, or strength training coach.	9	
Mechanical	Building, maintaining, repairing and using small and large machinery, including driving and operating heavy equipment or large vehicles. Includes jobs like mechanic, service repair person, mechanical engineer, factory or laboratory machinist, pilot, boat captain, and truck driver.	24	

Table 2.2. (*Continued)*

Basic Interests	Activities Associated with Each Dimension	Frequency	RIASEC Type
Electronics	Building, maintaining, repairing and using electronics including computer hardware and small electronics. Includes jobs like electrician, broadcast technician, electronic equipment installer and repair person, and electrical engineer.	8	
Outdoor	Working in the outdoors. Includes jobs like farmer, forest ranger, veterinarian, zoologist, landscaper, and groundskeeper.	24	
Medical Services	Applying medical knowledge and skills to the diagnosis, prevention, and treatment of disease and injury. Includes jobs like paramedic, physician's assistant, nurse, physical therapist, and dental hygienist.	10	Investigative
Mathematics	Working with data and applying quantitative and statistical concepts and mathematical formulas. Includes jobs like statistician, mathematician, engineer, or financial analyst.	10	
Science	Involves scientific activities such as studying biology, astronomy, geology, and physics; reading books about science; and doing scientific research or related activities. Includes jobs like scientist and laboratory worker or technology and medical paraprofessional. Also includes jobs in health, nutritional or pharmaceutical services involving scientific interests.	18	
Information Technology	Developing, maintaining, and using computer systems, software, and networks for the processing and distribution of data. Includes jobs like computer systems analyst, network administrator, software developer, web administrator, and database administrator.	4	
Management	Leading others and influencing people and decisions. Includes administrative or supervisory positions, such as a shop foreman, supervisor, school administrator, police or fire chief, head librarian, executive, hotel manager, or union official. Also includes owning or managing a store or business.	18	Enterprising

Table 2.2. (*Continued*)

Basic Interests	Activities Associated with Each Dimension	Frequency	RIASEC Type
Sales	Includes activities that involve selling products and services. Includes jobs that require selling products or services in stores, offices, or customers' homes such as auto sales, insurance, lobbying, public relations, or real estate.	26	
Human Relations	Arranging positive interpersonal interactions for individuals. Includes jobs that involve setting company policies, acting as a mediator in a conflict, solving interpersonal situations, etc.	2	
Office Work	Performing clerical, administrative, and business related activities (recording, data processing, typing, filing, etc.). This interest may be satisfied by work as an office manager, bookkeeper, receptionist, secretary, or administrative assistant.	23	Conventional
Finance	Managing assets and debt. Includes jobs that utilize numbers such as in business bookkeeping, accounting, and tax procedures.	6	
Food Service	Involves activities related to food processing, cooking, planning menus, and related activities. Includes jobs like short-order cook, cafeteria worker, caterer, food service manager, or waiter/waitress.	6	

Table 2.3. ***Additional Basic Interest Dimensions (Less Relevant for Military Contexts)***

Basic Interests	Activities Associated with Each Dimension	Frequency	RIASEC Dimension
Adventure	Taking risks and seeking novel situations. Includes jobs like entrepreneur, acrobat, animal trainer, or fisher.	1	Realistic
Social Science	Research, development, and consulting activities relevant to human behavior and social organizations. Includes jobs like psychologist, historian, sociologist, or survey researcher.	3	Investigative
Creative Arts	Activities involving the visual arts or music. Includes jobs like interior designer, fashion designer, composer, or artist.	12	Artistic
Performing Arts	Performing for an audience. Includes jobs like musician, actor, movie director, singer, or dancer.	9	Artistic
Social Service	Helping individuals and communities to cope with problems. Includes jobs like counselor, therapist, or social worker.	10	Social
Family Activity	Performing domestic activities. May also include jobs related to such activities such as child care worker, nursery school teacher, or child development specialist.	4	Social
Religious Activity	Leading spiritual groups or providing altruistic teachings. Primarily includes jobs like spiritual leader, chaplain, or counselor at a religious camp.	5	Social
Business	Dealing with structured wholesale and retail activities. Includes jobs in marketing, advertising, insurance, or real estate.	6	Enterprising
Law	Researching, documenting, and debating legal matters. Includes jobs like lawyer, court reporter, paralegal, or politician.	5	Enterprising
Professional Counseling	Advising people in meeting their professional goals. This interest may be satisfied by a job as a career counselor.	1	Enterprising/ Social

CHAPTER 3: DEVELOPMENT OF AVID STATEMENT POOLS AND CONSTRUCT VALIDATION

The next steps in the development of the AVID were to create statement pools for the 20 basic interest dimensions identified in Chapter 2 (see Table 2.2) and to pretest them using large samples of Soldiers so that IRT item parameters and social desirability ratings could be estimated. We also constructed a traditional single statement form of the AVID and gathered initial construct validity evidence by examining 1) score profiles of Active-Duty Soldiers across several MOS and 2) correlations between AVID dimensions and RIASEC scores measured by the Department of Labor's O*NET Interest Profiler (Rounds, Su, Lewis, & Rivkin, 2010).

DEVELOPING THE AVID STATEMENT POOLS

First, large pools of statements were developed for each basic interest dimension. Because the AVID can be administered in an adaptive format, it was necessary to create a sufficient number of statements reflecting high, intermediate, and low levels of the latent trait being measured. To develop these statements, we followed the process recommended by Drasgow et al. (2012) and by Cao, Drasgow, and Cho (2015). Specifically, content domains and available statements relevant to each new basic interest dimension were first identified to guide statement writing. Next, subject matter experts with Ph.D.'s in Industrial and Organizational Psychology wrote 70-80 initial statements assessing preferences for work activities. These statements were written to span the respective trait continua, varying in extremity from low to high. The resulting statements were then reviewed for grammar, sensitivity, readability, and content redundancy. Overly long or repetitive statements were either edited or discarded. Ultimately, 50 statements per new basic interest dimension were retained for pre-testing, resulting in a total pool of 1,000 AVID statements. For each AVID dimension, we retained 25 statements reflecting high levels of the dimension, 10 statements reflecting medium levels of the dimension, and 15 statements reflecting low levels of the dimension. Examples of statements reflecting low, medium, and high levels of the AVID Combat basic interest dimension are shown below for illustration:

Low (negative): *I don't like war movies.*

Medium: *I would like to work in a combat support role but not on the front lines.*

High (positive): *I would like to fire weapons, such as rifles, machine guns, or anti-tank missiles.*

ESTIMATING IRT AND SOCIAL DESIRABILITY PARAMETERS

As described in Chapter 1, the AVID statements are designed to be administered in a forced choice format to minimize the effects of faking and other potential response biases associated with self-report measures. Forced choice items consist of blocks of two statements that are matched on their social desirability and extremity to make the best or most socially desirable answer more difficult to discern. This is the same format that is used in the TAPAS, which has been researched extensively in the military context (Drasgow, Stark, Chernyshenko, et al., 2012; Stark et al., 2014).

To construct and score forced choice items, IRT and social desirability parameters for each statement are needed. IRT parameters for the dichotomous version of the Generalized Graded Unfolding Model (GGUM; Roberts, Donoghue, & Laughlin, 2000) were used for test construction and scoring, while social desirability parameters were used to facilitate resistance to faking. To estimate these parameters, the 1,000 newly created statements were administered to large samples of Soldiers at several Army installations. In total, over 3,300 Soldiers responded to the pretest assessment. Approximately 83% of the sample were men and 54% were Caucasian. 95% had a High School Diploma and 64% had attended college and earned a Bachelor's degree or higher. The sample was also comprised of Soldiers from various paygrades ranging from E-1 to E-8, with nearly 90% of the sample in grade E-5 or below.

For the pretest sessions, multiple assessment forms were developed to efficiently collect the data required for estimating the IRT and social desirability parameters for each statement. Across all forms, a common subset of statements was included so that parameter estimates could be placed on a common metric. One set of forms contained two main sections consisting of AVID statements and the Army Life Questionnaire (ALQ), which asked respondents about their experiences in the military. For these forms, all examinees were asked to respond honestly to all statements. Due to the large number of items available for pretesting, seven different versions of this assessment were created, each containing 125 ALQ questions and up to 160 AVID statements so that all statements could be administered to a large enough sample for estimating IRT parameters. To estimate the social desirability of each statement, a separate set of assessments was created that included the same AVID statements and the ALQ. However, for these forms, examinees were asked to answer AVID statements in a way that would make them look like "good Army material." Six different forms each containing up to 145 AVID statements were created to collect these social desirability ratings. In both the pretest and the social desirability assessments, data were collected using a four-point response format, in which 1 = *Strongly Disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly Agree*. In addition, each assessment contained up to 4 statements designed to flag unmotivated respondents by asking Soldiers to select a particular response option (e.g., Strongly Agree) for the corresponding statement.

After the pretest data collections had concluded, data from the samples of Soldiers were then processed and cleaned to remove examinees with more than 20% missing data or those who provided invalid responses to at least one of the response check statements. The final samples for the IRT pre-testing consisted of 380-750 useable cases per assessment version, which was sufficient for estimating the GGUM parameters (Roberts, Donoghue, & Laughlin, 2000). The final samples for estimating the social desirability parameters were smaller (samples sizes ranged from 30-55 cases per form) because only the average endorsement rates needed to be calculated to estimate these parameters.

Responses to the AVID statements in the honest conditions were dichotomized and analyzed separately for each AVID dimension using the GGUM2004 software (Roberts, Fang, Cui, & Wang, 2006). This software is widely used for estimating GGUM parameters in the empirical literature and has been used successfully on TAPAS data. Three GGUM parameters were estimated for each statement: discrimination (α), location (δ), and threshold (τ). GGUM parameters across different forms were linked via the mean-sigma linking method. Social desirability parameters for each AVID statement were estimated by averaging responses over examinees.

PRETEST RESULTS

In total, 1,000 statements from the 20 AVID dimensions were pretested. Several statements had to be dropped during parameter estimation to facilitate the convergence of the GGUM2004 software. Removing statements during pretesting is expected as some may be repetitive in content or too multidimensional, which can prevent the IRT model from converging. In addition, several statements had somewhat low GGUM discrimination parameters (below .50). Statements with low discrimination parameters are problematic because the CAT algorithm selects statements that provide the most information at an examinee's estimated level of the latent interest dimension they assess. Because the amount of information provided by a statement at each level of the latent construct is influenced by its discrimination, statements with low discrimination parameters (i.e., below .50) are unlikely to be selected by the CAT algorithm. Therefore, these items were removed from the final statement pools as well.

Table 3.1 shows the final number of statements for each of the 20 AVID dimensions. For each basic interest dimension, we show the final number of statements retained for the AVID pool and example statements reflecting high levels of each dimension. In total, this effort produced 930 usable statements, with at least 36 statements for each basic interest dimension.

Table 3.1. ***Numbers of Statements Representing Each of the AVID Scales***

Dimension Name	Final # of Statements	Example Statement
Construction	50	I like using tools to build or repair cabinets, doors, and wooden fixtures.
Protection	45	I would enjoy searching people and vehicles for weapons or other illegal goods.
Combat	45	I am interested in learning about urban warfare and door-to-door combat operations.
Physical Activity	36	I really enjoy high intensity workouts.
Mechanical	39	I would enjoy examining vehicles to determine the extent of damage or malfunctions.
Electronics	50	I would enjoy a job that involves repairing smart phones, computers, or other electrical systems.
Outdoor	48	I would enjoy being a wilderness tour guide.

Table 3.1. (*Continued)*

Dimension Name	Final # of Statements	Example Statement
Medical Services	47	I would like to provide care for patients in a hospital.
Mathematics	48	I would enjoy using statistics to predict the winner of an election.
Science	48	I would enjoy learning how scientists study genes.
Information Technology	49	I would enjoy designing and maintaining computer networks.
Writing	49	I would enjoy editing drafts of books or technical documents.
Teaching	48	I would enjoy organizing and conducting informal training sessions with new employees.
Personal Service	50	I would like planning vacations for other people.
Management	47	I like making decisions and being responsible for others.
Sales	49	I would enjoy describing the use of a product to a customer.
Human Relations	44	I would enjoy helping to negotiate labor agreements between employees and management.
Office Work	47	I would enjoy managing the schedules of executives in a company.
Finance	47	I would enjoy helping clients to understand their taxes.
Food Service	44	I really enjoy cooking for large groups of people.

INITIAL CONSTRUCT VALIDATION EVIDENCE

Methods. Using the final statement pools developed for the AVID dimensions, we created a single-statement measure of the AVID dimensions to collect some initial construct validity evidence. To assess all 20 AVID dimensions, we selected 8 statements from each basic interest for administration and respondents were asked to indicate the extent to which they agree or disagree with each statement on a 4-point Likert scale ("Strongly Disagree" to "Strongly Agree"). These statements were then administered in a static form to a sample of 1,025 Active-Duty Soldiers in Basic Combat Training. In addition to the AVID, a short form of the O*NET Interest Profiler (Rounds, Su, Lewis, & Rivkin, 2010) was administered to each Soldier to provide construct validity evidence.

The sample for this research was approximately 62% male and 54% White. The majority of the Soldiers were E-1 (48%) or E-2 (26%). In total, the sample was from 82 different MOS. The largest MOS in the sample were Combat Medics (68W, n = 255), Cannon Crew Members (13B, n = 70), Joint Fire Support Specialists (13F, n = 65), Human Intelligence Collectors (35M, n = 50), and Wheeled Vehicle Mechanics (91B, n = 45). The data were screened using random response flags that asked respondents to mark a particular response option (e.g., "Mark 'C' for this item"). Respondents were screened out if they missed any of these random response flags. After removing random responders, 925 individuals remained in the sample and this reduced dataset was used for all analyses.

To obtain initial validity evidence for the AVID scales, we first examined the correlations between the AVID scales and the Interest Profiler. Although the Interest Profiler only provides RIASEC scores, we examined the extent to which each of the AVID basic interest scales were consistent with expectations based on interest theory and research. Next, we also examined the extent to which the AVID scales could predict MOS membership using discriminant function analysis. Discriminant function analysis can be used to determine whether a group of variables discriminates between two or more groups by creating composites of the variables to predict group membership. For these analyses, the AVID scales were used to predict each Soldier's MOS. To demonstrate the utility of the AVID scales, we examined the amount of variance accounted for by the discriminant functions estimated to predict group membership. Higher levels of variance accounted for indicate that an individual's interest profile is a useful predictor of occupational membership.

Results. Table 3.2 shows the descriptive statistics and intercorrelations for each of the AVID scales. To put the scores for each basic interest dimension in a more intuitive metric, the means and standard deviations were calculated using the sum scores for the eight items representing each dimension instead of the IRT theta scores. Although the AVID statements were developed under the ideal point framework, which usually precludes the calculation of sum scores due to the presence of intermediate items, the medium items were excluded from the version that was administered to Soldiers for this data collection. Therefore, sum scores could be calculated for each dimension and are used to interpret the results.

As shown in Table 3.2, the overall sample scored highest on the Combat interest dimension. This finding is not surprising given the nature of the Army and the MOS in this sample. Individuals in this sample also tended to score higher on the Medical Services and Science dimensions. Again, this result was expected given that the single largest group in this sample was from MOS 68W (Combat Medics). As such, these results are consistent with expectations. The intercorrelations also seem consistent with the content of the scales. For example, the Construction dimension is most highly correlated with the Electronics (r = .46), Mechanical (r = .67), and Outdoors (r = .49) dimensions. Similarly, Management is most highly correlated with Human Relations (r = .47) and Information Technology also is highly correlated with Electronics (r = .68). However, there were also several unexpected findings such as the strong correlations between the Sales and Combat dimensions (*r* = .47) and between the Teaching and Finance dimensions (*r* = .58).

Next, we examined correlations with an existing interest inventory, the O*NET Interest Profiler, to determine the pattern of relationships between the AVID basic interest dimensions and the RIASEC interest types. These correlations are provided in Table 3.3. Results indicated that the 20 basic interest dimensions were strongly correlated with the corresponding RIASEC scales from the Interest Profiler. For example, the strongest correlations with Realistic interest scores on the Interest Profiler were for the Construction, Electronics, and Mechanical AVID dimensions. In addition, the Science basic interest scores had the strongest correlation with Investigative interests (*r* = .67) and the Writing dimension had the strongest correlation with Artistic interests (*r* = .63). These correlations are consistent with Holland's (1997) model of vocational interests and provide initial evidence for the construct validity of the AVID dimensions.

Table 3.2. ***Descriptive Statistics for the AVID Basic Interest Dimensions***

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Construction	19.62	5.30	1.00																			
2. Combat	23.17	3.71	.30	1.00																		
3. Electronics	19.98	5.62	.46	.24	1.00																	
4. Finance	16.74	3.80	.10	.05	.29	1.00																
5. Food	19.10	4.23	.19	.04	.10	.18	1.00															
6. Human Relations	18.79	3.86	.06	.02	.11	.32	.19	1.00														
7. Information Tech.	18.32	5.93	.14	.08	.68	.33	.11	.21	1.00													
8. Management	19.57	3.99	.05	.12	.04	.23	.21	.47	.10	1.00												
9. Mathematics	19.58	4.83	.05	.00	.28	.42	.15	.29	.33	.22	1.00											
10. Mechanical	15.29	4.81	.67	.34	.66	.19	.11	.05	.31	.05	.14	1.00										
11. Medical Services	22.55	5.56	-.06	-.02	-.06	.04	.18	.27	.03	.11	.19	-.12	1.00									
12. Office Work	16.66	5.11	-.07	-.24	-.01	.32	.21	.39	.20	.28	.33	-.10	.25	1.00								
13. Outdoors	20.64	5.15	.49	.30	.13	-.02	.21	.07	-.08	.06	-.02	.37	.07	-.06	1.00							
14. Personal Services	17.22	4.24	.12	-.11	-.01	.16	.39	.33	.06	.19	.15	-.02	.26	.45	.17	1.00						
15. Physical Activity	18.32	3.81	.28	.33	.07	.12	.11	.14	-.07	.18	.10	.21	.13	-.10	.30	.02	1.00					
16. Protection	19.63	4.80	.32	.39	.16	.03	.09	.11	.03	.14	-.04	.24	.00	-.13	.38	.10	.26	1.00				
17. Sales	16.02	4.01	.22	.47	.33	.49	.29	.35	.31	.16	.15	.42	.11	.39	.07	.10	.16	.10	1.00			
18. Science	21.91	4.99	.27	.19	.20	.19	.29	.12	.36	.13	.37	.10	.12	.12	.06	-.02	.06	-.02	.10	1.00		
19.Teaching	19.14	4.02	.06	.21	.25	.58	.15	.50	.33	-.01	.33	.35	.07	.28	.16	.07	.00	.07	.37	.26	1.00	
20. Writing	18.39	5.25	.14	.25	.30	.34	.33	.21	.26	.01	.16	.39	.02	.29	-.05	-.08	-.02	-.08	.30	.27	.40	1.00

Note: *n* = 952. All correlations above .07 in absolute value are significant, *p* < .05. Means and standard deviations are based on sum scores for each AVID dimension rather than IRT theta scores to put them on a more intuitive metric.

Table 3.3. ***Correlations between the AVID Basic Interests and the RIASEC Scores on the Interest Profiler***

AVID Basic Interests	RIASEC Scores on the Interest Profiler					
	Realistic	**Investigative**	**Artistic**	**Social**	**Enterprising**	**Conventional**
1. Construction	.70	.10	.13	.09	.18	.20
2. Combat	.26	.13	.10	.05	.05	.00
3. Electronics	.56	.21	.17	-.01	.27	.41
4. Finance	.21	.21	.15	.13	.51	.45
5. Food	.19	.24	.40	.31	.34	.19
6. Human Relations	.17	.25	.28	.52	.44	.37
7. Information Tech.	.31	.27	.27	.04	.33	.46
8. Management	.09	.12	.18	.36	.40	.21
9. Mathematics	.14	.33	.17	.22	.33	.46
1. Mechanical	.67	.13	.11	.02	.20	.26
11. Medical Services	.04	.53	.23	.48	.16	.14
12. Office Work	.05	.17	.25	.35	.42	.52
13. Outdoors	.48	.17	.16	.24	.08	.06
14. Personal Services	.17	.22	.35	.40	.35	.29
15. Physical Activity	.20	.10	.01	.27	.11	-.02
16. Protection	.34	.04	.07	.13	.13	.05
17. Sales	.26	.16	.25	.33	.60	.46
18. Science	.15	.67	.26	.25	.14	.21
19.Teaching	.08	.30	.34	.58	.33	.27
20. Writing	.10	.28	.63	.32	.33	.32

Note: n = 952. All correlations above .07 in absolute value are significant, $p < .05$.

Table 3.4 shows the interest profiles for the four largest MOS in the sample (sample sizes ranging from 50 to 255). This table shows that each of these MOS had somewhat different interest profiles. The six AVID scales with the highest means for each MOS are bolded and shaded for reference. Not surprisingly, all four MOS scored relatively high on the Combat dimension. However, although this was the primary interest for individuals in 13B (Cannon Crew Members), 13F (Joint Fire Support Specialists), and 35M (Human Intelligence Collectors), individuals in MOS 68W (Combat Medics) scored the highest on the Medical Services dimension. In contrast, this MOS did not score as high on the Protection dimension, which was one of the highest scores in the other three occupations. Overall, the AVID interest profiles of the 13 series MOS were more consistent with each other than with MOS 68W or 35M. However, it is important to remember that these results are based on relatively small sample sizes for all of the MOS except for 68W. Therefore, more research is needed to examine the interest profiles in each of these groups.

Table 3.4. ***AVID Profiles for the Four Largest MOS***

Variables	Combat Medics	Cannon Crew Members	Joint Fire Support Specialists	Human Intelligence Collectors
1. Construction	18.70	**20.94**	**21.29**	19.62
2. Combat	**23.65**	**24.12**	**24.94**	**23.17**
3. Electronics	18.51	**20.55**	**20.43**	**19.98**
4. Finance	16.26	17.16	16.58	16.74
5. Food	19.34	18.25	19.15	19.10
6. Human Relations	18.98	18.13	17.52	18.79
7. Information Tech.	17.21	17.99	17.60	18.32
8. Management	19.53	19.00	19.12	19.57
9. Mathematics	**20.13**	18.63	18.10	19.58
10. Mechanical	14.33	16.90	15.85	15.29
11. Medical Services	**26.44**	19.46	19.26	**22.55**
12. Office Work	16.73	14.81	15.11	16.66
13. Outdoors	**20.98**	**21.54**	**22.54**	**20.64**
14. Personal Services	17.48	16.24	16.37	17.22
15. Physical Activity	18.78	19.13	19.25	18.32
16. Protection	19.47	**21.33**	**21.73**	**19.63**
17. Sales	15.61	16.07	15.43	16.02
18. Science	**23.48**	**21.01**	**20.18**	**21.91**
19.Teaching	**20.03**	17.49	18.26	19.14
20. Writing	18.64	16.80	17.16	18.39

Note: Sample sizes ranged from 50 (MOS 35M) to 255 (Combat Medics). Shaded cells indicate the six largest means in each MOS.

Finally, we also examined the ability of the AVID scales to predict group membership in an MOS. To ensure more stable estimates of group membership, we only examined those groups with at least 10 Soldiers in the sample (total n = 746). The sample sizes for the MOS included in these analyses are shown in Table 3.5. Using these individuals, we then conducted a discriminant function analysis to determine whether the AVID basic interest profiles could be used to differentiate occupations. In other words, we wanted to know whether Soldiers' interest profiles differed across MOS and, therefore, may be useful for MOS assignments.

Table 3.5. ***MOS Included in the Discriminant Function Analysis***

MOS	N
68W (Combat Medic)	255
13B (Cannon Crew)	70
13F (Joint Fire Specialist)	65
35M (Human Intelligence Collector)	50
91B (Wheeled Vehicle Mechanic)	45
68C (Nursing Specialist)	30
35G (Geospatial Intelligence Analyst)	26
88M (Motor Transport Operator)	24
35N (Signals Intelligence Analyst)	24
68E (Dental Specialist)	23
15E (Unmanned Aircraft Repairer)	19
14T (Patriot Launching Station Operator/Maintainer)	17
09W (Warrant Officer Pilot)	15
68J (Medical Logistics Specialist)	14
35F (Intelligence Analyst)	14
68X (Mental Health Specialist)	13
68S (Preventive Medicine Specialist)	11
68G (Patient Administration Specialist)	11
14H (Air Defense Early Warning Operator)	10
13R (Field Artillery Radar Operator)	10

Results of the discriminant function analyses indicated that the average scores for most of the AVID dimensions were significantly different across groups with a few exceptions. For example, the Food Service, Management, and Personal Service means were not significantly different across these groups. This result is likely due to the fact that the specific MOS included in these analyses did not require activities related to these basic interests. The results indicated that four discriminant functions were significant predictors of group membership and combined accounted for 79% of the variance in group membership. These results indicate that the AVID scales can be used to differentiate interest profiles in each MOS. This differentiation is important because differences in the interest profiles of Soldiers in each MOS can be used to help future Soldiers make assignment decisions based on the MOS in which they are most interested. However, due to the small sample sizes in some groups, more research is needed to explore these results in larger samples of each MOS. In addition, to be useful for MOS assignment, it is important that the AVID interest profiles not only vary across MOS but also predict attitudes and performance within each MOS. Therefore, the next step in the development of the AVID was to collect criterion-related validity evidence to determine whether these basic interest scales could also predict performance outcomes in each MOS.

Summary: Pretesting and Construct Validity

The efforts described above resulted in large pools of statements that can be administered to assess the AVID dimensions. In addition, the pretest data collections provided the IRT and social desirability parameters necessary for creating pairwise preference items and for administering the AVID in a CAT format. Finally, the initial construct validity evidence suggested that the AVID assesses basic interest dimensions that are correlated with other interest measures in theoretically meaningful ways and can be used to differentiate the interest profiles of Army MOS. These findings provide initial evidence that the AVID may be useful for MOS assignment. However, additional work is needed to establish the criterion-related validity of this assessment.

Using the IRT and social desirability parameters estimated in the pretest data collections, two different versions of the AVID were created using the pairwise preference item format. The first version was a static form consisting of 123 pairwise preference items assessing 16 of the 20 AVID dimensions. The 16 dimensions that were assessed were selected based on their perceived relevance for the largest MOS in the Army. The four dimensions that were excluded from this version of the AVID were Science, Personal Service, Sales, and Finance. The second version of the AVID that was created was a computer adaptive version that also consisted of 123 pairwise preference items assessing the same 16 dimensions included in the static form. The static form was then used to collect subsequent criterion-related validity evidence for the AVID.

CHAPTER 4: VALIDATION OF THE AVID

As described in Chapter 1, vocational interests have demonstrated validity for predicting a broad range of work outcomes in previous research (Nye et al., 2017). Given these findings, we expect the AVID to predict important work outcomes in the Army as well. Therefore, this chapter describes efforts to demonstrate the validity of the AVID dimensions for predicting work outcomes in two large samples of U.S. Army Soldiers. In addition to examining the validity of the AVID in each of these samples, we also examined MOS-specific composites of the AVID dimensions within the largest MOS. Given that the AVID was developed to be able to differentiate military jobs, we expect this assessment to demonstrate validity in the full sample and differential validity across MOS.

METHODS

Sample 1. The data for the first sample were collected from U.S. Army Soldiers between April 2017 and October 2018. The data consisted of 1,957 Soldiers and were collected from Army installations across the United States. Approximately 84% of the sample was male and 46% of the sample was white, 19% black, and 22% Hispanic. The majority of the sample (67%) had one year or less of college education and most were E-4 (29%) or E-5 (27%).

As noted above, the match between individuals and their jobs is particularly important for predicting work outcomes. Therefore, to be able to focus on individuals in specific occupations and examine differences across MOS, we focused on four high-density MOS to ensure adequate sample sizes for analyses: Military Police (31B; n = 287), Combat Medics (68W; n = 273), Motor Transport Operators (88M; n = 529), and Wheeled Vehicle Mechanics (91B; n = 457). In addition, we had several Soldiers from the other MOS in the 68 series (i.e., 68A-68X; n = 116). Because all of the MOS in the 68 series (Medical Series MOS) were occupations in the medical field, we also examined the interest profile for this cluster of MOS.

Both the AVID and criterion measures in Sample 1 were administered to Soldiers simultaneously in a paper-and-pencil format. As the session began, Soldiers were informed of the purpose of the session and given instructions for filling out the Scantron forms. They were then given instructions for completing the assessments and were provided with an example AVID item to illustrate the question and response formats. Soldiers then completed three sections of the assessment. The first section consisted of AVID items while the second section contained the criterion measures. Finally, the third section asked Soldiers to rate the relevance of each AVID dimension to their MOS. Responses to the third section were used to calculate the fit between each individual and his or her MOS.

Sample 2. The data for the second sample were collected as part of the *Tier One Performance Screen* (TOPS) program of research. The data consisted of a total of 1,999 respondents and the majority of this sample were either E-3 (29%) or E-4 (47%). One difference between Samples 1 and 2 is that there were a greater number of MOS represented in Sample 2. Although Sample 1 data were collected by targeting Soldiers in specific high-density MOS, the data for Sample 2 were collected from a much broader sample. The MOS with the largest sample size was Infantry (n = 343). None of the other MOS had sample sizes larger than 100. Therefore, in addition to examining the validity of the AVID in the full sample, we also explored an MOS-specific composite of AVID scales in Infantry.

The data collection procedures were similar to the procedures used for Sample 1. However, there were two primary differences. First, although the purpose of Sample 1 was solely to evaluate the validity of the AVID, Sample 2 was part of a larger effort to validate several assessments. Therefore, this work was not designed specifically for the AVID but provided a useful source of additional data to examine the validity of this assessment. Second, the measures for Sample 2 were administered in a computerized static format. Soldiers were asked to log onto the computer to access the assessment and enter their ID number. Next, they were informed of the purpose of the assessment and asked to provide consent to participate. They then responded to a series of questions assessing demographic information, the AVID dimensions, the criteria, and each Soldier's ratings of his or her MOS on the AVID dimensions. Again, Soldiers' ratings of their MOS were used to calculate the fit between each individual and his or her MOS.

MEASURES

The same measures were used in both Samples 1 and 2. However, as noted above, these assessments were administered in a paper-and-pencil format for Sample 1 and in a computerized format for Sample 2. Because the data collection in Sample 2 was also designed for a broader validation effort with other assessments, this data collection included some additional assessments that were not used for the analyses presented in this report.

AVID. The 123 item static version of the AVID that was created using the pretest data was administered to Soldiers in both samples. As described above, this version of the AVID assessed 16 basic interests (all the AVID dimensions except for Science, Personal Service, Sales, and Finance). Only 16 of the 20 AVID dimensions were administered to reduce the amount of time for the assessment and alleviate concerns about test-taker fatigue. The four dimensions that seemed to be the least useful for our target sample were dThe AVID statements were administered in a forced choice format and Soldiers were asked to pick one statement out of the pair that was "more like you." Again, the statements for each pair were matched based on their extremity and social desirability to mitigate the effects of faking and response biases on the interest scores.

Army Life Questionnaire (ALQ). The criteria for both samples were assessed using the ALQ. The ALQ is a self-report attitudinal measure currently used in ARI validation research.[1] The ALQ includes sections on Soldiers' demographic characteristics, background, and experience information, as well as assessments of Soldiers attitudes, perceptions of fit (both in the Army and in their MOS), commitment, resilience, motivation to lead (MTL), organizational citizenship behavior/Leadership (OCB), counter-productive work behavior (CWB), and career intentions. Descriptions of the ALQ scales included in this research are presented in Table 4.1. In

[1] The Army Life Questionnaire was initially developed in 2005 (Van Iddekinge, Putka, & Sager, 2005) and has been updated on several occasions to meet the Army's requirements for measuring Soldier outcomes.

addition to these scales, the ALQ also asked about Soldiers' Army Physical Fitness Test (APFT) scores and experience with disciplinary incidents.

Table 4.1. ***Army Life Questionnaire Scales Included***

Construct	Definition
Counterproductive Work Behavior (CWB)	Intentional behaviors that harm or are intended to harm another Soldier or the legitimate interests of the unit
Army Fit	The extent to which Soldiers feel like the Army is a good match for them
MOS Fit	The extent to which Soldiers feel like their current MOS is a good fit for their interests
Affective Commitment	Soldiers' attachment to and identification with the Army
MOS Satisfaction	Satisfaction with the opportunities and daily work involved in the Soldiers' MOS
Career Intentions	Likelihood of staying in the Army until retirement
Reenlistment Intentions	Likelihood of reenlisting for another term of service
Motivation to Lead (MTL)	The factors that affect individual's decisions to assume leadership training, roles, and responsibilities, and affect his or her intensity of effort at leading and persistence as a leader (Chan & Drasgow, 2001). Their conceptual and empirical model of MTL includes three underlying dimensions: Affective, Noncalculative, and Social-Normative
Organizational Citizenship Behavior and Leadership (OCB)	Engaging in voluntary behaviors to help another individual or the organization itself (Bateman & Organ, 1983), including behaviors that Soldiers engage in to display leadership qualities, absent of an official leadership role
Resilience	The capacity to overcome difficult life events with minimal disruption or long-term negative impacts on psychological and physical functioning (Bonanno, 2004)

Table 4.2 provides the means, standard deviations, and intercorrelations for the criteria assessed by the ALQ. In this table, the correlations for Sample 1 are provided below the diagonal and the correlations for Sample 2 are provided above the diagonal. In addition to examining each outcome individually, we also examined the prediction of an overall performance composite. To do so, scores for each criterion were first standardized to account for differences in their standard deviations and then summed using unit weights to create an overall criterion score. Negatively worded scales (i.e., CWB) were reverse coded before calculating the overall performance scores so that all scales were in a consistent direction. Due to the relatively small relationships with

disciplinary incidents in the overall samples (see below for further details), this outcome was not included as part of overall performance. The goal of combining criterion scales in this way was to determine the utility of the AVID for predicting a broader criterion variable and to examine composites of AVID scales that might be useful for MOS assignment decisions. Table 4.2 also provides the descriptive statistics and intercorrelations for the overall performance composite. Because each of the scales comprising the overall performance composite was first standardized to account for differences in their distributions, the mean of this variable was near zero.

MOS Ratings. Soldiers also responded to items asking them to rate their MOS on each of the 20 AVID dimensions. These ratings served two purposes: 1) to indicate the perceived relevance of each AVID dimension for the activities performed in a particular MOS, and 2) to identify the interest profile of each MOS for calculating person-job fit. As noted above, past research has shown that the validity of interests is highest when considering the match between individuals and their environment. Therefore, these ratings were important for examining the validity of the AVID.

To collect these ratings, Soldiers were given the name and a description of each AVID dimension. Examples of activities that are associated with each dimension were also included to provide Soldiers with a clearer understanding of how these dimensions might relate to their MOS. Then, Soldiers were asked to rate "How descriptive is this dimension of your current MOS?" on a scale from 1 ("*Not at all descriptive*") to 7 ("*Extremely descriptive*"). The means and standard deviations for these ratings are provided in Table 4.3 for both samples and variation across samples reflect the different MOS that are represented in each. For example, the mean ratings for the Combat, Outdoors, and Physical Activity dimensions were strongest in Sample 2, which included a larger number of Infantry. In contrast, the mean ratings for Human Relations and Management dimensions were larger in Sample 1, which included more senior Soldiers.

Table 4.2. ***Descriptive Statistics and Intercorrelations between the Criteria***

Variables	Mean (Sample 1)	SD (Sample 1)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. MOS Fit	3.10	0.94	--	.47	.45	.77	.31	.32	.31	.33	.26	.07	.35	.03	-.03	-.05	.61
2. Army Fit	3.35	0.94	.38	--	.71	.49	.41	.46	.57	.59	.30	.25	.48	.11	-.09	-.24	.79
3. Affective Commitment	3.10	1.07	.37	.59	--	.47	.38	.41	.52	.56	.32	.07	.46	.09	-.05	-.12	.72
4. MOS Satisfaction	3.00	0.98	.66	.40	.37	--	.31	.35	.37	.37	.23	.04	.32	.01	-.05	-.07	.62
5. OCB	3.42	0.80	.27	.41	.41	.33	--	.55	.26	.27	.52	.27	.58	.17	-.06	.01	.65
6. Resilience	3.68	0.81	.24	.40	.34	.31	.59	--	.28	.28	.42	.20	.55	.16	-.10	-.09	.66
7. Reenlistment Intentions	3.32	1.50	.28	.56	.49	.40	.40	.34	--	.88	.21	.11	.31	.09	-.06	-.17	.66
8. Career Intentions	3.19	1.49	.28	.56	.49	.42	.40	.34	.83	--	.24	.12	.32	.07	-.08	-.20	.68
9. MTL (Affective)	3.43	0.98	.28	.34	.37	.24	.50	.42	.29	.27	--	.17	.63	.16	-.06	-.03	.58
10. MTL (Noncalculative)	3.65	1.00	.05	.35	.16	.04	.32	.26	.18	.17	.26	--	.31	.05	-.06	-.30	.39
11. MTL (Social-Normative)	3.74	0.98	.25	.42	.39	.24	.51	.48	.32	.28	.68	.38	--	.14	-.07	-.14	.73
12. APFT	3.85	1.57	.02	.11	.09	.05	.19	.16	.08	.05	.18	.11	.18	--	-.08	-.02	.28
13. Disciplinary Incidents	0.64	1.23	-.05	-.12	-.12	-.06	-.18	-.18	-.13	-.13	-.10	-.12	-.15	-.08	--	.13	-.12
14. CWB	2.25	0.69	-.12	-.36	-.21	-.12	-.26	-.31	-.24	-.21	-.20	-.39	-.32	-.10	.19	--	-.31
15. Overall Performance	0.00	7.83	.54	.75	.67	.59	.71	.66	.69	.68	.64	.47	.69	.29	-.20	-.49	--
	Mean (Sample 2)		3.08	3.35	3.01	2.95	3.23	3.86	3.00	2.78	3.42	3.59	3.87	243.34	.42	2.01	.00
	SD (Sample 2)		1.00	.93	1.04	.99	.79	.73	1.43	1.36	.90	.91	.81	36.49	.91	.64	7.65

Note: Sample sizes ranged from 1,749 to 1,757 for Sample 1 and from 1,725 to 1,756 for Sample 2. All correlations above .02 in absolute value are significant, $p < .05$. MTL = Motivation to Lead.

Table 4.3. ***Means and Standard Deviations of the MOS Ratings***

	Sample 1		Sample 2	
Variables	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
Combat	2.81	1.83	3.38	2.51
Construction	2.67	1.81	1.83	1.54
Electronics	2.66	1.84	2.90	2.08
Finance	2.04	1.59	1.34	1.10
Food Service	1.86	1.52	1.59	1.30
Human Relations	3.28	1.90	1.29	0.94
Information Tech.	2.10	1.59	2.09	1.80
Management	4.07	2.00	3.33	2.12
Mathematics	2.40	1.62	2.76	1.87
Mechanical	3.43	2.07	3.64	2.27
Medical Services	3.00	2.09	2.48	1.93
Office Work	3.11	1.88	1.87	1.68
Outdoors	2.69	1.81	3.57	2.38
Personal Service	2.28	1.81	1.78	1.47
Physical Activity	3.61	1.89	4.45	2.24
Protection	3.25	2.08	3.01	2.20
Sales	1.88	1.52	4.89	1.99
Science	2.20	1.67	2.69	1.88
Teaching	3.84	1.92	3.59	2.12
Writing	2.43	1.71	4.26	1.98

Note: Sample sizes ranged from 1,808 to 1,820 for Sample 1 and was 1,978 in Sample 2. There was a range of sample sizes for Sample 1 due to omitted responses from some Soldiers on the rating scales at the end of the survey. However, all Soldiers responded to all scales in Sample 2.

ANALYSES

Using the AVID and criterion data described above, we examined the validity of the AVID for predicting important military outcomes separately in both Samples 1 and 2. Before conducting these analyses, the data were first screened for unmotivated responders. In addition to the items assessing the AVID dimensions, three items were also included in both samples to detect unmotivated responding. These items instructed participants to select a particular option for that item (e.g., “Select option B” or “For data quality check, please select this option for this pair”). Individuals who responded incorrectly (i.e., marked a response other than the one they were instructed to mark) to more than one of these response flags were excluded from all analyses (excluded n = 124 in Sample 1 and n = 218 in Sample 2).

Next, we used the reduced dataset to examine the validity of the AVID. Given theory (Holland, 1997) and past research (Nye, Su, Rounds, & Drasgow, 2012, 2017) suggesting that the match between individuals and their environments is the best predictor of work outcomes, the focus of these analyses was on quantifying interest fit. In addition, consistent with past research demonstrating the benefits of regression-weighted composites for both interests (Van Iddekinge et al., 2011) and personality (Nye, Drasgow, Chernyshenko, Stark, Kubisiak, White, & Jose, 2012), we first used regression analyses to develop composites of the AVID scales to predict the criteria assessed in this research.

Despite the potential validity of regression-weighted composites of interest scales, this approach also has limitations. For example, in order to quantify the match (or congruence) between an individual and his or her job, it is necessary to include interest scores for both the individual and the job. However, the regression-weighted composites described above only include the interest scores for the individual. Therefore, adding the MOS ratings to the model could also improve the prediction of work outcomes by providing a more appropriate way to operationalize the match between individuals and their jobs.

Edwards (1993) provided the mathematical proof that regression models including both individual and environment scores can provide one way of operationalizing person-environment fit and suggested polynomial regression as an alternative to composites of individual scores alone. With this approach, individual interest scores are included in the model along with environment interest scores, quadratic terms for both the individual and environment scores, and the interactions between the individual scores and the corresponding environment scores. After estimating the full regression model, the predicted scores from this model represent the fit between an individual and the corresponding job. Nye, Prasad, Bradburn, and Elizondo (2018) demonstrated that operationalizing interest congruence in this way results in validities that are three to four times higher than using traditional congruence indices. Therefore, we used this approach as well.

To identify the best regression models for calculating fit with the AVID scales, we tested a series of models that increased in complexity. First, we tested a model with just the individual interest scores included. Next, we added the MOS interest scores to the model and examined the change in validity. Then we added the interactions between individual and MOS interest scores, the quadratic (i.e., squared) terms for individual interest scores, and the quadratic terms for the MOS interest scores in subsequent models. In each case, we examined the change in model fit (R^2) and in the overall validity of the model (multiple R) to determine the most appropriate model. The best fitting model was then used for further analyses.

The initial analyses with the polynomial regression model were conducted in the full sample. However, once we identified the best model for prediction, we also examined differences across specific MOS. For Sample 1, we examined prediction differences across the four largest MOS in the sample including MOS 31B, 68W, 88M, and 91B as well as MOS in the 68 series due to their similarities. Due to the smaller MOS-specific sample sizes in Sample 2, we only examined an MOS-specific AVID composite in Infantry and compared this composite to the results in the full sample. The purpose of examining differences across MOS was to determine if different composites of AVID scales would be useful for predicting work outcomes in each occupation. In order to be useful for MOS assignment, the AVID scales need to not only demonstrate validity for predicting work outcomes but also show differential validity across MOS. Therefore, we conducted an initial evaluation of differential validity in a subset of MOS by examining differences in AVID composites across the largest MOS in our samples.

RESULTS: SAMPLE 1

Table 4.4 shows the intercorrelations between the AVID scales in Sample 1. The results were largely consistent with the correlations in the construct validation analyses (see Chapter 3). For example, the Combat dimension was highly correlated with the Protection dimension (r = .54). Although this finding was slightly higher than the results for the construct validation sample, the pattern was consistent. In addition, Construction was highly correlated with the Mechanical (r = .42) and Outdoors (r = .37) dimensions. However, the Electronics dimension was not as highly correlated with Construction (r = .18) as it was in Table 3.2. Nevertheless, the overall results seem consistent with expectations based on previous interest research.

Table 4.5 shows the AVID scales that were significant predictors of each of the criteria in the dataset. The AVID scales predicted a number of criteria very well. The scales were the strongest predictors of motivation to lead (both affective and social-normative) and OCB, and the multiple R's for these outcomes were all .40 or above. This is consistent with previous meta-analyses showing that interest fit is most strongly related to OCB (Nye et al., 2017). Across all of the outcomes, the AVID Management and Physical Activity scales were the most consistent predictors.

Table 4.5 also shows that the AVID scales were strong predictors of the overall performance composite we created by combining each of the individual criteria. The multiple R for predicting this outcome was .47. Again, the strongest predictors of this outcome were the AVID Management and Physical Activity scales. Interestingly, the Writing dimension was also a significant predictor of this outcome but in the negative direction. In other words, individuals who were interested in writing activities were less likely to score high on the overall performance composite. This was consistent with the direction of the effects for several of the other outcomes as well. Information Technology also had a negative relationship with the overall criterion composite and several of the individual criteria. These results illustrate the importance of assessing both interests that are associated with a particular job and those that are not.

Table 4.4. ***Correlations between the AVID Basic Interest Dimensions in Sample 1***

AVID Dimensions	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Combat	1.00															
2. Construction	.17	1.00														
3. Electronics	.04	.18	1.00													
4. Food Service	-.20	.04	-.06	1.00												
5. Human Relations	-.17	-.14	-.07	.07	1.00											
6. Information Tech.	-.11	-.06	.48	-.02	.08	1.00										
7. Management	.09	.02	-.02	-.08	.32	-.01	1.00									
8. Mathematics	-.15	-.11	.22	-.02	.10	.36	.05	1.00								
9. Mechanical	.31	.42	.44	-.12	-.18	.01	.00	-.09	1.00							
10. Medical Services	-.18	-.25	-.08	.03	.14	.07	-.04	.14	-.25	1.00						
11. Office Work	-.29	-.18	.02	.10	.25	.31	.16	.27	-.24	.09	1.00					
12. Outdoors	.07	.37	-.02	.11	-.18	-.27	-.03	-.12	.24	-.11	-.15	1.00				
13. Physical Activity	.31	.14	-.09	-.10	-.04	-.15	.16	-.07	.14	-.06	-.20	.07	1.00			
14. Protection	.54	.14	-.05	-.17	-.03	-.14	.12	-.18	.21	-.10	-.17	.10	.23	1.00		
15. Teaching	-.14	-.15	-.12	.09	.37	.05	.17	.19	-.19	.20	.13	-.06	.04	-.09	1.00	
16. Writing	-.30	-.12	.03	.10	.22	.26	.03	.22	-.25	.11	.28	-.11	-.17	-.25	.28	1.00

Note: n = 1,833. All correlations above .05 in absolute value are significant, $p < .05$.

Table 4.5. ***Standardized Regression Weights for the AVID Scales Predicting Each Criterion in Sample 1***

AVID Dimensions	MOS Fit	Army Fit	Affective Commit.	MOS Sat.	OCB	Resilience	Reenlist. Intentions	Career Intention	MTL (Affective)	MTL (Noncal.)	MTL (Soc-Norm)	APFT	Disciplinary Incidents[a]	CWB	Overall Performance
Combat		.08	.08		.09	.10					.06				.07
Construction		-.07	-.06				-.06								
Electronics											.06				
Food Service	.06			.07							-.07				
Human Relations		.06		.07	.09	.10				.11	.08			-.10	.10
Information Tech.	-.10	-.06	-.09	-.11			-.07	-.08							-.08
Management	.10	.13	.11	.08	.22	.16	.16	.14	.32	.13	.22			-.08	.24
Mathematics	.05											.09			
Mechanical	.18			.13							-.07	-.09			
Medical Services	-.06					.07									
Office Work			.06	-.11				.05		-.08					
Outdoors				-.08											
Physical Activity	.05	.11	.05	.10	.06	.18	.09	.09			.07	.29	-.17	-.05	.15
Protection		.07	.09		.07		.07		.09	.10	.08		-.26	-.06	.10
Teaching	.07	.06	.06		.14	.09			.09	.07	.13			-.11	.12
Writing		-.08		-.07	-.13	-.11			-.12	-.11	-.18			.18	-.15
Multiple R	.29	.31	.27	.31	.40	.39	.28	.25	.42	.30	.41	.31	.14	.27	.47
Adjusted Multiple R	.28	.29	.25	.29	.39	.38	.26	.23	.41	.28	.40	.29	--	.07	.46

Note: Values in this table represent significant regression weights, $p < .10$. Sample sizes ranged from 1,757 to 1,833. [a] Because this variable was dichotomized to account for low base rates, these analyses are based on a logistic regression. Therefore, an adjusted multiple R could not be calculated. In addition, the regression weights presented for this outcome are the unstandardized regression weights.

Figure 4.1 illustrates the practical importance of the relationships between the AVID and several of the criteria assessed in this sample. We used the standardized regression weights for predicting overall performance from the analyses shown in Table 4.5 to calculate AVID composite scores for each individual. We then used these scores to plot the relationships between this AVID composite and several criteria. Figure 4.1 illustrates the relationships between the AVID composite scores and overall performance, motivation to lead (affective), OCB, and resilience. On the X-axes of these plots are the quintiles for the AVID composite scores. The Y-axes provide the average scores on the criteria. To standardize these graphs, the outcomes were scaled to have a mean of 100 and a standard deviation of 20 and the Y-axes for these figures are scaled to range from the mean of the outcome variable +/- 1 standard deviation.

The graphs shown in Figure 4.1 indicate that individuals who scored higher on the AVID composite had higher overall performance, greater motivation to lead, engaged in more OCB, and were more resilient. In addition, for most of these outcomes, there was nearly a full standard deviation difference between the highest and lowest scoring groups on the AVID composite, indicating that the effects were substantial. Again, these results suggest strong relationships between the AVID scales and performance criteria in this sample of Soldiers.

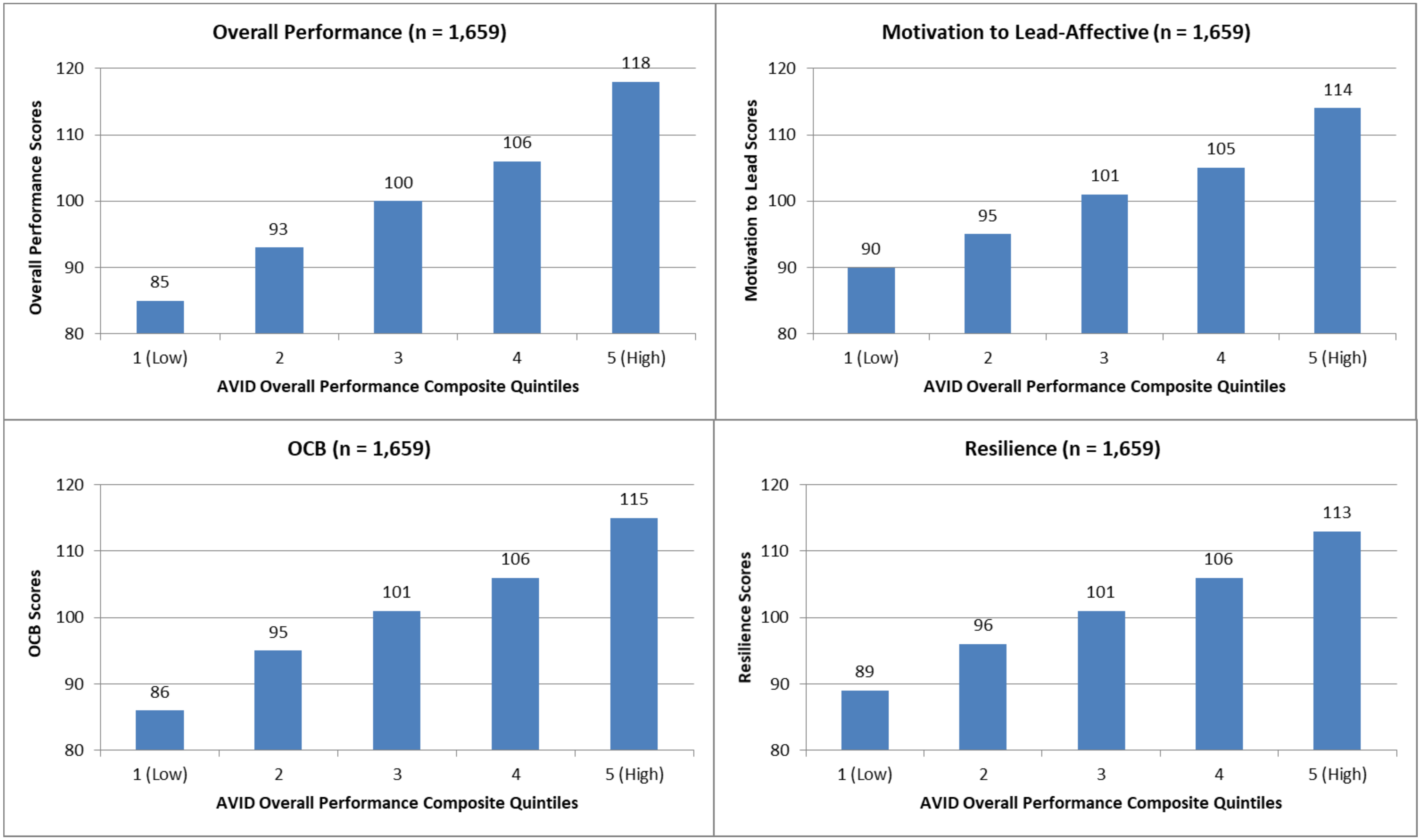

Figure 4.1. **AVID Composite Quintile Plots for Overall Performance, Motivation to Lead, OCB, and Resilience in Sample 1**

Next, we examined differences in the AVID predictors of overall performance across MOS. Again, we examined composites of the AVID scales in the four largest MOS (i.e., Military Police, Combat Medics, Motor Transport Operators, and Wheeled Vehicle Mechanics as well as in a combined group of MOS in the Medical series. The results of these analyses are shown in Table 4.6. The AVID scales that were significant predictors of overall performance varied across MOS. The Management scale was the most consistent predictor across all of the groups and had the strongest weight in each MOS. Writing was also a significant negative predictor of overall performance in most cases. The one exception was in Mechanics. Again, the negative relationship suggests that individuals with strong interests in writing activities are less likely to be successful with and satisfied in these MOS. Physical Activity was also a significant predictor in three of the five groups we analyzed.

With the exception of the Management, Writing, and Physical Activity AVID dimensions, the other predictors of overall performance varied across MOS. This finding suggests that the AVID dimensions that are relevant for each MOS vary. As a result, the AVID scores may be useful for MOS assignment.

Table 4.6. ***MOS-Specific Prediction of Overall Performance in Sample 1***

	MOS				
AVID Dimensions	**Military Police**	**Combat Medics**	**Medical Series**	**Motor Transport**	**Mechanics**
Combat	.13				
Construction					
Electronics					
Food Service					
Human Relations	.15			.11	.17
Information Technology					-.10
Management	.32	.22	.25	.24	.20
Mathematics			.09		
Mechanical	-.12				.13
Medical Services		.16	.09		
Office Work					
Outdoors					
Physical Activity	.14			.11	.21
Protection		.15	.15		
Teaching		.12	.19		
Writing	-.13	-.13	-.17	-.14	
Multiple R	.57	.50	51	.43	.49
Adjusted Multiple R	.52	.44	.47	.38	.45

Note: Values in this table represent significant regression weights, $p < .10$. Sample sizes were Military Police n = 271; Combat Medics n = 262; Medical Series MOS n = 378; Motor Transport Operators n = 449; Wheeled Vehicle Mechanics n = 409.

As described above, although a simple linear regression model has shown strong validity in past research (Van Iddekinge et al., 2011), this approach does not include interest scores for the MOS; therefore,it cannot effectively quantify interest fit. To address this issue, we tested a series of regression models predicting overall performance to identify the best operationalization of the match between Soldiers and their MOS. The results of these analyses are shown in Table 4.7. This table shows the multiple R, R^2, and adjusted (for capitalization on chance) R^2 for each of these models. Results indicated that adding the MOS ratings to the model significantly improved the prediction of overall performance, and the effect was substantial ($\Delta R = .10$, $p < .05$). Although adding the interactions to the model resulted in a significant increase in the multiple R ($p < .05$), the magnitude of this increase was small ($\Delta R = .01$). In addition, adding the quadratic terms for both individual scores and MOS ratings also resulted in small and non-significant increases in the multiple R. Based on these findings, further analyses were conducted using regression models that included only the individual scores and the MOS ratings to examine the validity of interest fit. As demonstrated by Edwards (1993), this model is consistent with congruence indices that quantify the difference between individual and environment score profiles. However, the regression approach used here is more effective than examining simple differences between these profiles because this approach reduces the constraints on the relationships between individual scores, environment scores, and the criterion.

Table 4.7. ***Polynomial Regression Analyses Predicting Overall Performance in Sample 1***

Regression Model	Multiple R	R^2	Adjusted R^2
Individual interest scores	.47	.22	.21
Individual scores + MOS ratings	.57	.33	.31
Individual scores + MOS ratings + Interactions	.58	.34	.32
Individual scores + MOS ratings + Interactions + Squared individual scores	.59	.35	.32
Individual scores + MOS ratings + Interactions + Squared individual scores + Squared MOS scores	.60	.36	.33

Note: Sample size was n = 1,697.

Table 4.8 shows the validity of the regression equations including both individual scores and MOS ratings in each MOS. These results indicate that the AVID interest fit scores have substantial validity for predicting overall performance in each MOS. The smallest adjusted multiple R was .51 while the largest was .64. In addition, the results indicated that both the individual AVID scores and the MOS ratings contributed to the prediction of this outcome. However, with this regression approach, the predicted scores from these equations represent the fit between an individual Soldier and his or her MOS. As such, these equations can be used to identify Soldiers that are the best fit for a MOS.

Table 4.8. ***MOS-Specific Validities of the AVID Interest Fit Composites in Sample 1***

Variables	Military Police	Combat Medics	Medical Series	Motor Transport	Mechanics	Full Sample
Combat	.11	.12	.10			.06
Construction					-.10	-.05
Electronics						
Food Service	-.12					
Human Relations					.12	.06
Information Tech.						-.06
Management	.24	.14	.18	.19	.19	.21
Mathematics			.09	.09		.04
Mechanical	-.13				.13	
Medical Services		.20	.10			
Office Work						
Outdoors						
Physical Activity	.15			.12	.16	.13
Protection		.14	.13	.09		.09
Teaching			.16			.08
Writing			-.14	-.11		-.09
Combat (MOS)	.12					
Construction (MOS)						
Electronics (MOS)					.17	
Food Service (MOS)	-.15		-.11	-.13		-.14
Human Relations (MOS)		.29	.23	.16	.24	.16
Information Tech. (MOS)						
Management (MOS)	.13	.15	.18			.12
Mathematics (MOS)					-.12	
Mechanical (MOS)						
Medical Services (MOS)		.15				
Office Work (MOS)			-.11	.12		
Outdoors (MOS)						-.05
Physical Activity (MOS)				.14	.09	
Protection (MOS)	.14					
Teaching (MOS)	.15			.11		.08
Writing (MOS)					-.12	
Multiple R	.70	.69	.64	.56	.63	.57
Adjusted Multiple R	.64	.62	.59	.51	.59	.56

Note: Values in this table represent significant regression weights, $p < .10$. Sample sizes were Military Police n = 271; Combat Medics n = 262; Medical Series MOS n = 378; Motor Transport Operators n = 390; Wheeled Vehicle Mechanic n = 392; Full sample n = 1,697.

To examine the differences between the AVID interest fit scores (i.e., the predicted scores from the models shown in Table 4.8) across MOS, we used the equations shown in Table 4.8 to calculate the fit between each individual in the sample and each of the four largest MOS as well as the MOS in the Medical Series. In other words, each Soldier in the sample had five predicted performance scores that represented their fit with each of the MOS groups in our sample. We then calculated the correlations between these predicted scores to quantify the similarities between them. These correlations are shown in Table 4.9.

The correlations presented in Table 4.9 suggest that the MOS-specific interest fit scores were strongly correlated. However, these correlations also indicated that there were some differences across MOS. Combined, Tables 4.8 and 4.9 indicate that the AVID interest fit scores will have substantial validity for predicting overall performance and differential validity across MOS. As such, these results suggest that interest fit may be useful for MOS assignment when estimated using the AVID scales.

Table 4.9. ***Correlations between the MOS-Specific Interest Fit Composites in Sample 1***

MOS	Military Police	Combat Medics	Medical Series	Motor Transport	Mechanic
Military Police	1.00				
Combat Medics	.65	1.00			
Medical Series	.72	.80	1.00		
Motor Transport	.75	.78	.75	1.00	
Mechanic	.45	.59	.64	.70	1.00

Note: Sample sizes ranged from n = 1,784 to 1,805. All correlations are significant.

RESULTS: SAMPLE 2

Table 4.10 shows the intercorrelations between the AVID scales in Sample 2. The results were largely consistent with the correlations both in Sample 1 and in the initial construct validation analyses. For example, the Combat dimension was highly correlated with the Protection dimension (r = .58). In addition, Construction was highly correlated with the Mechanical (r = .48) and Outdoors (r = .44) dimensions but was less highly correlated with the Electronics dimension (r = .12) than in the construct validation sample. Again, these results are consistent with the results from Sample 1 and with expectations based on previous interest research.

Table 4.11 shows the AVID scales that were significant predictors of each of the criteria in this sample. The results of these analyses are largely consistent with the results in Sample 1. As shown in Table 4.11, the AVID scales predicted a number of criteria very well. Across all of the outcomes, the AVID Management and Physical Activity dimensions were the most consistent predictors. In addition, the AVID dimensions were the strongest predictors of motivation to lead (both affective and social-normative) and OCB and the multiple R's for these outcomes were all .40 or above. The AVID scales were also strong predictors of overall performance with a multiple R of .47 and an adjusted (for capitalization on chance) multiple R of .46. Although the strongest predictors of this outcome were still the AVID Management and Physical Activity scales, a number of other predictors (both positive and negative) were also included in the AVID composite.

Table 4.10. ***Correlations between the AVID Basic Interest Dimensions in Sample 2***

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Combat	1.00															
2. Construction	.26	1.00														
3. Electronics	.05	.12	1.00													
4. Food Service	-.20	.06	-.04	1.00												
5. Human Relations	-.15	-.16	-.12	.04	1.00											
6. Information Tech.	-.12	-.11	.53	.01	.04	1.00										
7. Management	.08	.03	-.13	-.03	.35	-.04	1.00									
8. Mathematics	-.17	-.05	.26	.00	.06	.36	.06	1.00								
9. Mechanical	.35	.48	.39	-.07	-.18	.03	-.02	-.04	1.00							
10. Medical Services	-.18	-.17	-.01	.06	.17	.07	.07	.08	-.15	1.00						
11. Office Work	-.32	-.19	.03	.05	.25	.27	.21	.27	-.21	.10	1.00					
12. Outdoors	.08	.44	-.07	.13	-.18	-.29	-.03	-.13	.27	-.16	-.18	1.00				
13. Physical Activity	.34	.22	-.11	-.05	.03	-.14	.19	-.10	.19	-.02	-.19	.11	1.00			
14. Protection	.58	.23	.00	-.17	-.03	-.14	.14	-.19	.31	-.06	-.19	.14	.31	1.00		
15. Teaching	-.21	-.21	-.15	.13	.37	.03	.20	.16	-.29	.22	.18	-.10	-.01	-.17	1.00	
16. Writing	-.31	-.23	-.01	.08	.15	.18	.04	.18	-.31	.09	.26	-.09	-.15	-.32	.32	1.00

Note: n = 1,731. All correlations above .04 in absolute value are significant, $p < .05$.

Table 4.11. ***Standardized Regression Weights for the AVID Scales Predicting Each Criterion in Sample 2***

Variables	MOS Fit	Army Fit	Affective Commit.	MOS Sat.	OCB	Resilience	Reenlist. Intentions	Career Intention	MTL (Affective)	MTL (Noncal.)	MTL (Soc-Norm)	APFT	Disciplinary Incidents[a]	CWB	Overall Performance
Combat	.07	.07			.07		.07			.07	.10				.08
Construction		-.06	-.09				-.08	-.09	.05					.07	-.05
Electronics													.19		
Food Service				.05	-.04	-.06				-.04		-.07			
Human Relations		.07	.07	.06	.11	.07			.06	.09	.13			-.09	.11
Information Tech.														-.06	
Management	.06	.08	.11		.26	.12	.11	.13	.42	.15	.28	.05		-.07	.24
Mathematics					.06	.05			.07		.06	.06			
Mechanical	.07		.06				.06	.05				-.06			
Medical Services	-.07			-.05			.05					.05		-.06	
Office Work		-.05			-.06	-.07				-.10	-.06	-.07			-.05
Outdoors	.05				.06										
Physical Activity	.05	.16	.09	.05	.11	.27	.11	.10	.09	.07	.09	.28	-.20	-.11	.21
Protection		.05	.10			.05			.06		.09		-.19		.06
Teaching		.06			.10		.05	.05		.05	.05			-.06	.06
Writing		-.09				-.05	-.05	-.05	-.05		-.08			.11	-.07
Multiple R	.22	.31	.26	.15	.42	.38	.23	.23	.51	.29	.46	.32	.17	.25	.47
Adjusted Multiple R	.19	.29	.24	.12	.41	.37	.21	.21	.51	.27	.45	.31	--	.23	.46

Note: Values in this table represent significant regression weights, $p < .10$. Sample sizes ranged from 1,707 to 1,731. [a] Because this variable was dichotomized to account for low base rates, these analyses are based on a logistic regression. Therefore, an adjusted multiple R could not be calculated. In addition, the regression weights presented for this outcome are the unstandardized regression weights.

Figure 4.2 illustrates the practical importance of the relationships between the AVID and several of the criteria assessed in Sample 2. Similar to the analyses in Sample 1, we used the standardized regression weights from the analyses shown in Table 4.11 for predicting overall performance to calculate AVID composite scores for each individual. We then used these scores to plot the relationships between this AVID composite and several criteria in Sample 2. Figure 4.2 illustrates the relationships between the AVID composite scores and the overall performance criterion, motivation to lead (affective), OCB, and resilience. Consistent with Figure 4.1, the X-axes of these plots are the quintiles for the scores on the AVID composite and the Y-axes provide the average scores on the criteria. Again, the outcomes were scaled to have a mean of 100 and a standard deviation of 20 and the Y-axes for these figures are scaled to range from the mean of the outcome variable +/- 1 standard deviation.

The graphs shown in Figure 4.2 indicate that individuals who scored higher on the AVID composite had higher overall performance scores, greater motivation to lead, engaged in more OCBs, and were more resilient. In addition, for most of these outcomes, there was nearly a full standard deviation difference between the highest and lowest scoring groups on the AVID composite, indicating that the effects were substantial. Again, these results suggest strong relationships between the AVID scales and performance criteria in this sample of Soldiers.

In contrast to Sample 1, the overall validities of the AVID were smaller for predicting some criteria in Sample 2. For example, Table 4.11 shows that the validities of the AVID for predicting MOS satisfaction and MOS fit were smaller in Sample 2. One possible explanation for these findings is that the predictors of these outcomes varied across MOS. Again, Sample 1 was designed specifically to focus on four high-density MOS. In contrast, Sample 2 included a broader range of MOS and it is possible that the predictors of MOS-specific outcomes like satisfaction and fit varied across these MOS. This would have resulted in lower validities for these outcomes when the results were examined in the full sample. To explore this possibility, we next examined the validities for predicting each of the outcomes in Infantry, which was the largest MOS in Sample 2.

The results of these analyses are shown in Table 4.12. As shown in this table, the validities were generally stronger for some outcomes in Infantry. For example, the validities for MOS satisfaction and fit were .42 and .52, respectively, compared with .15 and .22 in the full sample. Again, these differences suggest that the scales that predict these outcomes in Infantry are different from the predictors in the overall sample. This finding indicates that the AVID may be useful for MOS assignment. Although the smaller sample size in Infantry certainly influenced the significance of the AVID dimensions, examining the basic interests that predicted each outcome in Infantry confirmed that some of the scales predicted differently in Infantry than in the full sample. For example, the AVID Construction scale was a significant negative predictor in the full sample but had significant and relatively strong positive effects in Infantry. The AVID Electronics dimension was also a significant positive predictor for several outcomes in Infantry while the Information Technology dimension was a significant negative predictor for some outcomes in this MOS. Neither of these interest dimensions were significant in the full sample. These results provide additional evidence of the utility of the AVID for differentiating between MOS.

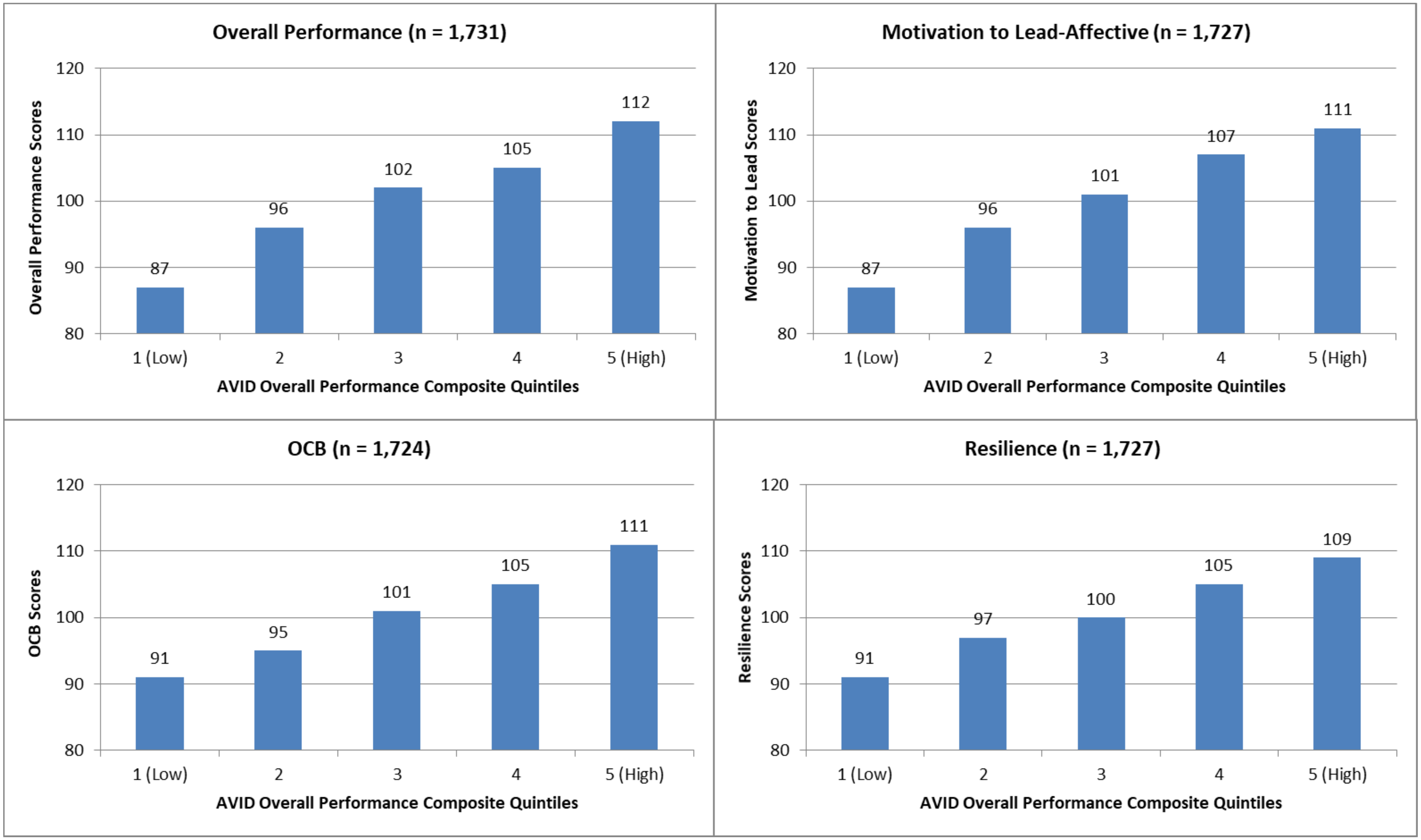

Figure 4.2. **AVID Composite Quintile Plots for Overall Performance, Motivation to Lead, OCB, and Resilience in Sample 2**

Table 4.12. ***Standardized Regression Weights for the AVID Dimensions Predicting Each Criterion in Infantry (Sample 2)***

Variables	MOS Fit	Army Fit	Affective Commit.	MOS Sat.	OCB	Resilience	Reenlist. Intentions	Career Intention	MTL (Affective)	MTL (Noncal.)	MTL (Soc-Norm)	APFT	Disciplinary Incidents[a]	CWB	Overall Performance
Combat															
Construction	.17	.18		.19	.21	.14			.16		.15				.17
Electronics					.19		.25	.18							
Food Service					-.11										
Human Relations		.16	.20												.12
Information Tech.		-.17	-.16		-.17		-.19	-.15			-.17				-.16
Management					.21				.37	.30	.18	.14		-.15	.18
Mathematics					.12				.17		.14				
Mechanical				-.15								-.13			
Medical Services												.13			
Office Work							.16			-.12					
Outdoors															
Physical Activity	.24	.27	.17	.15	.16	.40	.14	.16				.23	-.54	-.14	.26
Protection	.16										.16	-.15			
Teaching					.25										
Writing															
Multiple R	.52	.43	.36	.42	.56	.48	.30	.29	.56	.47	.47	.39	.37	.28	.53
Adjusted Multiple R	.46	.35	.24	.33	.51	.40	.12	.10	.51	.39	.40	.28	--	.17	.47

Note: Values in this table represent significant regression weights, $p < .10$. Sample sizes ranged from 214 to 215. [a] Because this variable was dichotomized to account for low base rates, these analyses are based on a logistic regression. Therefore, an adjusted multiple R could not be calculated. In addition, the regression weights presented for this outcome are the unstandardized regression weights.

For comparison with Sample 1, we also estimated regression models that included both individual interest scores and MOS ratings to calculate fit between Soldiers and their MOS.[2] Table 4.13 shows the results of these analyses both in the full sample and in Infantry. As shown in this table, adding the MOS ratings improved the prediction of overall performance. The multiple R was .52 in the full sample and .64 in Infantry. In other words, the overall prediction was still stronger in a specific MOS than in the overall sample, again suggesting that there may be differences in the AVID dimensions that predict performance in each MOS. In addition, the AVID scales that predicted overall performance in both analyses showed differences in both the weights and their significance when comparing across these models. Overall, these results are consistent with Sample 1 and suggest that the AVID has both validity and (potentially) differential validity across MOS.

[2] We also examined expanded polynomial regression models that included interactions between individual scores and the corresponding MOS ratings, quadratic terms for individual interest scores, and quadratic terms for the MOS ratings. As in Sample 1, the results indicated that adding these terms did not substantially increase the overall validity. Therefore, we only present results for the analyses with first-order terms for both individual scores and MOS ratings for comparison with the results in Sample 1.

Table 4.13. ***Validities of the AVID Interest Fit Composites in Sample 2***

Variables	Infantry	Full Sample
Combat		.10
Construction	.14	-.05
Electronics		
Food Service		-.04
Human Relations		.10
Information Tech.	-.14	
Management	.16	.22
Mathematics	.13	
Mechanical	-.14	
Medical Services		
Office Work		-.05
Outdoors		
Physical Activity	.23	.20
Protection		.09
Teaching		
Writing		-.05
Combat (MOS)		-.13
Construction (MOS)		
Electronics (MOS)		.05
Food Service (MOS)		
Human Relations (MOS)		
Information Tech. (MOS)		
Management (MOS)	.08	.09
Mathematics (MOS)		
Mechanical (MOS)		
Medical Services (MOS)		
Office Work (MOS)	-.12	-.07
Outdoors (MOS)		
Physical Activity (MOS)		
Protection (MOS)		
Teaching (MOS)		.10
Writing (MOS)	.19	.11
Multiple R	.64	.52
Adjusted Multiple R	.55	.51

Note: Sample size in Infantry n = 215; Full sample n = 1,731.

CHAPTER 5: SUMMARY AND CONCLUSIONS

Past research has demonstrated that vocational interests can be useful predictors of performance outcomes both at work and in school (Nye et al., 2012, 2017; Van Iddekinge et al., 2011). To help capture the benefits of vocational interests in a military context, this report describes the development of a new interest assessment known as the AVID. This assessment was developed to measure basic interest dimensions that are relevant to military occupations, to be flexible enough to differentiate between occupations, and to predict the attitudes and performance of Soldiers. In addition, the AVID was specifically designed to be administered in an applicant setting using a forced choice format and computer adaptive technology. Given the potential advantages of this measure, we expect that it would be useful for assisting with MOS assignment decisions.

The initial validation of the AVID indicated that this assessment does have utility in military settings. The AVID scales were shown to predict a broad range of criteria in two large samples of Active-Duty Soldiers. Importantly, the results also suggested that the AVID dimensions had differential validity across MOS. In other words, the AVID dimensions that predicted performance differed slightly in each MOS, indicating that these scales may be useful for informing MOS assignment decisions. In addition, the results also indicated that calculating the fit between individuals and their MOS by including scores for both in a regression model could improve the prediction of overall performance. This finding is consistent with recommendations and past research in the person-organization fit literature (Edwards, 1993; Nye et al., 2018). Again, these results also suggest that helping Soldiers to identify the MOS that are the best fit for their interests can help them to be more satisfied with and successful in their jobs.

The magnitudes of the relationships identified in the current research for the AVID dimensions are consistent with the findings for other non-cognitive assessments such as personality. For example, research on the TAPAS has found multiple R's ranging from .19 to .55 under different conditions and in different MOS (e.g., Horgen et al., 2013; Nye, Beal, Drasgow, Dressel, White, & Stark, 2014; Nye et al., 2012). Similarly, the multiple R's presented here for the AVID ranged from .14 to .47 in Sample 1 and from .17 to .51 in Sample 2, with some variation across MOS. As described above, the validity of the AVID scales was even stronger when considering the fit between individuals and their MOS. Although we were not able to examine the incremental validity of the AVID in the present research, given the differences between vocational interests and other predictors used by the Army such as cognitive ability and personality, these results suggest that vocational interests may be able to add to existing predictors of performance and that combining the full range of predictors may help to improve the accuracy of the assignment process. Still, more research is needed to examine the effects of combining these assessments on the prediction of outcomes and on the assignment process.

The results of this work provide a preliminary look at the validity of the AVID and its potential utility for MOS assignment. Despite these promising results, more research is needed to evaluate the use of the AVID. For example, the results presented in this report focused primarily on five high-density MOS across two samples. Therefore, more research is needed to examine the validity of the AVID in a broader range of MOS. Similarly, additional research is needed to identify the interest profiles for other MOS. In the current work, the interest profiles for each MOS were obtained by asking Soldiers to rate their MOS on each of the AVID dimensions at the same time that they provided their interest scores. This approach allowed us to calculate interest fit in a reduced set of MOS but is not feasible for applicants who may not have an accurate perception of the activities performed in a particular MOS. As a result, in order for the AVID to be most useful for MOS assignment, interest profiles for a broader range of MOS will be needed so that each applicant's interests can be evaluated with respect to his or her fit with several MOS. Therefore, collecting these ratings would be a useful direction for future research.

Another useful direction for future research would be to examine the validity of the AVID under operational conditions. A key concern with other non-cognitive measures is faking in high-stakes settings. Although there has been little research on faking on vocational interest measures, the research that does exist suggests that individuals can inflate their scores when they are motivated to do so (Abrahams et al., 1971; Garry, 1953, Hough et al., 2001). To address this issue and other response biases associated with self-report measures, the AVID is administered in a forced choice format that has been shown to be resistant to faking (Drasgow et al., 2012). Therefore, it would be useful to demonstrate the validity of this assessment when individuals are motivated to distort their responses and inflate (or deflate) their scores. However, it is important to note that the motivation to fake on an interest assessment may not be as strong as on personality measures. If interest measures are used to help individuals to find jobs in which they can be successful and satisfied, there does not seem to be a strong incentive to fake on these measures. Nevertheless, it is possible that individuals could fake good to get into a particular MOS that is not a strong fit for their interests because of social or normative pressures or misperceptions about the type of work performed in that MOS. Therefore, examining the AVID scores under operational conditions is important to demonstrate that this measure will maintain its utility for MOS assignment even in high-stakes contexts.

Finally, future research on the validity of the AVID should also examine the prediction of more objective criteria. In the present research, the AVID predicted a broad range of criteria that included self-ratings of attitudes and behavior. Although these outcomes provide useful information about the utility of the AVID, it would also be useful to examine their validity for predicting more objective outcomes as well. Self-reports can sometimes be inflated due to socially desirable responding. Therefore, examining the prediction of objective criteria such as attrition or training success will provide an additional source of evidence for the validity of this measure.

Despite potential directions for future research, the results presented here suggest that the AVID is a promising predictor of Soldiers' attitudes and behaviors related to their MOS. Importantly, the AVID also predicted an overall performance variable, indicating that this assessment may be useful for identifying high potential individuals who can be successful in a particular MOS and for differentiating individuals who may be successful in one (or multiple) MOS but not others. Therefore, these results provide preliminary evidence of the utility of the AVID for MOS assignment.

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