FUN WITH NUMBERS: Alternative Models for Predicting Salary Levels

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The increasing awareness and concern with equity issues in higher education, along with the escalating litigation, has prompted institutions to undertake salary prediction studies. Four prediction models (built on a males only and total sample) were compared: (1) entering all variables, (2) excluding rank and tenure, (3) using predicted rank and tenure, and (4) using only "objective" variables. Models were tested using all permanent full-time faculty at a large midwestern university. Using predicted rank and tenure was the most suitable for equity studies. Including all variables yielded the best results for explaining/predicting reward systems. The other two models did not appear appropriate for either purpose. The males only sample consistently produced the largest bias effects. Institutions considering a salary prediction study should find these outcomes helpful in determining appropriate analytical strategies.

Any salary administration procedure must be capable of withstanding questions of bias based on gender, race, and other individual characteristics unrelated to performance (Laws Administered by EEOC, 1981). Typically, analysis of salary equity in higher education institutions has involved the use of a multiple regression approach (Carter et al., 1984), which allows for a determination of factors (both job-related and non-job-related) that influence salary levels. For example, the existence of bias in gender or race groups may be evaluated by determining if such information accounts for a significant proportion of variance not previously accounted for by "relevant" factors. More specific information concerning differential treatment of particular groups is often obtained by analyzing between-group differences in the accuracy of predicted salaries. For example, if salary predictions for males are significantly more accurate than for females, one can infer that salary policies have been applied more consistently to males than females. Secondly, if women's salaries

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are more frequently overpredicted (predicted salary higher than actual salary) while men's are underpredicted, one can conclude that female gender negatively affected salary.

While multiple regression is a useful tool for evaluating salary policies and practices, the utility of the procedure and accuracy of the results are limited by the accuracy, objectivity, and relevancy of the data set and the model used to create the equation. To the extent that the variables are inaccurately assessed or are themselves contaminated with bias, the objectivity and/or accuracy of the prediction equation will suffer. If inaccurate samples or faulty predictors are used to test for salary equity, there can be little confidence in the resulting conclusions.

Since there is no one correct (acceptable) method for performing an equity analysis (Allard, 1984), the task becomes one of choosing the most appropriate model for the circumstances and intended purposes. Three major purposes for conducting a salary equity study are to (1) explain the salary reward system of the institution, (2) predict and monitor individual salaries, and (3) detect if bias exists (Allard, 1984). If the major purpose is to explain or predict salary levels, including both sexes in the equation with all variables thought to be related to salary level is appropriate. However, if the purpose is to detect existing bias, the equation is generally built on the nonprotected class (e.g., males) and applied to the protected class (e.g., females). Furthermore, including potentially tainted variables may mask the degree of assessed sex bias.

The major purpose of this study was to examine different models for studying salary equity, along with their assumptions and conclusions. The models examined vary along two dimensions: the sample (male vs. two-sex model) and the predictor variables used to build the regression equations.

The two-sex model uses the entire data set (both sexes) to build the salary equation. This model is based on the administrative assumption that there is no bias in salary, and for this reason may be more likely to be accepted by administrators who are concerned with admitting guilt. This method is appropriate when the purpose of the salary equity study is to predict or explain salaries (Allard, 1984), or when the observed values for the predicted variables are markedly different for the protected and nonprotected groups (Greenfield, 1977). However, some argue that it is inappropriate when determining if bias exists (Braskamp, Muffo, and Langston, 1978; Gray and Scott, 1980; Scott, 1977).

The alternative suggested for studying bias is the male model, which uses data from males to build the salary equation and then applies the equation to females to predict what their salaries would be if they were being paid on the same basis as males. The difference between actual and predicted female salaries indicates how well female faculty are treated with respect to their male counterparts. The male model is based on the assumption that there is potential for salary inequity, and works well when there are many males and few females (Allard, 1984), and where there are not large differences between protected and nonprotected groups on predictor variables (Hengstler and McLaughlin, 1985).

Although there are claims that the model chosen will differentially affect conclusions, an empirical examination of results with different models would more clearly portray their differences. The empirical effects of using the male versus the two-sex model were investigated in this study. In addition to determining which sample is most appropriate to include when developing the regression equation, the investigator must also determine which predictor variables to use. Omitting relevant variables from the equation may severely reduce prediction and not allow for an accurate test of sex bias in salary. Including relevant but tainted variables in the equation may also mask the degree of bias in salary (Barnes, 1983). Empirically examining the effects of various predictor sets was also undertaken in this study. The goal was to choose the alternative that gave the most accurate indication of bias, yet maintained a sufficient level of predictive accuracy.

Since a comprehensive salary analysis requires an analysis of discrimination in rank and tenure as well, discriminant function analyses were used to predict rank and tenure status from information contained in official university records. Assuming that reasonably accurate predictions could be made, the study determined whether or not gender biases could be inferred as existing in these variables. Furthermore, incorporating predicted rank and tenure into the regression equation was compared with other models to determine if sufficient predictive accuracy was achieved.

METHOD

Subjects

All 9 or 10 tenths permanent teaching, research, and library faculty (including department heads) who were appointed at a large midwestern university for FY 1986 were identified. Part-time and temporary personnel were excluded. Of the 1,057 eligible faculty members, 19 were excluded on the basis of missing information for the two-sex model. Of the 871 eligible male faculty members, 13 were excluded on the basis of missing information for the male model.

Procedure

Seventeen items of information were used as independent variables in this study: years of education, educational level, years since degree, initial monthly salary, years since last appointment, type of appointment (9 or 12 month), split pay (from two or more departments), rank, years in rank, tenure, years tenured, average merit score, years in merit system, department, terminal degree level required by department, department responsibility (department head status combined with size of department), and prior work experience. Descriptive statistics for these variables for males, females, and the total sample are provided in Table 1.

In this study, "Department Head Status" and "Educational Level" were both treated as continuous variables. Non-department heads were assigned a value of 0, while department heads were given values ranging from 1 to 4 depending on the size of the department. Similarly, those whose highest degree was a bachelor's were assigned a value of 2, while those with master's, doctoral, and postdoctoral educations were categorized 3, 4, and 5, respectively.

"Prior Employment" and "Department" were treated using a "dummy variables" approach (Cohen and Cohen, 1975). A value of 1 was used to indicate that the individual was a member of the category (prior employment group or specific department) and 0 was used to show nonmembership. By treating "department" in this way, market factors were accounted for in our equation (e.g., Engineering faculty receiving higher average salaries than English faculty). The larger issue of women concentrating in lower-paying disciplines (or the decrease in discipline salary when the field becomes predominantly female) was not directly addressed in this study, but market differences were accounted for by the dummy coding. Only biasing factors "internal" to the university were assessed.

The two "merit" variables also require an explanation. By policy, salary adjustments at KSU are intended to reflect "merit" exclusively, and recommended percentage increases are reviewed annually for consistency with written merit evaluations. Therefore, the size of the percentage increase, relative to that for all faculty members, is a good proxy for "merit" or "level of professional contribution" during the preceding year. Because the amount available for merit increases varies from year to year, the study employed a "standardized" measure of merit. Beginning with the year 1976–77, each faculty member's percentage increase for a given year was expressed as a T-score (mean = 50; standard deviation = 10). The average of these standardized measures was used as a measure of "merit." The number of years used in calculating this average was also used as an indicator of the stability of the merit T-score.

The dependent variables in this study were salary, rank, and tenure for FY 1986. Rank and tenure were also used as independent variables in some cases. Only regularly appointed individuals with ranks of instructor through professor were used, and tenure status was coded as not eligible, not tenured, and tenured.

Analysis

Different analytical approaches were required to predict salary versus rank

TABLE 1. Descriptive Statistics for Independent Variables: Male, Female, and Total Samples

		Males (N=871)		Females (N=186)		Total (N=1057)	
Predictor		Mean	S.D.	Mean	S.D.	Mean	S.D.
Years of education[a]		20.1	1.9	19.2	1.7	19.9	1.9
Years since degree		15.5	8.8	10.8	7.7	14.6	8.8
Initial salary month		1435.5	885.6	1197.7	738.0	1394.1	866.1
Years since last appt.		12.0	9.1	8.3	7.6	11.4	9.0
Years in rank		5.1	5.5	3.6	4.3	4.9	5.3
Years tenured		8.5	8.4	4.0	6.2	7.7	8.2
Merit index		50.2	5.4	51.2	6.0	50.4	5.5
Years, merit index		6.3	3.4	4.7	3.5	6.0	3.4
Educational level		3.8	0.5	3.5	0.6	3.7	0.5
Dept. responsibility[b]		0.2	0.6	0.0	0.3	0.1	0.6
Terminal degree level[c]		1.9	0.3	1.8	0.4	1.9	0.3
		N	%	N	%	N	%
Rank:	Instructor	35	4.0	47	25.3	82	7.8
	Asst Prof	186	21.4	73	39.2	259	24.5
	Assoc Prof	255	29.3	44	23.7	299	28.3
	Professor	395	45.4	22	11.8	417	39.5
Type appt.:	9 mos.	470	54.0	116	62.4	586	55.4
	12 mos.	401	46.0	70	37.6	471	44.6
Split appt.:	Yes	5	0.6	1	0.5	6	0.6
	No	866	99.4	185	99.5	1051	99.4
Dept head:	Yes	55	6.3	4	2.2	59	5.6
	No	816	93.7	182	97.8	998	94.4
Tenure:	Not eligible	19	2.2	12	6.5	31	2.9
	No tenure	192	22.0	84	45.4	276	26.1
	Tenured	660	75.8	89	48.1	749	70.9
Prior Emp.:	4-yr coll	478	54.9	104	55.9	582	55.1
	Jr. coll	4	0.5	3	1.6	7	0.7
	High sch	12	1.4	8	4.3	20	1.9
	Student	77	8.8	21	11.3	98	9.3
	Government	55	6.3	4	2.2	59	5.6
	Self-empl	20	2.3	2	1.1	22	2.1
	Industry	86	9.9	5	2.7	91	8.6
	Other	49	5.6	14	7.5	63	6.0
	Unknown	90	10.3	25	13.4	115	10.9

[a] 1 = High school; 2 = B.A.; 3 = M.A.; 4 = Ph.D.; 5 = postdoctoral.

[b] 0 = Non-head; 1 = head, small dept.; 2 = head, med. dept.; 3 = head, large dept.; 4 = head, very large dept.

[c] 1 = M.A. is terminal degree; 2 = Ph.D. is terminal degree.

and tenure. Since salary is a continuous variable, a multiple regression approach was employed. Discriminant analysis was appropriate for predicting rank and tenure because they are best conceptualized as categorical variables.

The following models were analyzed using data from the total sample (two-sex model) and from males only (male model):

All Variable Model

This model used multiple regression analysis to predict salary on the basis of the 17 variables described previously. All variables hypothesized to be related to salary level (for which data could be obtained), regardless of possibility for bias in predictor variables, were included.

Model with Rank and Tenure Excluded

This model used multiple regression analysis to predict salary on the basis of variables described previously, with the exception of rank, tenure, years at current rank, and years tenured.

Model with Predicted Rank and Tenure

This model involved initially predicting rank and tenure from more objective predictor variables, and then entering the resulting predicted values into the equation to predict salary (Ramsay, 1979; Riggs et al., 1986). Rank and tenure were predicted using the following variables: years of education, educational level, years since degree, split pay, years since last appointment, prior work experience, average merit score, years in merit system, terminal degree required by department, and total years at the institution (including discontinuous service).

Discriminant function analyses were used to weight and linearly combine the predictor variables to maximize the statistical distinctions between those faculty with different ranks and tenure status. All predictors were entered into the equation concurrently, regardless of their discriminating power. Since the proportion of faculty members in each rank and tenure status group was known, prior probabilities based on the size of each group were used to adjust the projected probabilities of group membership for each analysis.

The final step in this model was to replace actual rank and tenure with predicted rank and tenure in the regression equation to predict salary. Other variables used to predict salary for this model were those not previously used to predict rank and tenure: department, initial monthly salary, type appointment, date rank, years tenure, and department responsibility.

Objective Model

This model predicted salary with only those variables that have little potential for internal bias (i.e., bias resulting from procedures at the employing university): years of education, educational level, years since degree, split pay, years since last appointment, department, terminal degree required by department, and prior work experience.

RESULTS

Rank and Tenure Predictions

Discriminant function analysis was conducted to obtain the predicted rank values for the predicted rank and tenure model. For rank, overall prediction accuracy for both total and male models was approximately 70%. Males, however, were predicted more accurately than were females (71.9% for males vs. 61.7% for females—total model; 72.1% for males vs. 57.7% for females—male model). Overprediction (predicted salary higher than actual salary) and underprediction (predicted salary lower than actual salary) occurred at different rates for males and females. Both models resulted in a higher percentage of overpredictions for females; 12.0% under and 26.3% over for females vs. 15.2% under and 12.9% over for males—total model; and 12.0% under and 30.3% over for females vs. 13.6% under and 14.3% over for males—male model.

In the discriminant function analyses conducted to predict tenure, both models predicted with approximately 90% accuracy.[1] As with rank prediction, males were more accurately predicted (92.0% for males vs. 83.9% for females—total model, 91.4% for males vs. 79.3% for females—male model). For both models, females were once again more likely to be overpredicted, while males were more likely to be underpredicted: 4.6% under and 11.5% over for females vs. 5.7% under and 2.2% over for males—total model; 5.7% under and 14.9% over for females vs. 6.3% under and 2.2% over for males—male model.

Salary Predictions

The R^2 and standard error of prediction for the eight regression models implemented in this study are listed in Table 2. All of the R^2 showed little shrinkage when corrected for number of subjects and variables. Predictive accuracy was good for the all variables model, the rank and tenure excluded model, and the predicted rank and tenure model. The objective variables only model was less accurate.

Standardized beta weights from the eight regression solutions are not listed.

TABLE 2. Regression Statistics and *t*-Test Results for Comparisons Between Predicted Male and Predicted Female Salaries from All Models

Regression Models	*R* Squared	Std. Error	Actual-Predicted: Males	Actual-Predicted: Females	Difference: Males-Females
1. All variables					
Total Sample	0.82	4250.1	57.37	−284.54	341.91
			t (305.4) = 1.20, p = .11		
Males only	0.79	4419.0	0.00	−534.70	534.70
			t (1029) = 1.55, p = .06		
2. Rank and tenure out					
Total sample	0.76	4875.8	184.14	−908.00	1092.14
			t (309.9) = 3.38, p <.001		
Males only	0.73	5049.9	0.00	−1517.68	1517.68
			t (1030) = 3.86, p <.001		
3. Objective variables					
Total sample	0.51	7053.1	423.39	−2059.55	2482.94
			t (328.2) = 5.48, p <.001		
Males only	0.44	7297.1	0.00	−3206.99	3206.99
			t (299.6) = 6.62, p < .001		
4. Predicted rank and tenure					
Total sample	0.75	5062.6	159.21	−787.73	946.94
			t (360.7) = 2.79, p<.01		
Males only	0.71	5252.8	0.00	−1392.87	1392.87
			t (277.8) = 3.80, p < .001		

Note: t-tests were one-tailed.

Since variables were entered simultaneously, their order and relative importance to each solution is somewhat arbitrary. A different order would produce different relative weights, but would not affect the overall level of prediction. The inclusion of department as a dummy coded variable to account for market differences in salaries was successful, and these differences did not appear to contaminate the results. This approach is recommended as a way to deal with this problem.

Results of the salary predictions based upon each of the eight regression solutions are also shown in Table 2. Differences between actual and predicted salaries were computed for all subjects. The means of these differences are reported separately for males and females by model. Positive numbers indicate that actual salaries were higher than those predicted by the equation; negative numbers mean actual salaries were lower than those predicted. Male differences were positive for all total sample models and zero for all male model solutions (as dictated by the nature of the solution). Female differences were negative for all models.

Differences between the means of actual minus predicted salaries for men and women are also reported in Table 2, along with *t*-test results for each pair of means. Where variances were found to be significantly different between the male and female samples, an approximation of the *t*-test was used (Nie et al., 1975, p. 269). The mean differences can be interpreted as indicators of the degree of gender-based favoritism suggested by each model. Male models always produced larger differences between males and females within variable choice models, but *t*-test conclusions were always the same for both male and total sample models within variable choice conditions. Neither regression solution based upon the all variables model produced significant differences between men and women. The remaining *t*-tests for all other models and samples were significant.

DISCUSSION

The results indicate that model choice significantly affects the investigator's conclusions regarding bias in salary, and that the use of biased predictors (i.e., those that inequitably favor males over females) can mask the occurrence of salary bias. Although similar conclusions were reached regarding the existence of bias within each variable choice model whether the sample included only males or both sexes, the extent of potential bias was always greater in the male only condition. Using the male model instead of the two-sex model magnified sex differences in actual-predicted salary, decreased R square, and increased standard error because information based on females was not included in the equation and the number of subjects was smaller. Variable choice had a more significant impact than did choice of sample. The all variables model indicated no bias in salary, whereas the other three variable choice models indicated potential for bias in varying degrees.

The major purpose of the paper was to investigate potential models for studying salary equity and to compare the benefits and drawbacks of each. Two variable choice models were deemed inappropriate for a sufficient equity analysis with this data set. The all variables model, even though it resulted in the highest level of predictive accuracy, was discarded due to the inclusion of tainted variables (i.e., rank and tenure status) in the model. The separate analysis on rank and tenure indicated that women's rank and tenure levels were predicted at a lower level of accuracy than men's. Furthermore, women's rank and tenure were overpredicted (predicted rank and tenure higher than actual rank and tenure) more often than underpredicted, while the opposite was true for men. This indicates that the policies for granting rank and tenure are applied more consistently to men, and in a more favorable fashion. The inclusion of tainted variables (rank and tenure) in the regression equation to predict salary would mask the degree of sex bias in salary.

The objective variables model was also limited with this data set because of its low level of predictive accuracy. This model indicated the greatest degree of bias against women; however, relevant variables (e.g., rank and tenure), have been omitted from the equation, thereby magnifying the level of apparent bias. If relevant variables were included that were positively associated with being male, the level of apparent bias would be reduced.

Two variable choice models remained: rank and tenure excluded and predicted rank and tenure. Rank and tenure are sometimes excluded from the model in order to avoid the problem of bias within rank or tenure (Scott, 1977), but this procedure has not always succeeded in the courts (*Presseisen* v. *Swarthmore College*, 1978) and ignores the issue of whether or not bias has occurred in rank or tenure status. Including *predicted* rank and tenure in the model allows for the influence of these variables in a more objective way, and gives a more accurate indication of salary bias.

These two models essentially obtained the same level of predictive accuracy, and both indicated bias against women in salary. In retrospect, the equivalence of predictive accuracy for the two models is not surprising since the same set of variables was entered in both equations in slightly different ways. Actual rank and tenure were eliminated from both models, and variables used to predict rank and tenure plus salary (predicted rank and tenure model) were the same as those used to predict salary only (rank and tenure excluded model). The standard error of estimate was slightly greater in the predicted model because more variables were being predicted rather than actual values entered. The level of bias appeared to be slightly greater in the rank and tenure excluded model since predicted rank and predicted tenure (which were higher for men than for women) were excluded from this model. The excluded model, therefore, overestimated the degree of bias. With this sample, the difference between the two models was slight, and the resulting conclusion of existing bias remained, regardless of the model chosen.

The impact of model choice may be greater within a different institution. For example, if women have higher predicted rank and tenure than men, one would expect the rank and tenure excluded model to show an *underestimate* of degree of bias. In any case, the predicted rank and tenure model should give a more accurate indication of level of bias at the institution as compared to the rank and tenure excluded model, since some attempt is being made to account for differential levels of rank and tenure for men and women.

Choice of sample was not of significant consequence with this data set. The similarity of results with the male only and two-sex models was primarily due to the large number of men compared to women in the sample, and consequently the relatively heavy weighting of men's information in the equation. If women make up a larger proportion of the sample and/or their characteristics are much different than men's, results from the male only and total sample would be more divergent.

We do *not* recommend testing all of the above models as a matter of course in an equity analysis. The choice of model should be made on an a priori basis as much as possible. Choosing a sample depends on such things as purpose of study and characteristics of the sample. The decision process can be demonstrated as a series of choice points.

1. If the goal is to explain the salary reward system or to predict and monitor individual salaries, use the two-sex, all variables model to achieve the highest level of accuracy.

2. If the goal is to determine whether equity exists, the decision process is more complex.

a. To determine choice of sample, two questions must be asked: (1) Is the administration concerned with admitting guilt? (2) Are males and females relatively divergent on predictor variables? If the answer to either of these questions is "yes," a two-sex model would be more easily accepted (in the first case) and more statistically appropriate (in the second).

b. To determine which variables to include, follow these guidelines.

1. Simply excluding rank and tenure via the objective variables or rank and tenure excluded models ignores the issue of whether bias exists in these variables and is not recommended. An inaccurate estimate of salary bias is obtained with these models due to the elimination of important relevant variables.

2. A comprehensive equity analysis should include a separate analysis of rank and tenure processes (Szafran, 1982). Because salary, rank, and tenure are intimately linked, evidence of bias in either rank or tenure supports the contention that salary bias also exists (Riggs et al., 1986). Furthermore, action should be taken to correct inequity wherever it occurs—whether in salary, rank and/or tenure.

3. If rank and tenure (or other relevant variables) appear to be tainted, the all variables model should not be used because the degree of bias in salary will be masked. In contrast, if there is no indication of bias in those variables or others included in the model, the all variables model would be the recommended choice because it yields the highest level of predictive accuracy.

4. The model of choice when rank and tenure are tainted is the predicted rank and tenure model, which yields a relatively high level of predictive accuracy. This model also allows for the most accurate indication of salary bias

under these conditions by making some attempt to account for differential levels of rank and tenure for men and women.

A number of caveats are in order with regard to these results. Only two of the variables used in the salary regression analysis were tested for potential bias before being included—rank and tenure. Other variables that were included directly or indirectly but not separately tested may have been tainted to some degree (e.g., written merit evaluations upon which salary increases were based), thereby again masking the degree of sex bias. However, inspection of the data and some preliminary analyses indicated that this did not appear to be a problem in this data set. For example, an earlier analysis predicting initial salary for men and women revealed no bias. Also, the average merit score for women was slightly higher than for men (51.2 vs. 50.2). Researchers should be sensitive to this issue and, where possible, inspect variables for tainting before including them in the analysis.

Caution should also be exercised in concluding that bias exists even when the predicted male-female salary differential is significant. Such a conclusion assumes that all relevant variables have been included in the model (Oschner, Brown, and Markewich, 1985), or that for those relevant variables not included, women tend to score neither higher nor lower than men (Gray, 1985). Variables that are not included in the model because they are difficult to obtain or quantify (e.g., teaching evaluations, commitment to service/administrative functions of the university, number and quality of publications, etc.) could potentially affect the results. If relevant factors are omitted from the model, their effects are included with the random part of the model. Whatever is not included in the regression analysis, relevant or irrelevant, is perhaps mistakenly attributed to sex discrimination (Bodner, 1983).

Since equity analysis results are not conclusive, they should be used as a guide for further investigation (Ott, Brown, and Schmidtlein, 1983). Other relevant variables may be examined to determine their impact on the equity system (Hurley, Brown, and Schmidtlein, 1981). Individuals can be "flagged" for further review to determine if upgrading salary, rank, and/or tenure is appropriate (Braskamp et al., 1978; Riggs et al., 1986). Gray and Scott (1980), however, noted several problems with the flagging technique and suggested a class-action approach to the problem: increasing all women's salaries, thereby bringing the regression line for women up to what it is for men. Whatever approach(es) are taken toward achieving equity, a comprehensive equity analysis should involve a separate investigation of rank and tenure before an investigation of salary is undertaken.

A final caution concerns generalizing results beyond this institution. While the general procedures discussed in the paper can be used at any institution with a large enough sample size and appropriate predictor and criterion data, results achieved when testing the models will differ across institutions with divergent characteristics.

The increasing awareness and concern with equity issues by higher education, along with the escalating litigation, has prompted institutions to undertake salary prediction studies. The major purpose of this study was to compare the results of several alternative methods for conducting these studies. The separate models tested in this study yielded different results that are more or less suitable for specific questions. Institutions that are considering conducting a salary prediction study should find these outcomes helpful in determining an appropriate analytical strategy. Efforts to achieve salary equity, either on an individual or group basis, are not easy endeavors; the search for methods that will help to identify and rectify such inequities needs to continue.

NOTES

1. For the sake of brevity, only a limited number of tables were included. Additional tables on the accuracy of rank and tenure decisions and weighting factors for the regression and discriminant analysis are available upon request from the first author.

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