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ABSTRACT

In visual performance experiments, accuracy is as much a function of the relative worth of speed and accuracy as it is of visibility. In a task that consists of subtasks, such as comparing two lists, it may be necessary to explicitly model the effect of each subtask's visibility on speed and accuracy. Finally, changes in print may be significant in that they can lead to changes in visual performance without a corresponding change in visibility.

The current Commission Internationale de L'Elairage (CIE) model for visual performance, CIE 19/2, does not consider the above factors. Although we believe that the CIE model is not useful as an application model, we do feel that the general features of the visibility/visual performance relationship are clear and are important to lighting design. We close with a brief discussion of the failure of the RQQ #6 lighting recommendations to explicitly consider cost-effectiveness.

INTRODUCTION

In the execution of most tasks, speed and accuracy are related to each other.[1] The level of performance for a task depends upon this relationship and the relative values of each factor.

Some tasks contain multiple subtasks. Before modeling the performance/visibility relationship, it is necessary to specify the visibility of each subtask and determine the manner in which the performance (speed and accuracy) of each subtask affects overall performance. The redundancy and ambiguity of the information in the tasks are additional factors which may significantly affect performance.

The 1981 Commission Internationale de L'Eclairage (CIE) report on visual performance, CIE 19/2,[2] either superficially treats or simply ignores the above factors, and hence does not present a useful application model. We attempt to show how this model must be reformulated before it will give useful results. Finally, we examine the current IES recommendations for light level, RQQ #6,[3] in terms of visual performance and cost-effectiveness.

Performance, Speed, and Accuracy

We begin by presenting a brief description of the visual performance problem and the CIE visual performance model, CIE 19/2.[2]

Performance is a combination of speed and accuracy. Most office tasks are self-paced; speed is fixed by the worker. Beside the speed (exposure time of a task), the factors that affect accuracy are those that directly affect the intensity (visibility) of the stimulus: contrast, size, luminance, luminance distribution, and age[2,4,5,6]; and those that affect the ability to utilize the stimulus: information content, practice, motivation and physical well-being.[2,6,7]

By specifying or measuring the visibility at a fixed speed, a "reference" visibility can be defined as a function of only the intrinsic properties of a task and its surroundings. In the CIE model a reference visibility is estimated by the "visibility level," VL, which is equal to the ratio of the task's physical contrast, C_p, to its threshold contrast C_t (the contrast level at which accuracy is 50%), at a fixed exposure time of 1/5 second.[2,8] The threshold contrast can be measured directly or, given values of the visibility-related variables, can be estimated to within a multiplicative constant from fits contained in the CIE report. The fits assume that the subject is motivated and has had practice at the task.

The CIE model appears to have grown out of studies of accuracy at a fixed exposure time. Under the proper conditions the accuracy of detection can be fit to a lognormal distribution (the Gaussian distribution of the logarithm of the independent variable)[2,9] with VL as the independent parameter. A single fitted parameter, the task demand level, D, is used to fit both the mean difficulty and the standard deviation of the lognormal distribution. The relative visual performance, RVP, of the task is the accuracy (performance) divided by the maximum accuracy (performance) P_{max}, attainable, for the task. For the more general problem, where the subject has to search and scan and where neither speed nor accuracy is fixed, performance is modeled as affected by three critical visual subtasks (detection, mentioned above, control of saccadic motion, and fixation), and two non-critical visual subtasks. Each of the visual subtasks is assumed to be fit by a lognormal distribution of VL. The "Relative Task Performance," RTP, is assumed to be the sum of the RVP's of the individual subtasks:

$$RTP(v,X) = w_{123} \sum_{i=1}^{3} w_i(D) RVP_i(v,D) + (1-w_{123}) \sum_{i=4}^{5} w_i RVP_i(v) \qquad (1)$$

$$\simeq w_{123} \sum_{i=1}^{3} w_i(D) RVP_i(v,D) + (1-w_{123})$$

Here v=VL, and X represents the fitted parameters P_{max}, w_{123}, and D. The factor w_{123} is called the "critical component weight." It is the fraction of the task that is affected by changes in visibility at normal visibility levels. The relative weights of subtasks, w_i, and the means and standard deviations of RVP_i are all either constants or are functions of D, the task demand level. The two non-critical subtasks saturate at very low visibilities; hence for practical purposes RTP is given by approximating the non-critical subtasks by a constant.

No formal definition of performance is given in the CIE report. Instead, the analysis of visual performance data is based on the "measure of task performance selected by the investigator...."[2] The type of performance measure chosen by the investigator will affect P_{max}. If, however, P_{max} is the only fitted parameter affected, then RTP will not depend on the performance measure chosen since P_{max} is divided out in computing RTP.

We show that specifying the performance measure is part of analyzing the task. It affects the functional form of the visibility/performance relationship. If Eq. (1) is used as just a fit, the performance measure affects the values of D and w_{123} so that fit is not predictive. We clarify these points below.

Performance, P, is a function of speed (1/t) and accuracy, A:

$$P = P(t, A(v,t,x)) \qquad (2)$$

We have replaced X in Eq. (1) with t, x to make the time dependence explicit. We assume x is a constant (motivated, trained subjects). The simplest performance functions are accuracy at a fixed speed, t_o, and speed at a fixed accuracy, A_o.

For accuracy at a fixed speed, $P=A(v,t_o, x)$ and $P_{max}=A(\infty,t_o,x)$. Hence:

$$RTP(v,X) = A(v,t_o,x)/A(\infty,t_o,x). \tag{3}$$

The parameters X are fixed by t_o and x. Since the w_i in Eq. (1) are unitless, substition of Eq. (3) into Eq. (1) leads to the conclusion that the RVP_i are ratios of accuracies. Equation (1) implies that overall accuracy is the weighted <u>sum</u> of the accuracies of the visual processes. However, probabilities (accuracies) sum only when overall success results from success on process 1, <u>or</u> process 2, <u>or</u> process 3. This is inconsistent with the physical interpretation of these processes as saccadic motion, fixation, and then detection.

To analyze performance as a function of speed at a fixed accuracy, A_o, we write time, t, as a function of accuracy: $t = T(v,A_o,x)$. Then $P = (T(v,A_o,x))^{-1}$, and $P_{max} = (T(\infty,A_o,x))^{-1}$, and

$$RTP(v,x) = \frac{T(\infty,A_o,x)}{T(v,A_o,x)} \; ; \quad RVP_i(v,D) = \frac{T_i(\infty,A_o,x)}{T_i(v,A_o,x)} \tag{4}$$

the expression for RVP_i again being derived from the consideration that the w_i are unitless. The units in Eq. (1) are consistent with the definitions in Eq. (4), but it is not a physically correct equation. It is <u>times</u>, <u>not</u> <u>speeds</u>, that sum. The correct form is:

$$RTP(v,x) = \left(t_{nv} + \sum_{i=1}^{5} w_i/RVP_i\right)^{-1} \; ; \quad w_i \equiv T_i(\infty,A_o,x)/T(\infty,A_o,x). \tag{5}$$

We have added the term t_{nv} to represent the fractional time taken on strictly non-visual components of the task. Equation (1) agrees with

Eq. (5) for RTP $\rightarrow$ 1, but it is not correct.[10,11]

When neither speed nor accuracy are fixed, Eq. (2) is a function of both speed and visibility. We therefore need another condition before we can reduce performance to a function of visibility alone. We get a second condition from our assumption that we have trained, motivated subjects. This is equivalent to assuming that performance is maximized with respect to speed at any given visibility; i.e.,

$$\partial P/\partial t = 0 \; ; \quad \partial^2 P/\partial t^2 < 0. \tag{6}$$

Equations (2) and (6) together are sufficient to give a 1:1 relationship between performance and visibility.

Equation (6) gives t as a function of v, x, and the performance measure. There is no counterpart to this expression in the CIE model. This implies that the interpretation of fits of Eq.(1) to performance data in terms of the physical processes of detection, fixation, etc., is incorrect. In short, the manner in which the performance measure accounts for the tradeoff between speed and accuracy is part of the specification of the task and must be part of any model attempting to relate visibility to performance.

We use Smith's check-reading experiment[12,13] as an example to illustrate this point. In this experiment the subject's score, or performance, P, was related to the time taken on the task, t, and the number of errors, E, by a relationship of the form

$$P = C_1 + C_2(C_3 - t) - C_4E. \tag{7}$$

The subject's pay was equal to P. The values of the constants chosen by Smith were: C_1=10¢, C_2= 0.2¢/sec., C_3= 30 sec., and C_4= 2¢.

The number of errors, E, is related to accuracy by the relationship

$$E(v,t,x) = (N - g)\ (1 - A(v,t,x)), \tag{8}$$

where N is the number of checks examined per run (10) and g is the probability of getting a correct answer by chance. For convenience we assume g=0.

For convenience we also assume that we can treat P as a continuous function although pay is a discrete function. In Smith's experiment the pay per run was small enough that pay sometimes did not reflect substantial changes in actual performance (e.g., a ~50% change in speed). Nonetheless, pay is the measure of performance that was analyzed. From Eqs. (6), (7), and (8) we get

$$\partial P/\partial t = \partial A(v,t,x)/\partial t - C_2/C_4 = 0. \qquad (9)$$

Let

$$t = T_1(v,x,c) \;;\quad c = C_2/C_4 \qquad (10)$$

be the solution to Eq. (9). Substitution of Eq. (10) into Eq. (7) leads to the following formula for RTP($\equiv P/P_{max}$):

$$RTP(v,X) = w[w_1 A(v,T_1,x) + w_2 T_1(v,x,c)] + (1-w) \qquad (11)$$

where we use the following definitions for clarity:

$$K = C_1 + C_2 C_3 - C_4 N \;;\; P_{max} = K + C_4 N\, A(\infty,T_1,x) - C_2 T_1(\infty,x,c) \qquad (12)$$

$$w = (P_{max} - K)/P_{max};\; w_1 = C_4 N/wP_{max} \;;\; w_2 = -C_2/wP_{max}.$$

The constant w is the sum of the arbitrarily determined constants of the score function and therefore may be negative or greater than one. Conversely, the constant w_{123} in Eq. (1) is the fraction of performance affected by the critical visual subprocesses--detection, fixation, and saccadic motion--and is therefore bounded in the interval from 0 to 1. Comparison of Eq. (11) with Eq. (1) shows that w must be fit by w_{123} in direct contradiction to the proposed physical interpretation of w_{123}. A direct confirmation of this point is that one of Smith's experiments was not analyzed in the CIE report because some of the scores were negative $(w > 1)$.[14,15]

Similar comments apply to the task demand constant, D. The function T_1 in Eq. (11) has no counterpart in Eq. (1), but it still must be fit by the sum of the RVP_i's in Eq. (1). This implies that D is in part determined by the performance measure chosen, contrary to its proposed meaning.

In the CIE report, Eq. (1) was used to fit the data from 20 visual performance experiments. It is tempting to use the fits as a summary of experimental results even though as we have shown there is no physical basis for the form of Eq. (1). However, Eq. (1) is very complex. This complexity makes the equation too sensitive to statistical noise to be a good function for curve-fitting.

In fact, most of the fits in the CIE report are not statistically significant. For example, in some of the fits the data has been aggregated to the point where there is only one degree of freedom (4 data points and 3 unknowns). In other fits a separate maximum performance parameter was used for each group of subjects or each condition, again reducing the degrees of freedom. In one case it appears that the data was used in fitting normally fixed parameters (the constants in w_4RVP_4 and w_5RVP_5),[16] again reducing the degrees of freedom. The statistical significance of the remaining fits is spoiled either because the error bars include variance from aggragation of the data over subsets of the independent parameters or because there are no error bars.

In fact a fundamental problem in evaluating the statistical significance of fits to Eq. (1) is that it is not monotonic with respect to the task demand parameter, D, at low visibilities $(VL<4)$[17]. The existence of dual solutions for the least-squares fitting problem invalidates the basic statistical tests used for "goodness" of fit. This means that there is no way of telling, with Eq (1), whether it is noise or signal that is being fit. We feel that the data should be fit with a simpler function.

Actually, it is not certain that fits of relative performance will be very useful. The vision scientist needs to look at how accuracy is affected by speed and information content. The user needs to be able to calculate cost-effectiveness, which is based on absolute, not relative, performance. Relative performance may not even make sense in some cases since performance may be negative at low visibilities.

A further problem is that performance in laboratory experiments can be based on <u>any</u> combination of speed and accuracy that the investigator desires to use. In the workplace, performance is most likely to be measured by the rate of correct completions of a task minus a penalty for incorrect completions (at least where these concepts make sense). For example:

$$P = (N_R - CE)/t = N((C + 1)A(v,t,x) - C)/t \qquad (13)$$

where C is a constant giving the cost of errors relative to the value of correct completions, N_R. The cost of errors could alternatively, or also, be added in as a time penalty. In any event the optimum relationship between time and visibility is found by simply setting $\partial P/\partial t=0$. Since the relative cost of errors will vary for different jobs, the user too needs to know how accuracy depends upon speed.

Multiple Visual Tasks

Several serious complications are involved in the analysis of realistic tasks. In the next two sections we discuss some of the problems that arise.

Smith ran several visual performance experiments that involved two distinct subtasks. In the numerical verification experiments [15,18,19] subjects compared two lists for discrepancies. One list, the reference list, used typed high-contrast print. Test lists were both high and low contrast. Visibility (as measured by VL) of the reference list, v_2, was always greater than or equal to v_1, the visibility of the test list. Tests were run at several light levels (different v_i).

There has been confusion about the proper method of analyzing the data from these experiments. Ross plotted the scores as a function of v_1.[15] At any given v_1 the subjects scored highest with the low-contrast material. Ross claimed this showed that VL and visibility are not equivalent.

In the CIE report the scores on each test list were normalized to the estimated maximum score on that list before being fit to v_1.[2] This eliminates the discrepancy in the visibility/score relationship. The rationale presented for this procedure is that the subject's motivation increases when the task is more difficult.[20] This rationale is not credible, as task difficulty should depend on v_1 and D, not contrast. Furthermore, there are no obvious reasons performance should vary for these experiments and not others.

In the Smith experiments there is no single fixed relationship between v_1 and v_2. Therefore, the analysis of performance in terms of v_1 alone involves assuming that performance does not depend upon v_2. This occurs when visibility is high enough for performance to saturate ($v>v_s$) where v_s is the saturation level of VL. The two analyses above are based on the assumption that $v_2>v_s$ for all v_2.

Let $P(v_{1i},v_{2i})$ represent the raw performance data as a function of the visibilities on the test (v_{1i}) and reference (v_{2i}) lists. The subscript i is l or h for the low- and high-contrast test runs respectively. The experiments were set up so that $v_{2l}>v_{1l}$ and $v_{2h}\approx v_{1h}\equiv v_o$. From $v_2>v_s$ we get

$$P(v_{1h}=v_o>v_s, v_{2h}=v_o>v_s) = \text{constant}. \tag{14}$$

Table 1 shows that in the Smith experiments performance with the high-contrast test lists was not constant over the range of v_2. This shows that one cannot simply ignore the easy tasks when analyzing performance data.

Smith has suggested compensating for the effect of changes in v_2 by subtracting an estimate of the performance on the reference list from the total performance:

$$P'(v_{1i},v_{2i}) = 2P(v_{1i},v_{2i}) - P(v_{2i},v_{2i}). \tag{15}$$

For the raw data, the difference in score, Δ, between tests having low- and high-contrast lists when $v_{1l}=v_{1h}=v_o$ is:

$$\Delta = P(v_o,v_{2l}) - P(v_o,v_o). \tag{16}$$

Since $\partial P/\partial v \geq 0$, and $v_{2l}>v_o$ we expect $\Delta \geq 0$ (see Figs. 1 and 2). For the transformed scores, the difference Δ' is:

$$\Delta' = P'(v_o,v_{2l}) - P'(v_o,v_o) \tag{17}$$

$$= (P(v_o,v_{2l}) - P(v_{2l},v_{2l})) + (P(v_o,v_{2l}) - P(v_o,v_o))$$

where $P(v_{2l},v_{2l})$ is the performance on the high-contrast test list at the same luminance, not visibility, as for the low-contrast test list. The second term in the right-hand side of the equation is Δ. To the extent that $\partial P/\partial v$ is constant, the first term will tend towards $-\Delta$. Since performance saturates at high visibilities ($\partial^2P/\partial v^2<0$), the magnitude of the first term will generally be less than Δ, hence $\Delta \geq \Delta' \geq 0$. Figures 1 and 2 show that this analysis is consistent with the data.

As shown in the previous section, the fundamental visibility relationships are to speed and accuracy, not performance *per se*. This does not obviate the need, which Smith noted, to explicitly analyze both subtasks.

Let t be the total time required to compare C items. Then, since times add:

$$t = Ct_t = C(t_1 + t_2 + t_{nv}). \tag{18}$$

Here t_t is the time required to do a single comparison; t_1 and t_2 are the times required to read one number on the test and reference lists respectively, and t_{nv} is the time required to do everything else.

Unfortunately, the manner in which accuracies combine depends upon how the tasks are related. The simplest case is when the accuracy on one list is independent of that on the other list. Overall accuracy is then:

$$A(v_1,t_1,x_1,v_2,t_2,x_2) = A(v_1,t_1,x_1)A(v_2,t_2,x_2). \tag{19}$$

Let P be a performance measure defined in terms of A and t. Performance follows from Eqs. (8) and (19) and the conditions for optimization:

$$\partial P/\partial t_1 = \partial P/\partial t_2 = 0 \ ; \quad \partial^2 P/\partial t_1{}^2 < 0, \ \partial^2 P/\partial t_2{}^2 < 0. \tag{20}$$

For simplicity we assume that t_{nv} is a constant.

If there is a probability, u, that an error on one list cancels the same error on the second list (a comparison task), then Eq. (19) can be simply amended by the addition of the term $u(1 - A(v_1,t_1,x_1))(1-A(v_2,t_2,x_2))$. However, when the accuracy on one list is not independent of the accuracy on the other list, there is no simple fix to Eq. (19), and the model could become excessively complicated. Redundancy of information between lists, or re-examination of the discrepancies in a comparsion task, are examples of factors that could cause this problem.

The multiple-task experiments are close to real tasks and may provide insight into how people process information. However, at present even single-task experiments have not been properly analyzed, and the function $A(v,t,x)$ is not known. Until more work has been done it would be best to be very cautious about drawing conclusions from the results of multiple-task experiments.

TABLE 1

PERFORMANCE CHANGES WITH THE HIGH-CONTRAST
TYPED LIST COMPARED TO TOTAL PERFORMANCE CHANGES

CHANGE IN PERFORMANCE	EXPERIMENT NVT - 1976		EXPERIMENT NVT- 1977
	YOUNGER SUBJECTS	OLDER SUBJECTS	ALL SUBJECTS
Total range	3.3	14.6	22.3
Range over high-contrast lists only	.9	3.7	8.2
% change in the high-contrast list to total change	~25%	25%	36%

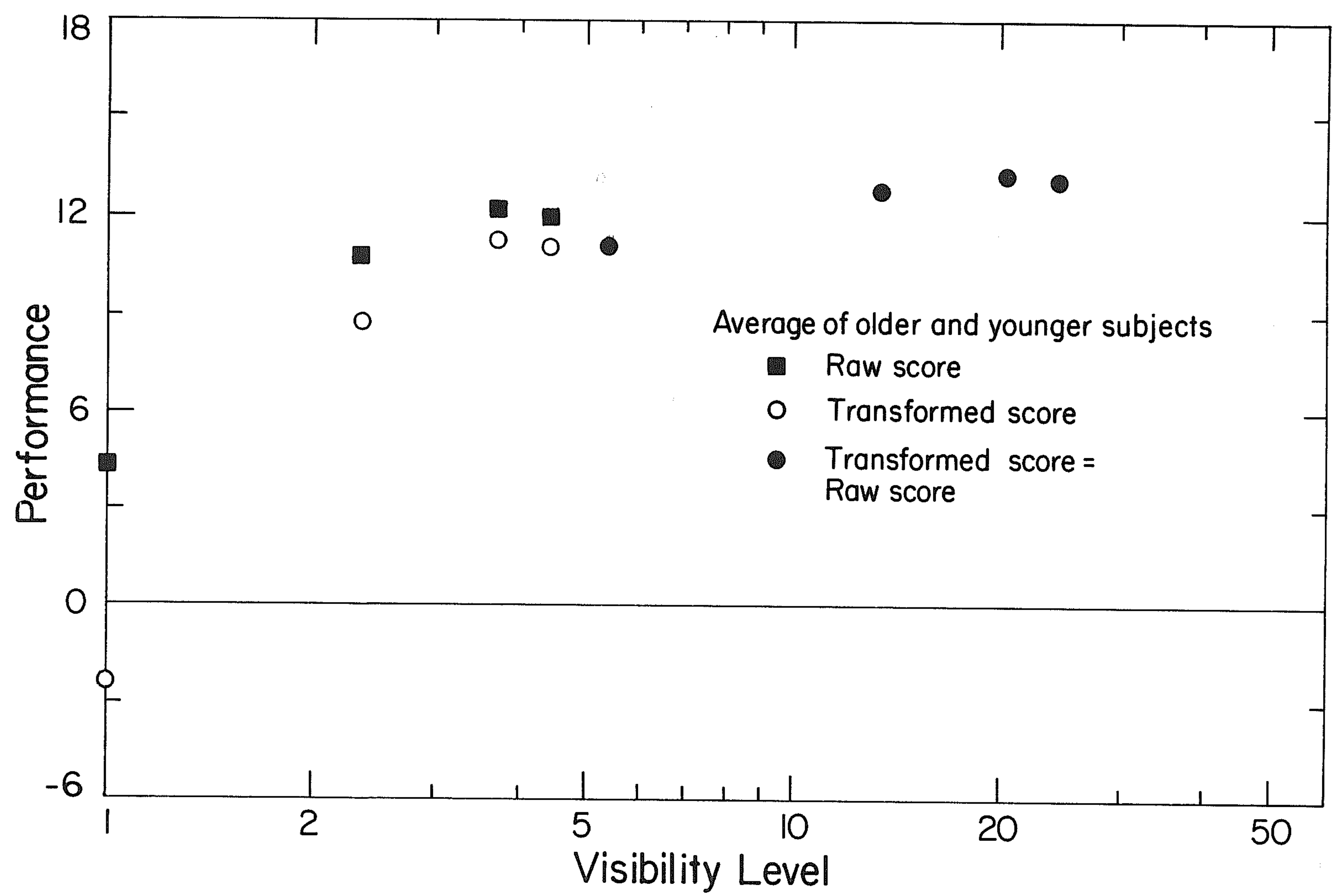

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Figure 1. Comparison of raw and transformed scores: Smith's 1976 numerical verification experiment.

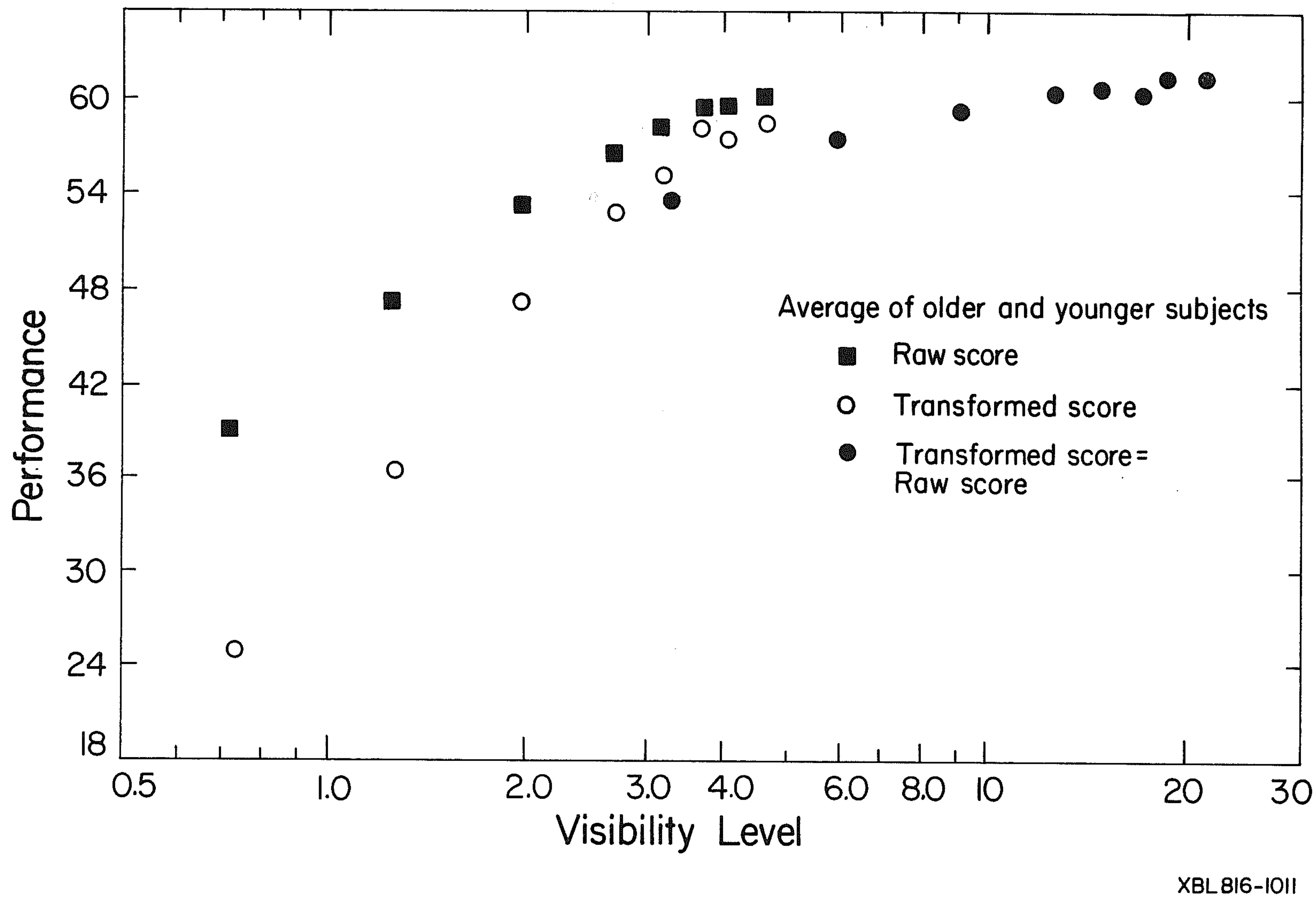

Figure 2. Comparison of raw and transformed scores: Smith's 1977 numerical verification experiment.

Pattern Recognition and Performance

Smith's 1976 numerical verification experiment used both printed and handwritten test lists.[12,15] Scores for the handwritten lists were lower than scores at the same VL for the printed lists. Ross felt that this was another failure of the VL/performance relationship.[15]

We believe that it may be a pattern-recognition problem, not a visibility problem, which is responsible for the differences in scores. There is also a minor problem in the specification of VL which may contribute to the observed discrepancies.

The VL values used in the analyses are actually the averages over a sample of the numbers on the lists. This creates a minor technical problem in that the average performance level $\overline{P(v)}$ is less than or equal to the performance calculated at the average visibility, $P(\bar{v})$.[10,11] The more variable v is, the bigger the difference between $\overline{P(v)}$ and $P(\bar{v})$. The visibility of handwritting is more variable than that of print; hence, at a given value of $\bar{v}$ performance will be better with print. This problem can be partly alleviated by using the geometric, rather than the arithmetic, mean for VL.[10,11]

The factors affecting pattern recognition are the redundancy of information and the variability and ambiguity of visual cues.

There is usually more than one shape cue that distinguishes one character from another. Let a be the accuracy of discrimination given one cue. If the subject needs to recognize only one out of n cues to make a discrimination, then overall accuracy is $A=(1-(1-a)^n)$. Since $\partial A/\partial n \neq 0$, a difference in the level of redundancy, n, between print and handwriting should make the threshold contrast levels, C_t, different. No major differences were noted in the Smith experiments;[21] hence redundancy was probably not a major factor in the performance differences between print and handwriting. Redundancy will probably be important when analyzing performance with reading text.

Variability in shape increases both the number of patterns that a subject must recognize, and the difficulty in discriminating among them.

This may noticeably increase cognition time, thus reducing performance. In a VL measurement the target is visible for only 1/5 second, but cognition time is unlimited. Since handwriting varies greatly, subjects should score less well with it than with printed lists having the same visibility.

An example of an ambiguous cue is a badly shaped 9 that looks like a 4 or a 7. Ambiguities add to the difficulty and time required to make a correct decision. Again, since cognition time is not part of the VL measurement, performance with bad handwritting should drop, even though the VL level remains high.

As experiments become more complex, more factors may be found to affect performance. In the present case, it is not reasonable to draw conclusions about the VL/visibility relationship without being able to estimate the importance of the pattern-recognition factors discussed above.

Conclusion: Performance and Lighting Recommendations

The present IES illumination recommendations, RQQ #6, are based on considerations of visual performance.[3,22] They differ from the previous recommendations[23] in that they include correction factors for age, reflectivity, and the importance of speed and accuracy. Light levels in the new recommendations were established by consensus, instead of being calculated from a specific model.

Visual performance is important because it is related to overall performance. A lighting recommendation should provide sufficient visibility (visual performance) so that overall performance does not suffer. Unfortunately, this still leads to a somewhat arbitrary choice of a satisfactory level of visual performance.[23,24]

In commercial and industrial applications, performance is related to productivity. In this case one could potentially calculate the cost-effectiveness, or net benefit (productivity versus lighting cost) of a given light level. A decision about light levels can then be thought of as an investment decision, with the optimal light level being that which gives the best return on investment.

The previous sections of this paper should have made it clear that much is still unknown about visual performance, let alone about the relationship between visibility and productivity. An accurate calculation of cost-effectiveness cannot be made. However, it is fairly clear what factors affect cost-effectiveness.[10,11] Furthermore, one can often determine the magnitude, and almost always the sign, of the effects of different factors. We feel that this is sufficient knowledge to make it useful to analyze the cost-effectiveness of lighting recommendations.

For example, relative values of VL (visibility) can be calculated for each of the illuminance categories in RQQ #6 under the assumptions of fixed age, reflectivity, glare, and CRF (the ratio of the contrast of the task under the actual lighting to its contrast under hemispherical (reference) lighting). Values of C_{eq} (the contrast of a reference task of equal visibility as the real task) for each category were taken from Table 3 of the RQQ #6 report.[3] VL is more sensitive to C_{eq} than to illuminance. Thus, the target VL values are lower for the more difficult task categories, even though target illuminances increased. This trend appears consistent with considerations of cost-effectiveness. Higher light levels cost more; thus it is more expensive to maintain a given level of performance for more difficult tasks. Therefore, the optimum trade-off between cost and performance will be at a lower level of performance (and VL) than for easier tasks.

However, if the cost of lighting is responsible for the VL trend, we would expect correction terms for other factors that affect costs. For example, the cost of electricity and fixtures, considerations of "sunk" costs during remodeling, the cost of money, the discount rate, and finally the size of the task area, are all costs where the potential variations are of comparable size to the variations in cost from different illuminance levels. None of these other factors are explicitly considered in the RQQ #6 recommendations. Since the differences in VL among the different lighting categories are significant, we feel that the committee should be more explicit about why some lighting costs are not considered, or should provide correction factors for these costs.

As another example of this type of analysis, consider the recommended 5:1 limit on the ratios of illuminances in adjacent areas.[3] This recommendation can easily lead to an area being lit from 5 to 10 times more brightly than it normally would be. Two possible reasons for this type of uniformity constraint are glare and transient adaptation. Again, we feel that the reasons should be made explicit. For instance, if the concern is glare it may be worthwhile for the designer to consider some type of glare control in place of uniformity. Options might include baffles on the lighting fixtures, privacy panels, or some other methods of restricting or directing the worker's field of view to control glare. Similar methods might help control transient adaptation problems. These latter problems may in many cases be less significant anyway because of their transitory nature.

Analysis of other facets of the RQQ #6 recommendations lead to similar concerns. Either specific recommendations are not cost-effective, or there are important factors that are not mentioned explicitly. It appears to us that the importance of speed and accuracy is being grossly underestimated, that the correction factors for age and reflectance are low, that the overall levels are high, and that there should be correction factors for CRF and task difficulty.[2,10,11]

Undoubtedly one can design a lighting system that meets the RQQ #6 guidelines and satisfies the user. We assume that users were also satisfied with the IES recommended light levels of 30 years ago, which were as much as five times lower than present levels. The problem is not user satisfaction, but the usefulness of the guidelines. We feel that cost-effectiveness is a reasonable criterion for lighting recommendations. Furthermore, we feel that the tabulation of light levels, whether arrived at by model calculation or by consensus, is less than half the job. The more important half is to provide details about how particular levels were chosen.

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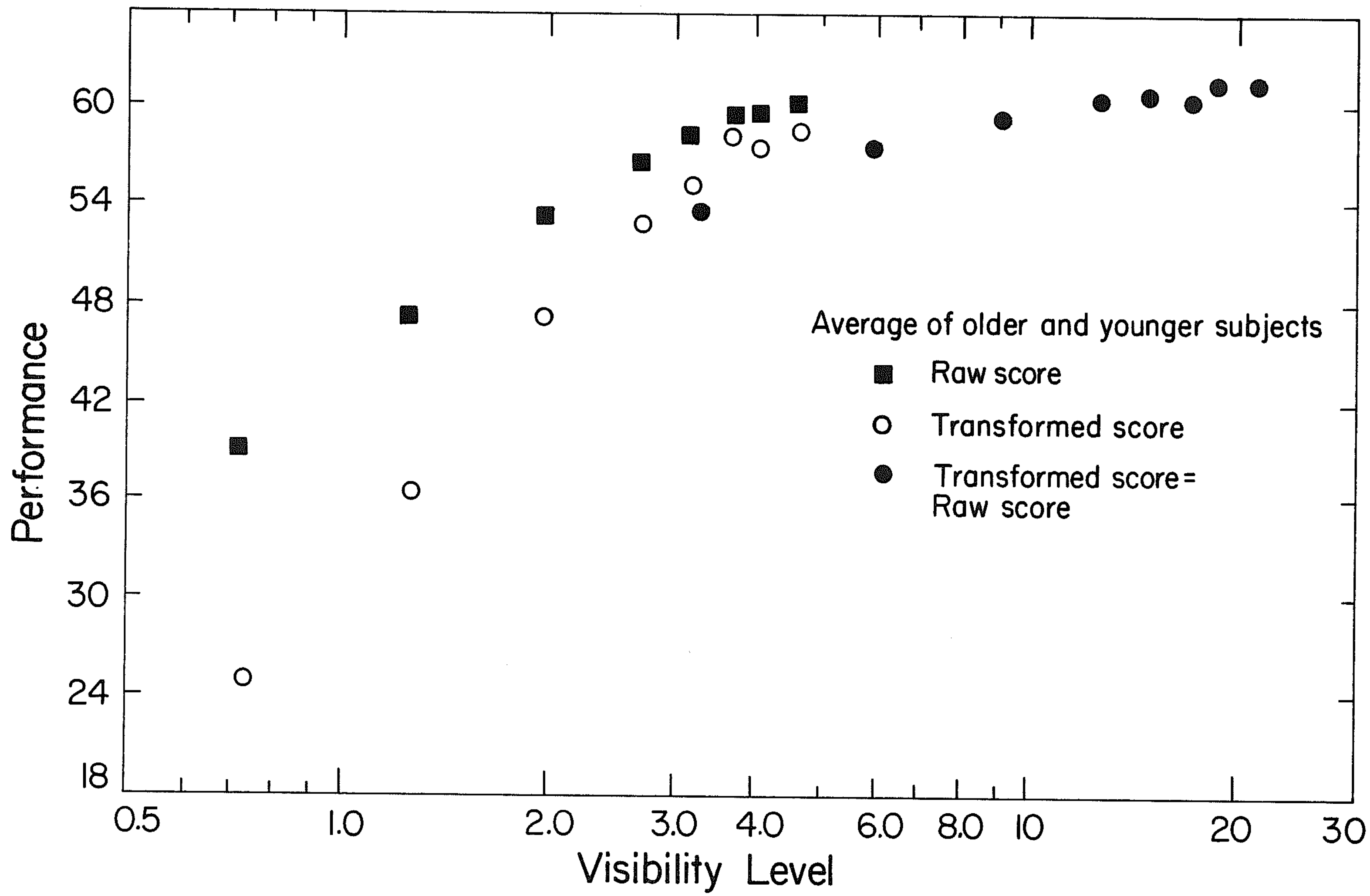
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Visibility Level
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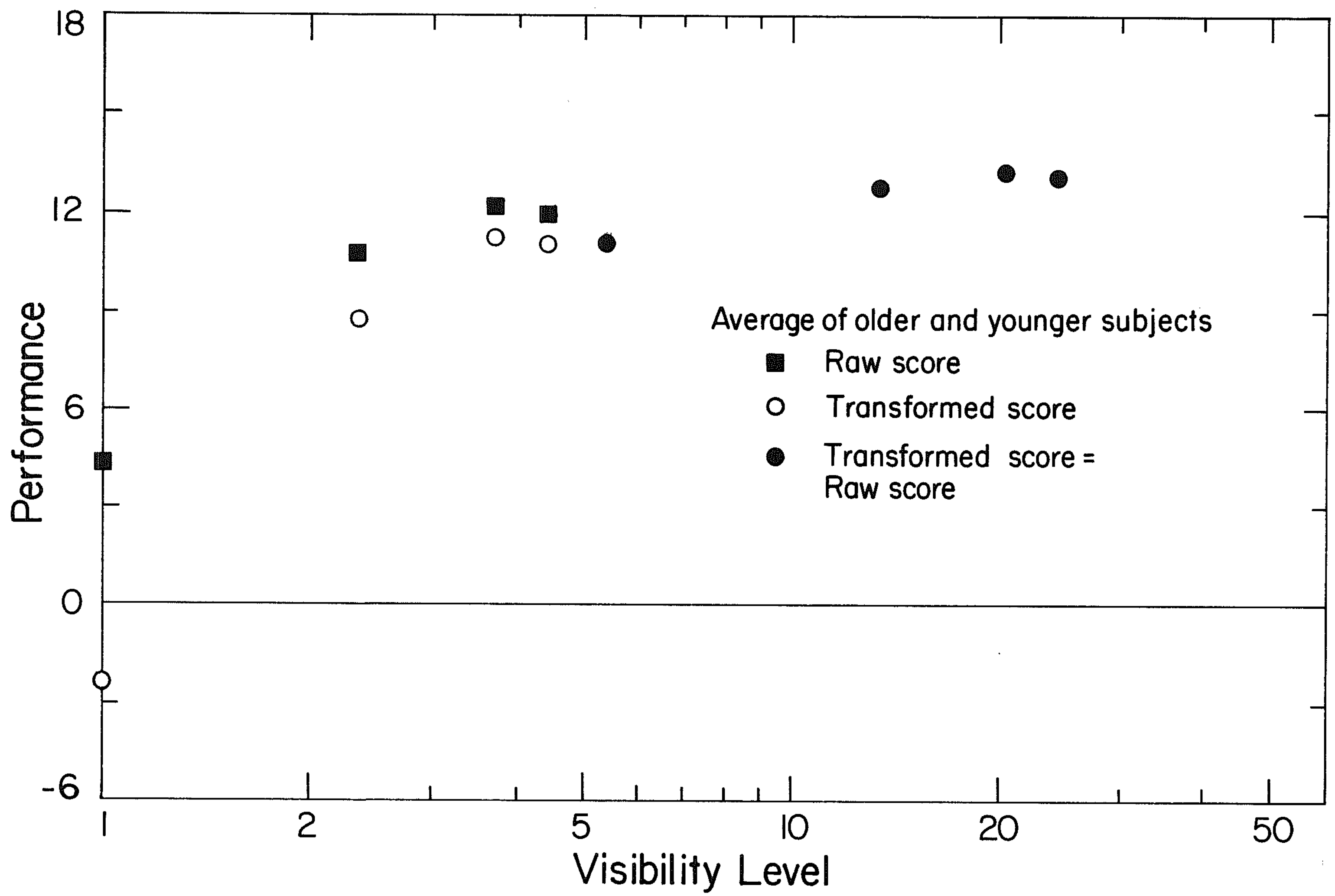

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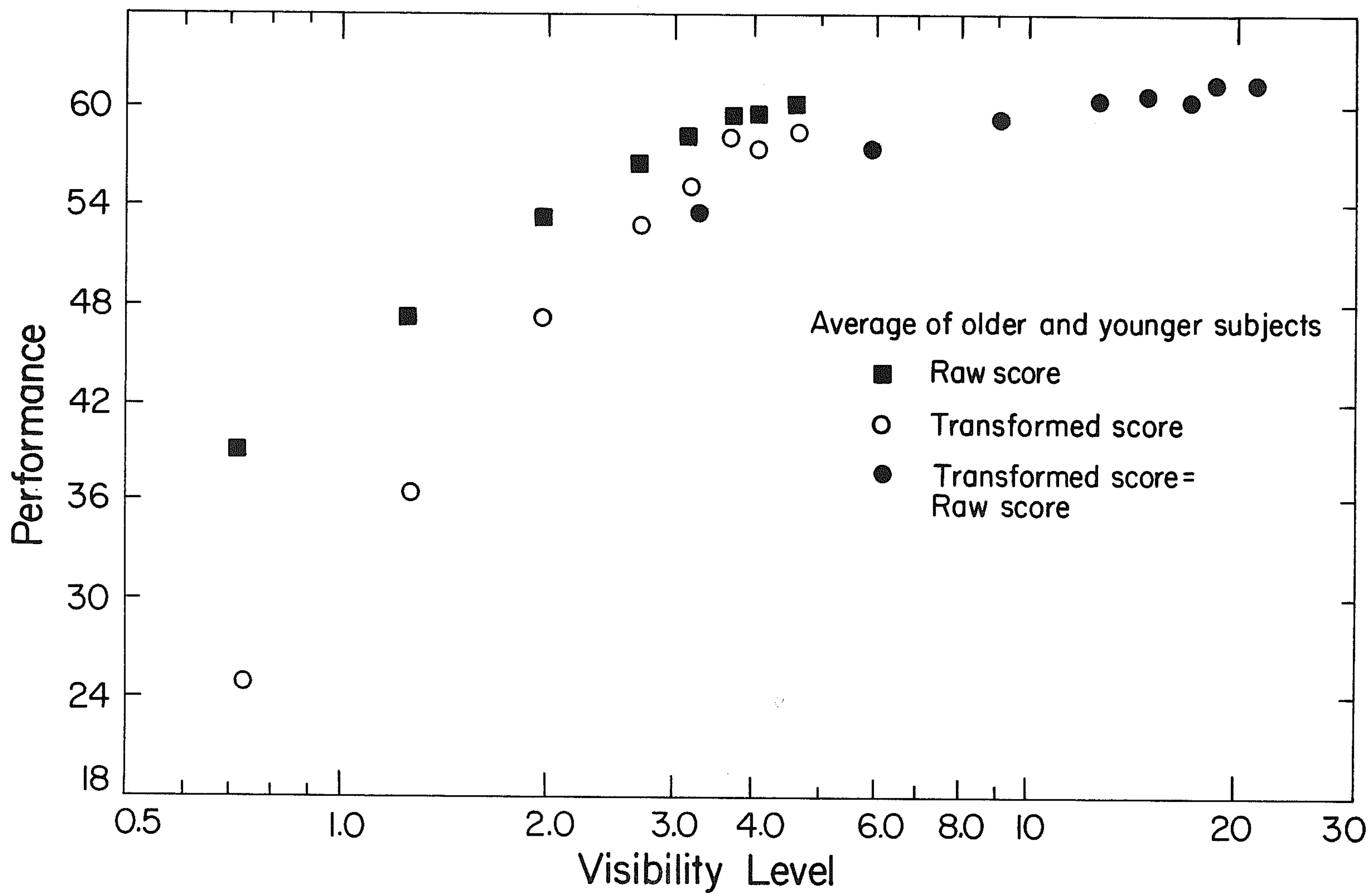
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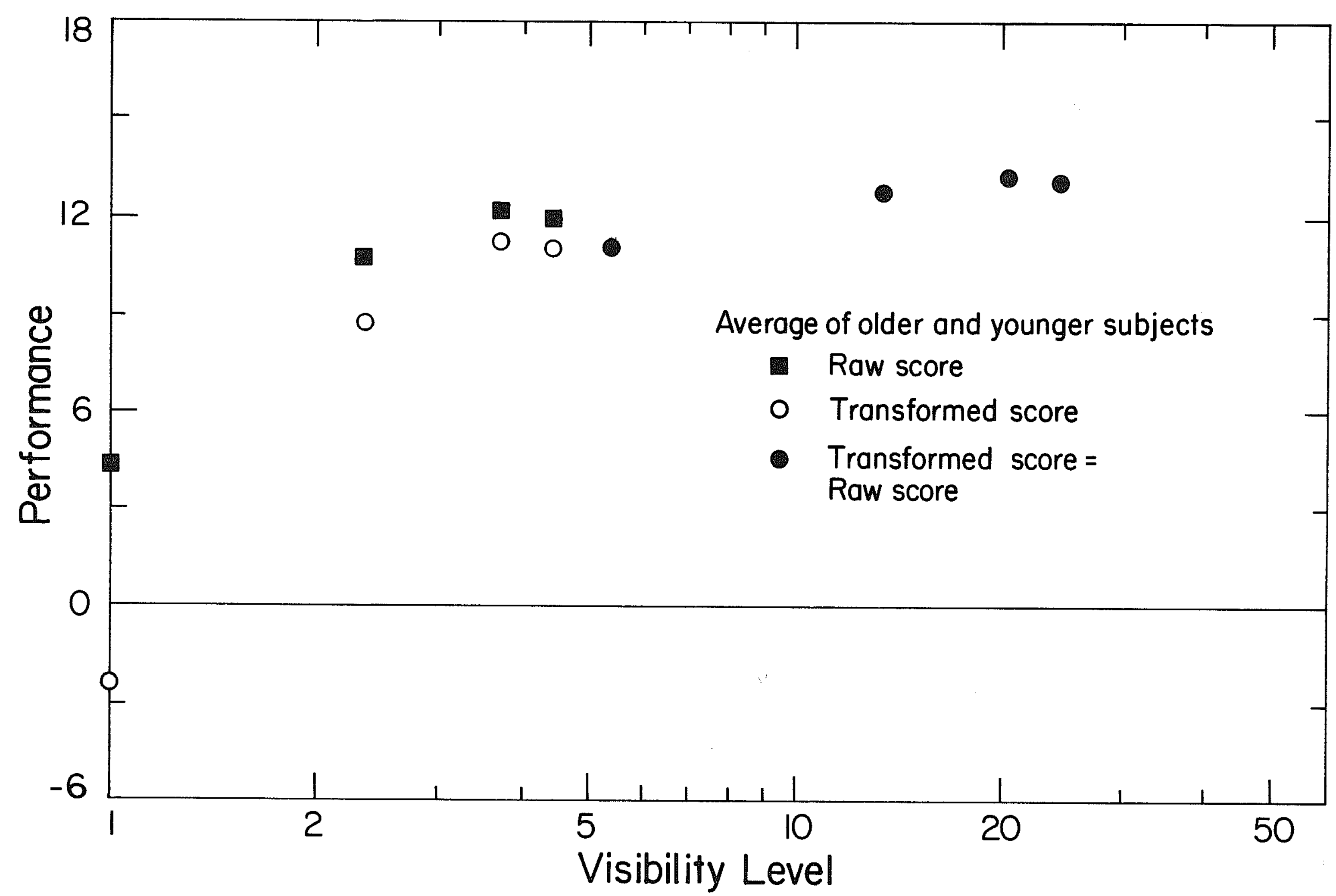
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