



Practical Polygraph: ESS-M Made Simple

Raymond Nelson¹ and Jennifer Rider²

ESS-M offers improvements and advantages in both its scientific foundations and field practice. Use of the ESS-M is identical to the ESS, but with different cut-scores. Classification accuracy of the ESS-M has been found to equal or exceed that of the ESS. ESS-M cut-scores have been calculated for examinations with

three to five repetitions of two to four relevant questions. Table 1 shows simplified ESS-M cut-scores when – selected as the median of cut-scores for event-specific diagnostic and multiple-issue screening polygraphs with two to four relevant questions (RQs) with $\alpha = .05$ for deception and truth, using an equal prior probability.

Table 1. ESS-M cut-scores for 3 to 5 presentations simplified^{*} for 2, 3, or 4 RQs[†]

	Grand Total Cut-scores		Sub-total Cut-scores	
	Truthful	Deceptive	Truthful	Deceptive
Event-specific diagnostic exams	+3	-3	-	(-7) [‡]
Multiple-issue screening exams	-	-	(+1) [†]	-3

^{*} Determined as the median of the set of cut-scores for 2, 3 and 4 RQs.

[†] Cut-scores are the same with and without the vasomotor sensor.

[‡] Cut-scores in parenthesis are calculated with statistical correction for multiplicity

1 Raymond Nelson is a research specialist with Lafayette Instrument Company. Mr. Nelson is a psychotherapist with and field polygraph examiner who has published numerous articles on many aspects of the polygraph test. Mr. Nelson is a past APA President, and is currently serving as an elected member of the APA Board of Directors. Mr. Nelson is one of the developers of the widely used OSS-3 and ESS scoring algorithms. Development of the ESS-M was made possible by Lafayette Instrument Company. The views and opinions expressed herein are those of the authors and not the APA or LIC.

2 Jennifer Rider is the President and CEO of Lafayette Instrument Company, which develops and markets polygraph instrumentation and other technologies for life-science research, and which supported the development of the ESS-M.



ESS-M Includes the Vasomotor (PPG/PLE) Sensor

The original ESS and other most algorithms did not include the vasomotor sensor. ESS-M can be used with or without the vasomotor sensor. ESS-M is a practical and mathematically sound solution to the complex task of validating a statistical classifier with new or different input/

sensor data. ESS-M can be easily adapted for other new sensors in the future. It is an un-planned/un-intended convenience that the addition of the vasomotor sensor does not change the ESS-M cut-scores. A complete set of ESS-M cut-scores is shown below, illustrating the similarities and differences for exams with two, three, or four RQs both with and without the vasomotor sensor.

Table 2. ESS-M cut-scores for event-specific diagnostic polygraphs

	2 RQs	3 RQs	4 RQs
Respiration, EDA, Cardio	+3/-3 (-5)	+3/-3 (-7)	+3/-3 (-9)
Respiration, EDA, Cardio, Vasomotor	+3/-3 (-5)	+3/-3 (-7)	+3/-3 (-9)
cut-scores in parenthesis include statistical correction for multiplicity			

Table 3. ESS-M cut-scores for multiple-issue screening polygraphs (assumed independence)

	2 RQs	3 RQs	4 RQs
Respiration, EDA, Cardio	(+2) /-3	(+1)/-3	(+1)/-3
Respiration, EDA, Cardio, Vasomotor	(+1)/-3	(+1)/-3	(+1)/-3
cut-scores in parenthesis include statistical correction for multiplicity			

ESS-M Is a Mathematical Expression of the Analytic Theory of the Polygraph

An analytic theory of the polygraph holds that greater changes in physiology are loaded at different types of test stimuli as a function of deception or truth-telling in response to the relevant target stimuli. The mathematical/theoretical distribution of ESS-M scores is multinomial because each score can take one of three possible values (+, 0, -). The multinomial for ESS scores is the distribution of likelihoods for all possible combinations of scores for all repetitions of all RQs for all recording sen-

sors. Multinomial distributions are available for both ESS scores and for Federal 3-position scores. These can be obtained from (<https://www.polygraph.org/reference-tables>).

ESS-M Uses Bayesian Analysis

Bayesian analysis can be used to calculate the degree of certainty that can be assigned to some knowledge or information. Whereas frequentist probability theory is limited to inferences about observed data, Bayesian probability theory uses observed data, together with a prior probability and statistical likelihood function, to calculate a probability value that can be more di-

rectly and easily assigned to unobserved phenomena such as future events or past causes.

ESS-M Bayesian Probabilities Are in the Form of the “Odds of Deception” or “Odds of Truth.”

In contrast, the original ESS relied on frequentist p-values (i.e., probability under a specified model) that were used as an estimate of misclassification error. ESS-M results are designed to be a more direct and intuitive quantification of the effect size of practical interest to field examiners – the statistical likelihood that the observed test data was caused by an individual who has been deceptive or truthful. ESS-M odds can also be easily expressed as a Bayesian probability.

How to Use the ESS-M Reference Tables

ESS-M reference tables can be used for two purposes. The first use for the ESS-M reference tables can be used to determine the numerical cut-score that is required to achieve a desired level of statistical significance (commonly using $\alpha=.05$). When scoring an exam, the ESS-M reference tables are used to determine the likelihood statistic associated with truthful or deceptive classifications – expressed in form of a posterior odds of deception or odds of truth. Use of the ESS-M reference tables can be divided into four simple steps: 1) locate the ESS-M reference tables, 2) determine the alpha levels and cut-scores, 3) calculate the posterior odds of truth or deception, and 4) interpret the results.

1. Locate the ESS-M reference tables.

ESS-M reference tables are shown in Appendix A for grand total scores and Appendix B for sub-total scores. These tables are the median value from the set of reference tables for two, three and four RQs. Because the table values are intended only as a likelihood statistic for use with Bayesian analysis, it is reasonable to use these tables to simplify the selection and calculation of likelihood values for all exams with or without the vasomotor sensor and regardless of the number of RQs. Examiners who require greater precision in the calculation of likelihood statistics are referred to other publications in the reference list. The top portion of the reference tables for grand total and sub-total scores are shown in Figures 1, and 2. Columns intended for use with event-specific diagnostic exams are shaded in yellow, and those for use with multiple-issue screening exams are shaded in orange.



Figure 1. ESS-M reference table for grand total scores.

Appendix A: Simple ESS-M Cutscores for Grand Total Scores with 2, 3, or 4 Relevant Questions with or without the Vasomotor Sensor						
Prior = .5 (1 to 1), Alpha = .05 / .05 (truth / deception)						
score	ways	pmf	cdf	cdfContCor	odds	oddsLL05
-24	9915	.0008*	.0023	.0019	518.7	21.4
-23	10248	.0011	.0034	.0028	352.2	20.18
-22	10572	.0015	.0048	.0041	242.7	18.69
-21	10888	.0020	.0069	.0059	169.7	16.95
-20	11193	.0027	.0096	.0082	120.4	17.25
-19	11488	.0036	.0132	.0114	86.55	14.98
-18	11770	.0047	.0179	.0156	63.05	13.98

Figure 2. ESS-M reference table for sub-total scores.

Appendix B: Simple ESS-M Cutscores for Sub-total Scores with 2, 3 or 4 RQs with or without the Vasomotor Sensor								
Prior = .5 (1 to 1), Alpha = .05 / .05 (truth / deception) – all statistical corrections are included								
score	ways	pmf	cdf	Cdf ContCor	odds	Odds234RQs	oddsLL05	odds234LL05
-15	161	.0005*	.0009	.0007	1517	11.49	7.71	3.32
-14	200	.0011	.0020	.0015	682.2	8.8	7.56	2.84
-13	243	.0021	.0041	.0030	328.4	6.9	7.27	2.42
-12	287	.0037	.0077	.0059	168	5.52	6.79	2.07
-11	333	.0062	.0139	.0109	90.88	4.5	6.1	1.81
-10	378	.0099	.0236	.0190	51.67	3.73	5.22	1.56
-9	423	.0150	.0383	.0315	30.72	3.13	4.84	1.37

2. Determine the alpha boundaries and cut-scores.

Locate the smallest lower-limit posterior odds (shown in the right-hand column labelled oddsLL05) that exceed the value 1 – which represents the prior odds of truth or deception – then locate the cut-score in the corresponding row of the left-hand column labeled score. Alpha is commonly set at .05 and ESS-M cut-scores are determined using this level for both truth and deception. Examiners should be aware of any different alpha requirement for their agencies or referring agents. Alpha levels

may differ for high-value or high-interest cases. Tables are shown only for the equal prior and only for alpha=.05. Solutions for non-equal priors and other priors can be calculated with Bayes Theorem and the Clopper-Pearson method. The procedure to locate the cut-scores is illustrated in Figure 3 for grand total scores and in Figure 4 for sub-total scores.

Figure 3. Locate the cut-scores for grand total scores.

-7	13900	.0336	.2122	.2030	3.93	2.39
-6	14000	.0369	.2471	.2383	3.2	2
-5	14086	.0398	.2847	.2766	2.62	1.67
-4	14155	.0424	.3247	.3177	2.15	1.39
-3	14210	.0446	.3667	.3611	1.77	1.16
-2	14248	.0461	.4102	.4064	1.46	0.97
-1	14272	.0471	.4548	.4529	1.21	0.8
0	14279	.0475	.5000	.5000	1	0.67
1	14272	.0471	.5452	.5471	1.21	0.8
2	14248	.0461	.5898	.5936	1.46	0.97
3	14210	.0446	.6333	.6389	1.77	1.16
4	14155	.0424	.6753	.6823	2.15	1.39
5	14086	.0398	.7153	.7234	2.62	1.67
6	14000	.0369	.7529	.7617	3.2	2
7	13900	.0336	.7878	.7970	3.93	2.39
8	13783	.0303	.8197	.8290	4.65	2.95

Figure 4. Locate the cut-scores for sub-total scores.

-10	378	.0099	.0236	.0190	51.67	3.73	5.22	1.56
-9	423	.0150	.0383	.0315	30.72	3.13	4.84	1.37
-8	465	.0216	.0592	.0500	19.01	2.67	4.11	1.19
-7	505	.0297	.0875	.0758	12.19	2.3	3.3	1.05
-6	540	.0389	.1242	.1104	8.06	2.01	2.66	0.93
-5	571	.0489	.1697	.1546	5.47	1.76	2.06	0.83
-4	595	.0588	.2236	.2087	3.79	1.56	1.58	0.74
-3	615	.0678	.2852	.2720	2.68	1.39	1.19	0.66
-2	628	.0750	.3531	.3432	1.91	1.24	0.89	0.59
-1	637	.0797	.4254	.4201	1.38	1.11	0.65	0.53
0	639	.0814	.5000	.5000	1	1	0.48	0.48
1	637	.0797	.5746	.5799	1.38	2.63	0.65	1.18
2	628	.0750	.6469	.6568	1.91	7.01	0.89	2.45
3	615	.0678	.7148	.7280	2.68	19.17	1.19	4.13
4	595	.0588	.7764	.7913	3.79	54.52	1.58	5.31
5	571	.0489	.8303	.8454	5.47	163.4	2.06	6.77
6	540	.0389	.8758	.8896	8.06	522.8	2.66	7.47



3. Calculate the posterior odds of truth or deception.

Use the ESS-M reference tables to calculate the posterior odds of truth or deception by locating the observed score in the left-hand score column, then locate the corresponding odds of truth or deception in the same row using the odds column. Select the ESS-M reference table for grand totals when using the grand total to classify a polygraph test result as truthful or

deceptive. Figure 5 shows the procedure with a grand total score that is indicative of truth, and Figure 6, shows the procedure with a grand total that is indicative of deception. Figure 7 shows the use of the ESS-M reference table for sub-total scores to calculate the posterior odds of deception using the lowest sub-total score with statistical correction for multiplicity, when the grand total is not statistically significant.

Figure 5. Calculate the posterior odds of truth for a grand total score.

-8	13783	.0303	.1803	.1710	4.85	2.85
-7	13900	.0336	.2122	.2030	3.93	2.39
-6	14000	.0369	.2471	.2383	3.2	2
-5	14086	.0398	.2847	.2766	2.62	1.67
-4	14155	.0424	.3247	.3177	2.15	1.39
-3	14210	.0446	.3667	.3611	1.77	1.16
-2	14248	.0461	.4102	.4064	1.46	0.97
-1	14272	.0471	.4548	.4529	1.21	0.8
0	14279	.0475	.5000	.5000	1	0.67
1	14272	.0471	.5452	.5471	1.21	0.8
2	14248	.0461	.5898	.5936	1.46	0.97
3	14210	.0446	.6333	.6389	1.77	1.16
4	14155	.0424	.6753	.6823	2.15	1.39
5	14086	.0398	.7153	.7234	2.62	1.67
6	14000	.0369	.7529	.7617	3.2	2
7	13900	.0336	.7878	.7970	3.93	2.39
8	13783	.0303	.8197	.8290	4.85	2.85
9	13652	.0269	.8486	.8576	6.02	3.41

Figure 6. Calculate the posterior odds of deception for a grand total score.

-8	13783	.0303	.1803	.1710	4.85	2.85
-7	13900	.0336	.2122	.2030	3.93	2.39
-6	14000	.0369	.2471	.2383	3.2	2
-5	14086	.0398	.2847	.2766	2.62	1.67
-4	14155	.0424	.3247	.3177	2.15	1.39
-3	14210	.0446	.3667	.3611	1.77	1.16
-2	14248	.0461	.4102	.4064	1.46	0.97
-1	14272	.0471	.4548	.4529	1.21	0.8
0	14279	.0475	.5000	.5000	1	0.67
1	14272	.0471	.5452	.5471	1.21	0.8
2	14248	.0461	.5898	.5936	1.46	0.97
3	14210	.0446	.6333	.6389	1.77	1.16
4	14155	.0424	.6753	.6823	2.15	1.39
5	14086	.0398	.7153	.7234	2.62	1.67
6	14000	.0369	.7529	.7617	3.2	2



Figure 7. Calculate the odds for a subtotal with statistical correction if the grand total is inconclusive

-10	378	.0099	.0236	.0190	51.67	3.73	5.22	1.56
-9	423	.0150	.0383	.0315	30.72	3.13	4.84	1.37
-8	465	.0216	.0592	.0500	19.01	2.67	4.11	1.19
-7	505	.0297	.0875	.0758	12.19	2.3	3.3	1.05
-6	540	.0389	.1242	.1104	8.06	2.01	2.66	0.93
-5	571	.0489	.1697	.1546	5.47	1.76	2.06	0.83
-4	595	.0588	.2236	.2087	3.79	1.56	1.58	0.74
-3	615	.0678	.2852	.2720	2.68	1.39	1.19	0.66
-2	628	.0750	.3531	.3432	1.91	1.24	0.89	0.59
-1	637	.0797	.4254	.4201	1.38	1.11	0.65	0.53

Select only the ESS-M reference table for sub-total scores when using the sub-totals score rule with multiple issue screening exams. Locate lowest sub-total score in the left-hand score column, then locate the corresponding odds of truth or decep-

tion in the same row using the odds column. Figure 8 shows the procedure for a deceptive sub-totals score of a multiple issue screening exam. Figure 9 shows the procedure for a truthful result of a multiple issue screening polygraph.

Figure 8. Calculate the posterior odds of deception for a multiple-issue screening polygraph.

-8	465	.0216	.0592	.0500	19.01	2.67	4.11	1.19
-7	505	.0297	.0875	.0758	12.19	2.3	3.3	1.05
-6	540	.0389	.1242	.1104	8.06	2.01	2.66	0.93
-5	571	.0489	.1697	.1546	5.47	1.76	2.06	0.83
-4	595	.0588	.2236	.2087	3.79	1.56	1.58	0.74
-3	615	.0678	.2852	.2720	2.68	1.39	1.19	0.66
-2	628	.0750	.3531	.3432	1.91	1.24	0.89	0.59
-1	637	.0797	.4254	.4201	1.38	1.11	0.65	0.53
0	639	.0814	.5000	.5000	1	1	0.48	0.48
1	637	.0797	.5746	.5799	1.38	2.63	0.65	1.18
2	628	.0750	.6469	.6568	1.91	7.01	0.89	2.45
3	615	.0678	.7148	.7280	2.68	19.17	1.19	4.13
4	595	.0588	.7764	.7913	3.79	54.52	1.58	5.31
5	571	.0489	.8303	.8454	5.47	163.4	2.06	6.77



Figure 9. Calculate the posterior odds of truth for a multiple-issue screening polygraph

-8	465	.0216	.0592	.0500	19.01	2.67	4.11	1.19
-7	505	.0297	.0875	.0758	12.19	2.3	3.3	1.05
-6	540	.0389	.1242	.1104	8.06	2.01	2.66	0.93
-5	571	.0489	.1697	.1546	5.47	1.76	2.06	0.83
-4	595	.0588	.2236	.2087	3.79	1.56	1.58	0.74
-3	615	.0678	.2852	.2720	2.68	1.39	1.19	0.66
-2	628	.0750	.3531	.3432	1.91	1.24	0.89	0.59
-1	637	.0797	.4254	.4201	1.38	1.11	0.65	0.53
0	639	.0814	.5000	.5000	1	1	0.48	0.48
1	637	.0797	.5746	.5799	1.38	2.63	0.65	1.18
2	628	.0750	.6469	.6568	1.91	7.01	0.89	2.45
3	615	.0678	.7148	.7280	2.68	19.17	1.19	4.13
4	595	.0588	.7764	.7913	3.79	54.52	1.58	5.31
5	571	.0489	.8303	.8454	5.47	163.4	2.06	6.77

4. Interpret the results.

Interpretation of an ESS-M statistical result is first a matter of the use of structured decision rules that transform the numerical and statistical result into categorical results that have more obvious practical value. A number of decision rules are described in publication. Decision rules commonly use grand-total rule, two-stage rules, sub-total score rule, and Federal zone rule. An equally important aspect of the interpretation of any scientific test results will be to explain the actual meaning of the test result and how that result was derived from the test data. Reported information should communicate

information about the theory of the test, the operational procedures, along with all parameters and assumptions that influenced the choice of analytic methods. Scientific test results should be communicated in sufficient detail that the use of objective information can be easily differentiated from subjective information and arbitrary choices. Information should be documented with sufficient detail to convey the use of evidence-based practices. In this way other professionals can reproduce and verify the analytic result without guesswork or misunderstanding as to what assumptions and procedures were used.

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