CRESST REPORT 755

Sam O. Nagashima
Gregory K. W. K. Chung
Paul D. Espinosa
Chris Berka
Eva L. Baker

ASSESSMENT OF RIFLE MARKSMANSHIP SKILL USING SENSOR-BASED MEASURES

MARCH, 2009

National Center for Research on Evaluation, Standards, and Student Testing

Graduate School of Education & Information Studies
UCLA | University of California, Los Angeles

Assessment of Rifle Marksmanship Skill
Using Sensor-Based Measures

CRESST Report 755

Sam O. Nagashima, Gregory K. W. K. Chung, and Paul D. Espinosa
CRESST/University of California, Los Angeles

Chris Berka
Advanced Brain Monitoring, Inc.

Eva L. Baker
CRESST/University of California, Los Angeles

March, 2009

National Center for Research on Evaluation,
Standards, and Student Testing (CRESST)
Center for the Study of Evaluation (CSE)
Graduate School of Education & Information Studies
University of California, Los Angeles
300 Charles E. Young Drive North
GSE&IS Building, Box 951522
Los Angeles, CA 90095-1522
(310) 206-1532

Copyright © 2009 The Regents of the University of California

The work reported herein was supported by a grant from the Advanced Brain Monitoring, Inc., PR/Award Number 20064169.

The findings, conclusions, recommendations, and opinions expressed in this report are those of the authors and do not necessarily reflect the positions or policies of the Advanced Brain Monitoring, Inc.

ASSESSMENT OF RIFLE MARKSMANSHIP SKILL USING SENSOR-BASED MEASURES[1]

Sam O. Nagashima, Gregory K. W. K. Chung, & Paul D. Espinosa
CRESST/University of California, Los Angeles

Chris Berka,
Advanced Brain Monitoring, Inc.

Eva L. Baker
CRESST/University of California, Los Angeles

Abstract

The goal of this report was to test the use of sensor-based skill measures in evaluating performance differences in rifle marksmanship. Ten shots were collected from 30 novices and 9 experts. Three measures for breath control and one for trigger control were used to predict skill classification. The data were fitted with a logistic regression model using holdout validation to assess the quality of model classifications. Individually, all four measures were significant; when considered together, only three measures were significant predictors for level of expertise ($p < .05$). Overall percent correct in shot classification for the testing data was 90.0%, with a sensitivity of 67.5%, and 96.0% specificity.

Introduction

Rifle marksmanship is an inherently complex task. Shooters must position various body parts to achieve maximum rifle support and at the same time establish and maintain proper sight alignment and correct sight picture, all prior to initiating the coordinated steps necessary in the execution of a shot (Chung, Delacruz, de Vries, Bewley, & Baker, 2006).

Skilled shooters have been found to be able to hold a rifle steadier than unskilled shooters (McGuigan & MacCaslin, 1955). Similarly, research on pistol shooting found that, while both novices and experts shared a single dominant pattern of movement, experts tended to hold their bodies in similar positions, favoring those that minimized the effects of movement on the target (Penn State, 2001). It is clear that skilled shooters minimize body movements by proper positioning.

In studies dealing with marksmanship, such as correlation studies between simulators and live fire (Hagman, 1998; Schendel, Heller, Finley, & Hawley, 1985; Smith & Hagman,

[1]We would like to thank the staff at Camp Pendleton WTBN. We would also like to thank the following people from UCLA/CRESST: Joanne Michiuye for her help with the preparation of this manuscript and with data collection, and Daniel Parks for hardware design and development.

2000), and studies on the impact of nutrition on performance (Tharion & Moore, 1993) and the role of anxiety for novices (Chung, O'Neil, Delacruz, & Bewley, 2005), assessment of marksmanship performance has relied on shot placement (e.g., score, accuracy, tightness of shots) to make judgments about a shooter's skill level. Although appropriate as a broad measure of relative ability, evaluation solely on the basis of shot placement carries with it the potential to conceal underlying differences in shooter skill. In the context of training, the use of such an outcome measure as a metric can be detrimental, making identification and subsequent remediation of problematic aspects of performance difficult, if not impossible (AERA, APA, NCME, 1999; Wiggins, 1998).

Good metrics must be objective, intuitive, at the level of detail appropriate for decision-making, acceptable, precise, generalizable, sensitive, reliable, and most important, valid (ANSI, 1993). An important consideration in establishing a metric is that an individual's performance needs to be referenced to a criterion, for example an expert. Expert performance is considered the referent or gold standard against which to compare trainee performance (Chi, Glaser, & Farr, 1988).

A potential reason for the absence of a valid objective measure in evaluating marksmanship skill performance is the subtle nature of the actions involved. While position quality, coarse movement of the muzzle, and the trigger break are easily observed by the evaluator, the steps leading up to the trigger break (e.g., aiming, trigger squeeze, control of respiration) are less perceptible, making direct visual observation and proper diagnosis difficult.

One approach to objectively capture and measure subtle human movements is with the use of sensors. Sensors have the potential to serve as a reliable and unobtrusive surrogate in situations where human observations are impractical (De Ketelaere, Bamelis, Kemps, Decuypere & De Baerdemaeker, 2004; Wide, Winquist, Bergsten, & Petriu, 1998). As a methodology for evaluating human performance, sensors have already been shown to be effective in the medical field differentiating levels of experience of arthroscopic surgeons (Chami, Ward, Phillips, & Sherman, 2008) and laparoscopic surgeons (Rosen, Solazzo, Hannaford, & Sinanan, 2001).

The goal of this study was to test whether sensor-based measures designed to assess key aspects of marksmanship skill are sensitive enough to differentiate between levels of marksmanship skill performance. Sensors were developed, concentrating on two areas of marksmanship believed to impact performance: breath control and trigger control. Each shot was then evaluated, using expert criteria, to judge the quality of skill performance.

Methods

Participants

Shots were collected from 39 participants, 30 novices and 9 experts. Novices ranged in age from 19 to 29 years (*M* = 22.20, *SD* = 2.57). Of the 30 novices, 23 (77%) were male, and 7 (23%) were female. Twelve (40%) reported having prior experience shooting a rifle. Of those reporting prior experience, 3 (25%) reported having shot a rifle within the last year, 3 (25%) within 3 to 5 years, and 6 (50%) reported firing a rifle over 5 years ago. None of the novices reported experience with competitive shooting and 2 (7%) reported having coached rifle shooting.

All nine experts selected for study were active-duty members of the armed forces with a primary military occupation specialty (MOS) as marksmanship coaches. All were male and ranged in age from 21 to 25 years (*M* = 23.33, *SD* = 1.41). Coaching experience ranged from 1 to 24 months (*M* = 12.44, *SD* = 7.52). In addition to being rifle marksmanship coaches, five (56%) were also qualified as rifle marksmanship instructors.

While several subjects in the novice sample had some familiarity with marksmanship, none had training consistent with marksmanship instruction as delivered in the armed forces. Accordingly, all subjects were regarded as novices.

Design

Holdout validation was used to assess the quality of shot classifications based on estimated model parameters (Kerlinger & Pedhazur, 1973). Participants were randomly assigned to two groups, model training and model testing. Cases in model training were used to estimate model parameters, while observations in model testing are held back from the estimation procedure and later fitted to the data. Sample distribution of subjects across data files is presented in Table 1.

Table 1

Distribution of Subjects in Model Training and Model Testing Data

	Data		
Status	Training	Testing	Total
Novice	15	15	30
Expert	5	4	9
Summary	20	19	39

Note. Ten shots were collected from each subject.

Apparatus

Data were collected in an indoor controlled environment. An instrumented weapon was developed using off-the-shelf sensing components and a demilitarized M16/A2 housing a pneumatic recoil system designed to approximate the weight, noise, and action of a real weapon firing real rounds (LaserShot, 2008). Four performance skill measures were collected using two sensors, a force-pressure sensor attached to the trigger to measure the amount of pressure exerted on the trigger during firing, and a respiration belt used to measure participants' respiration. Both sensors were wired to a microprocessor and data were wirelessly downloaded onto a remote laptop. Shots were directed against a projection of a circular target equivalent to 20 inches wide at 200 yards. A camera identified shot placement on target by recognizing infrared laser strikes delivered by the rifle. For more detailed information on the development of the sensor-based measures and targeting system, see Espinosa, Nagashima, Chung, Parks, and Baker (2009, CRESST Tech. Rep. No. 756).

Procedure

All novices were provided basic instruction on shooting position, weapons handling, and proper sight alignment. Initial instructions were delivered to all novices by the same researcher. Although participants were instructed to shoot in the kneeling position, they were given the option of choosing between low, medium, or high kneeling. Variations in the kneeling position were modeled by the instructor; in addition, illustrations depicting left- and right-handed variations on the kneeling position were provided. Ten shots were collected and analyzed from each subject across two trials. No time constraints were imposed on the shooters and they were not provided feedback regarding shot placement until the end of each trial.

Measures

Four performance skill measures were evaluated for each shot, three related to breath control (*breath location*, *breath duration*, and *shot-percent breath*) and one for trigger control (*trigger duration*).

Breath location represents the location in the respiratory cycle at trigger break. Values can range from 0 to 100, with 0 indicating that the shot was taken while fully exhaled, and 100 indicating that the shooter was fully inhaled. Doctrine dictates shots be taken during a natural respiratory pause, therefore a value near zero is desirable.

Breath duration is a measure of the time, in seconds, between full inhales flanking the shot. Larger values indicate longer periods of time between breaths (slower rate of respiration); conversely, smaller values indicate a shorter period of time between breaths (faster rate of respiration).

Shot-percent breath is used to approximate the location, in percent, of where the trigger break occurred relative to the full inhales spanning the trigger break. For example, .50 indicates that a shot was fired equidistant from two full inhales.

Trigger duration was the only measure of trigger control and represents the amount of time, in seconds, pressure is exerted on the trigger prior to a shot being fired. Larger values indicate a greater amount of time taken to pull the trigger.

Analysis

A logistic regression model was developed to test the extent to which shots can be classified as originating from a novice or expert using the skill measures as predictors. An extension of simple logistic regression is used to account for multiple predictors as follows:

$$\text{logit}(Y) = \ln(\pi/(1-\pi)) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p$$

$$\pi = \text{Probability } (Y = \text{outcome of interest} \mid X_1 = x_1, X_2 = x_2, \ldots, X_p = x_p)$$

$$= [(e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta p X p}) / (1 + e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta p X p})]$$

where π is the probability of the classification, α is the Y intercept, βs are regression coefficients, and Xs are the set of predictor variables. The value of the coefficient β determines the direction of the relationship between X and the logit of Y. When β is greater than zero, larger X values are associated with larger logits of Y. Conversely, if β is less than zero, larger X values are associated with smaller logits of Y. αs and βs are estimated using the maximum likelihood (ML) procedure designed to maximize the likelihood of reproducing the data given the parameter estimates.

The outcome variable (Y) is expertise status (*status*) and was used to designate cases as either expert or novice (1 = expert, 0 = novice). The logistic procedure predicts the "1" category of the dependent variable, making the "0" category the reference category. The skill measures were used as four continuous predictor variables—*breath location, breath duration, trigger duration,* and *shot-breath location*. The logistic regression analysis was carried out using the binary logistic regression command in Statistical Package for the Social Sciences (SPSS,® 1999) version 16 in Windows 2000 environment.

The statistical significance of individual regression coefficients (i.e., βs) was tested using the Wald chi-square statistic, and the Hosmer-Lemeshow (H–L) test was used to assess the goodness-of-fit for the final logistic model.

Several indices describing the predictive performance were calculated to assess predicted model classifications—sensitivity (true positive fraction), specificity (true negative fraction), false positive, false negative, and the c statistic.

Sensitivity is the proportion of correctly classified experts and specificity represents the proportion of correctly classified novices. False positive is the proportion of cases misclassified as experts, while false negative is the proportion of cases misclassified as novices.

The c statistic is a measure of discrimination, ranging from 0.5 to 1. A value of 0.5 indicates that the model is no better than assigning observations randomly into outcome categories; A value of 1 indicates that the model assigns higher probabilities to all observations with the event outcome, compared with nonevent observations.

Results

Descriptive Statistics

Mean and standard deviations for the skill variables are provided in Table 2. For all shots, *breath location* ranges from 0.00 to 91.80 (M = 35.34, SD = 23.86), *breath duration* ranges from 0.31 to 13.16 seconds (M = 3.45, SD = 2.35), *shot-percent breath* ranges from 0.01 to 1.00 (M = .54, SD = .25), and *trigger duration* ranges from 0.00 to 95.27 seconds (M = 4.32, SD = 8.06).

Mean *breath location* was 42.1 (SD = 22.9) for novices, and 13.0 (SD = 8.7) for experts. When a shot was fired, novices, on average, were partially inhaled, while experts were nearly fully exhaled at trigger break. The mean *breath duration* for novices was only 2.5 seconds (SD = 1.1), and 6.5 seconds (SD = 2.8) for experts. These values indicate that the average respiratory cycle for novices around the trigger break lasts 2.5 seconds, whereas for experts, the respiratory cycle lasts 6.6 seconds. The mean *shot-percent breath* for novice was .52 (SD = .27) and .64 (SD = .17) for experts. The novice group mean of .52, or 52%, indicates that the average shot was fired midway between two full inhales, while the expert group has a mean of .64, or 64%, which indicates that experts take shots closer toward the end of a respiratory cycle. For the measure of trigger control, the mean *trigger duration* for novices was 5.2 sec (SD = 8.9), and 1.4 sec (SD = 2.3) for the expert group. Novices appear to take longer pulling the trigger, 5.2 seconds, compared to experts, 1.4 seconds.

Table 2

Mean and Standard Deviation for Skill Measures

Variables	Status: Novice *M (SD)*	Status: Expert *M (SD)*	All subjects *M (SD)*
Breath control			
Breath location	42.05 (22.85)	12.97 (8.71)	35.34 (23.86)
Breath duration	2.54 (1.10)	6.46 (2.85)	3.45 (2.35)
Shot-percent breath	0.52 (0.27)	0.64 (0.17)	0.54 (0.25)
Trigger control			
Trigger duration	5.20 (8.93)	1.42 (2.29)	4.32 (8.06)

Note. $n = 300$ for novice group and $n = 90$ for expert cases.

Pearson correlations among the skill variables are reported in Table 3. The correlation of *breath location* and *breath duration* was significant, r (388) = -.488, $p < .001$, as was *breath location* and *shot-percent breath* at r (388) = -.216, $p < .001$, and *breath duration* and *shot-percent breath*, r (388) = .280, $p < .001$. Trigger duration did not correlate significantly with the other variables.

Table 3

Correlations for Measures of Skill Performance

Variables	1	2	3	4
1. Breath location	--			
2. Breath duration	$-.488^{**}$	--		
3. Shot-percent breath	$-.216^{**}$	$.280^{**}$	--	
4. Trigger duration	.096	-0.049	0.005	--

Note. $N = 390$.
$^{**}p < 0.01$ (two-tailed).

Given the significant correlation values between the variables for breath control, tolerance values were calculated to assess the threat of collinearity. Tolerance values range from .730 for *breath duration* to .990 for *trigger duration* (Table 4). Based on the critical value tolerance < .2, the potential threat of collinearity is negligible (Menard, 1995).

Table 4

Collinearity Statistics for Independent Variables

Variable	Tolerance
Breath control	
Breath location	.750
Breath duration	.730
Shot-percent breath	.913
Trigger control	
Trigger duration	.990

Note. Tolerance is equivalent to 1/variance inflation factor.

Logistic Regression Model

We first estimated individual univariate logistic regression models for the variables in the training data to test the research hypothesis regarding the relationship between the likelihood of classification as expert based on the individual measures of skill performance. Again, the outcome variable, *status*, was used to designate the shot classification as expert marksman (1 = yes, 0 = no). The four continuous predictor variables include the three variables for breath control *(breath location*, *breath duration*, *shot-percent breath*) and one measure for trigger control (*trigger duration*). Table 5 presents the results from the analysis for the univariate relationship between the skill measures and predicted marksmanship status.

Table 5

Summary of Univariate Logistic Regression Results for Marksmanship Skill Variables Using Training Data (n = 190)

Variables	*B*	*SE*	Wald statistic	OR	95% CI
Breath control					
Breath location	-0.137	0.022	37.559	0.872**	.834 - .911
Breath duration	2.039	0.335	37.060	7.686**	3.986 - 14.820
Shot-percent breath	2.892	0.758	14.572	18.029**	4.084 - 79.584
Trigger control					
Trigger duration	-0.237	0.075	9.902	0.789*	.681 - .915

Note. OR = odds ratio, CI = confidence interval.
$^{*}p < .01$. $^{**}p < .001$.

Considered individually, all four variables are significant ($p < .01$) predictors relative to the null model. Next, we estimated a multiple logistic regression model to investigate the simultaneous effects of all four skill measures on status. Given the significance of the four predictor variables in the univariate model, a four-predictor multiple logistic model was fitted to the data. Table 6 presents the results of multiple regression analysis.

Table 6

Summary of Multiple Logistic Regression Results for Marksman Skill Variables Using Training Data (n = 200)

Variables	*B*	*SE*	Wald statistic	OR	95% CI
Breath control					
Breath location	-0.148	0.052	7.946	0.862**	.778 - .956
Breath duration	2.111	0.491	18.502	8.256***	3.155 - 21.604
Shot-percent breath	2.241	3.752	0.357	9.398	.006 - 14691
Trigger control					
Trigger duration	-0.540	0.200	7.282	0.583**	.393 - .863
Constant	-6.381	2.604	6.003	0.002*	

Note. OR = odds ratio, CI = confidence interval.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .0001$.

When all four predictors are considered jointly, the overall model significantly differentiates between expert and novice skill performance relative to the null model, χ^2 =188.18, df = 4, $p < .001$. The variables *breath location*, *breath duration*, and *trigger duration* are significant ($p < .05$). The variable *shot-percent breath*, while a significant predictor when used alone, was not a significant predictor when used concurrently with all four variables. The test of the intercept (i.e., constant in Table 6) suggests the intercept should be included in the model.

The log odds of expert classification is as follows:

log (π/1-π) = -6.381 - 0.148*(breath location) + 2.111*(breath duration) + 2.241*(shot-percent breath) - 0.540*(trigger duration)

When interpreting the logistic regression results, an odds ratio greater than 1.0 implies a positive association between the skill measure and status, while an odds ratio less than 1.0 implies a negative association. Odds ratios close to 1.0 indicate that unit changes in that skill variable do not affect the odds of predicted status. The variable *breath location* with an odds ratio of .862 indicates that as *breath location* increases, the odds of expert skill diminish. Specifically, the odds of expert classification diminished by a factor of .137, for one unit increase in location, controlling for other variables in the model. Additionally, for *breath duration*, a one-second increase in *breath duration* results in an 8.26 times greater chance of expert classification. Lastly, the odds ratio of .583 for *trigger duration* signifies that for every one-second increase in *trigger duration*, the odds of expert classification decreases by a factor of .417. The variable *shot-percent breath* was not a significant predictor.

Overall Model Evaluation

The Hosmer–Lemeshow test of inferential goodness-of-fit yielded a $\chi^2(8)$ of .196 and is non-significant ($p > .05$), suggesting that the model exhibits a considerable degree of fit to the data. In other words, the null hypothesis of a good model fit to data was tenable. The logistic model resulted in a c statistic of .973, indicating that for 97.3% of all possible pairs of shots—one expert and the other novice—the model correctly assigned a higher probability to those who were expert.

For the model training data, 147 of 150 novice shots and 46 of 50 expert shots were accurately classified. Accordingly, the sensitivity, the ability to identify expert shots, was 92%, and the specificity, the power to identify novice shots, was 98% for the training data. For the model testing data, 144 of 150 novice shots and 13 of 40 expert shots were accurately classified, resulting in a sensitivity of 96% and specificity of 67.5%. A 2 × 2 classification table showing observed versus predicted classifications, based on a cutoff value of .50, or 50%, can be found in Table 7 for the training data, and Table 8 for the testing data.

Table 7

Summary of Predicted Classification for Model Training Data

	Predicted		
Observed	Novice	Expert	% Correct
Novice	147	3	98.0
Expert	4	46	92.0
Overall % correct			96.5

Note. Cut value set at .50.

Table 8

Summary of Predicted Classification for Model Testing Data

	Predicted		
Observed	Novice	Expert	% Correct
Novice	144	6	96.0
Expert	13	27	67.5
Overall % correct			90.0

Note. Cut value set at .50.

Table 9

Classification Performance for Testing Data

Measure	Computation	Value	Definition
Sensitivity	27 / (27+13)	0.675	The proportion of correctly classified events (expert).
Specificity	144 / (6+144)	0.960	The proportion of correctly classified nonevents (novice).
False positive	6 / (6+27)	0.182	The proportion of observations misclassified as expert over all of those classified as experts.
False negative	13 / (13+144)	0.083	The proportion of observations misclassified as novices over all of those classified as novice.

As shown in Table 9, the predictions for experts were less accurate than novice classification. This observation is supported by the magnitude of sensitivity (67.5%) compared to that of specificity (96.0%). Both false positive and false negative rates were modest at 18.2% and 8.3% respectively. Given the distribution of expert and novice across the two data files, the default accuracy in classification by identifying all cases as novice (the most prominent classification) in the training data was 75% and 78.9% in the testing data. Compared with the overall percent correct classification in the training data (96.5%) and the testing data (90.0%), there was a 21.5% and 11.5% improvement, respectively.

Discussion

In this study, our objective was to test whether sensor-based skill measures provided discriminatory power in differentiating novice and expert skill performance. A key finding in our analysis is that sensor-based skill measures, considered jointly, provide a reliable method of discriminating differences in expert-novice marksmanship performance. Specifically, breath location, breath duration, and trigger duration prove to be significant predictors in expert-novice shot classification.

In evaluating the predicted probabilities, the training data exhibited an accuracy rate of 96.5% and the testing data only 90.0%. One possible explanation for this discrepancy is the variability in skill performance across experts. Whereas the 6 false positive cases in the testing data are distributed nearly evenly across five novice shooters, all 13 false negative cases are distributed across only two experts; one expert shooter accounted for 9 of the false negative classifications, with the remaining 4 attributed to another. Given that in the testing data, all 4 false negative cases came from a single expert shooter, there is reason to believe that, even across experts, there is a considerable amount of variability in skill performance. Since the criteria for expert selection were based in part on active-duty marksmanship coaches, further refinement of the expert group into subgroups may lead to improved predictions and shed light on additional levels of skill performance.

Although we are confident in the results of sensor-based measures in differentiating skill performance, we remain cautious in extending the generalizability of these results to live-fire environments. Additional studies are needed to assess the reliability of sensor-based assessment of skill performance in live-fire environments in supporting skill diagnosis.

References

American Educational Research Association, American Psychological Association, & National Council on Measurement in Education (AERA, APA, NCME). (1999). *Standards for educational and psychological testing.* Washington, DC: American Educational Research Association.

American National Standards Institute (ANSI). (1993). *Guide to human performance* measurement (G-035-1992). Washington, DC: Author.

Chami, G., Ward, J. W., Phillips, R., & Sherman, K. P. (2008). Haptic feedback can provide an objective assessment of arthroscopic skills [Electronic version]. *Clinical Orthopaedics and Related Research, 466,* 963–968.

Chi, M., Glaser, R., & Farr, M. J. (Eds.). (1988). *The nature of expertise.* Hillsdale, NJ: Lawrence Erlbaum Associates.

Chung, G. K. W. K., Delacruz, G. C., de Vries, L. F., Bewley, W. L., & Baker, E. L. (2006). New directions in rifle marksmanship research. *Military Psychology, 18,* 161–179.

Chung, G. K. W. K., O'Neil, H. F., Jr., Delacruz, G. C., & Bewley, W. L. (2005). The role of anxiety on novices' rifle marksmanship performance. *Educational Assessment, 10*(3), 257–275.

De Ketelaere, B., Bamelis, F., Kemps, B., Decuypere, E., & De Baerdemaeker, J. (2004). Non-destructive measurements of the egg quality. *World's Poultry Science Journal, 60,* 289–302.

Espinosa, P. D., Nagashima, S. O., Chung, G. K. W. K., Parks, D., & Baker, E. (2009). *Development of sensor-based measures of rifle marksmanship skill and performance* (CRESST Tech. Rep. No. 756). Los Angeles: University of California, National Center for Research on Evaluation, Standards, and Student Testing (CRESST).

Hagman, J. D. (1998). Using the Engagement Skills Trainer to predict rifle marksmanship performance. *Military Psychology, 10,* 215–224.

Kerlinger, F. N., & Pedhazur, E. J. (1973). *Multiple regression in behavioral research.* New York: Holt, Rinehart & Winston.

LaserShot. (2008). Military Skills Engagement Trainer [Military training simulator system]. Stafford, TX: Author.

Menard, S. (1995). *Applied logistic regression analysis.* Thousand Oaks, CA: Sage Publications.

McGuigan, F. J., & MacCaslin, E. F. (1955). The relationship between rifle steadiness and rifle marksmanship and the effect of rifle training on rifle steadiness. *Journal of Applied Psychology, 39,* 156–159.

Penn State. (2001, July 2). Technique to analyze steadiness of marksmen's aim may help patients with tremors. *ScienceDaily.* Retrieved October 7, 2008, from http://www.sciencedaily.com/releases/2001/07/010702090143.htm

Rosen J., Solazzo, M., Hannaford, B., & Sinanan, M. (2001). Objective laparoscopic skills assessments of surgical residents using hidden Markov models based on haptic information and tool/tissue interactions. *Studies in Health Technology and Informatics, 81,* 417–23.

Schendel, J. D., Heller, F. H., Finley, D. L., & Hawley, J. K. (1985). Use of Weaponeer marksmanship trainer in predicting M16A1 rifle qualification performance. *Human Factors, 27,* 313–325.

Smith, M. D., & Hagman, J. D. (2000). *Predicting rifle and pistol marksmanship performance with the Laser Marksmanship Training System* (Tech. Rep. No.1106). Alexandria, VA: U.S. Army Research Institute for the Behavioral and Social Sciences.

Statistics Package for the Social Sciences (SPSS®). (1999). Version 16. Base Application Guide [Computer Software]. Chicago: Author

Tharion, W. J., & Moore, R. J. (1993). *Effects of carbohydrate intake and load bearing exercise on rifle marksmanship performance* (T5-93). Natick, MA: U.S. Army Research Institute of Environmental Medicine.

Wide, P., Winquist, F., Bergsten, P., & Petriu, E. (1998). The human-based multisensor fusion method for artificial nose and tongue sensor data. *IEEE Transactions on Instrumentation and Measurement, 47,* 1072–1077.

Wiggins, G. (1998). *Educative assessment: Designing assessments to inform and improve student performance.* San Francisco: Jossey-Bass.