Analysis of 2x2 Contingency Tables in Educational Research and Evaluation

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Abstract: In research and program evaluation, it is sometimes useful to organize data into 2x2 contingency tables which include frequencies of those which display the presence or absence of one condition along with the presence or absence of a second condition. The present manuscript presents researchers and evaluators with alternative methods for analyzing such data. The reader is introduced to alternatives to the Pearson Chi Square, specifically the Odds Ratio and the Relative Risk Ratio.
Keywords: categorical data; odds ratio; risk ratio

In research and/or program evaluation, it is frequently the case that the type of information of interest is not easily (or meaningfully) translated into convenient measures of average and variability. Instead, we are left with percents or frequencies. The purpose of this manuscript is to discuss how researchers and program evaluators can make use of the 2x2 contingency table as a helpful way to conceptualize, organize, and report data. This is a widely used strategy in medical epidemiology and has been advocated for influencing public policy in the social sciences (Scott, Mason, & Chapman, 1999). In this manuscript, I will draw upon two examples, one in the context of evaluation and the other in research, and offer two useful indices of association, the odds ratio and the relative risk ratio.

A contingency table is constructed of two intersecting categorical variables. For categories to be useful, they must be exhaustive and mutually exclusive (Everitt, 1977). To be exhaustive, the classification scheme must account for <u>all</u> cases. To be mutually exclusive, an individual or case must fit into only one category. In the special condition of the 2x2 contingency table, each category must also be dichotomous; that is, each category has two possibilities. A 2x2 contingency table can thus be thought of as the intersection of the presence or absence of condition 1 with the presence or absence of condition 2. The four resulting combinations can be identified by the letters a to d as follows (table 1).

Table 1
Pattern of Categories in a 2x2 Contingency Table

	Condition 2	
Condition 1	Present	Absent
Present	a	b
Absent	c	d

Use of a 2x2 Contingency Table in Evaluating an Intervention

Getting busy professionals to engage in a new behavior is often difficult. In the case of physicians in training, they are beleaguered with multiple demands for new procedures. Diabetes is a complex metabolic disease that, when poorly controlled, has a high risk of multiple, negative complications. The arrival of a new, relatively simple blood test to assess quality of patients' diabetes control was thus an important step forward in their treatment. Unfortunately, physicians were not routinely ordering the test. The problem facing the team was how to alter their behavior.

A simple intervention was conceived. When a patient with diabetes was scheduled for an appointment a computerized reminder was randomly generated for some but not other patients. The computerized reminder was posted on the front of the patient's chart and it told the physician not to forget to give the blood test. The results of the intervention were as follows (table 2).

Table 2
Physician Administered Blood Tests When Reminded or Not Reminded

Administered the Blood Test			
Received Reminder	Yes	No	All
Yes	33	3	36
No	10	14	24
All	43	17	60

Chi Square (χ^2)

A simple test of the relationship between the two categorical variables is often assessed through the application of the Chi-Square (χ^2) statistic (sometimes called the Pearson Chi-Square). The null hypothesis tested with χ^2 using a 2x2 contingency table is described as a test of independence. If the null hypothesis is valid, the observed frequencies should not differ by more than chance from the expected frequencies. Expected cell frequencies are the values that would result if the two independent dichotomous proportions were combined. As the observed frequencies diverge from the expected frequencies, the value of χ^2 increases. Computationally, for each cell of the contingency table, the investigator compares the Observed Frequency (O) and the Expected Frequency (E). These comparisons are combined using the formula:

$$\chi^2 = \Sigma \frac{(O-E)^2}{E}$$

That is, in each cell the difference between the Observed and Expected Frequencies is squared, then that product is divided by the cell's Expected Frequency. The results of these computations for each cell are then summed.

To hand calculate the value of χ^2 one must find the E values for each cell; to do that one must first compute the "marginal values" and the total number of cases (N). The marginal values are simply the number of cases in each row and the number of cases in each column. The expected likelihood of a case falling into row 1 ($\boldsymbol{p}_{r1}$) or row 2 ($\boldsymbol{p}_{r2}$) is simply the marginal number of cases for the row, divided be the total number of cases. For the data in Table 2, 36 of 60 patients' charts (60 percent) were so noted. Likewise the respective column probabilities ($\boldsymbol{p}_{c1}$ and $\boldsymbol{p}_{c2}$) are the marginal column totals divided by the overall total. If variable 1 and variable 2 are independent, that is randomly associated, the expected frequency for each cell_{ij} is the product of the corresponding row ($\boldsymbol{p}_{ri}$) and column ($\boldsymbol{p}_{cj}$) probabilities multiplied by the total number of cases or, more simply, the product of the marginal totals for the respective row (R_i) and column (C_j) divided by the total number of cases:

$$E_{ij} = \left(p_{ri}\right)\left(p_{cj}\right)N = \frac{R_i C_j}{N}$$

The expected frequency for cell a (cell_a) of the intervention data is thus:

$$E_{11} = \frac{R_1 C_1}{N} = \frac{36 * 43}{60} = 25.8$$

Repeating this process for each cell results in a 2x2 table of expected ($\boldsymbol{E}_{ij}$) value. To compute, the value of χ^2 requires that, for each cell, the difference for each observed cell frequency and its expected frequency be squared and the result divided by the expected frequency. The result of each of those computations is then summed.

$$\chi^2 = \Sigma \frac{\left(O - E\right)^2}{E} = \frac{\left(33 - 25.8\right)^2}{25.8} + \frac{\left(3 - 10.2\right)^2}{10.2} + \frac{\left(10 - 17.2\right)^2}{17.2} + \frac{\left(14 - 6.8\right)^2}{6.8} = 17.73$$

Fortunately for all concerned, however, most standard statistical packages, such as SPSS and others provide, in their procedures, chi square computations that create contingency tables. In the case of SPSS, one relies on the CROSSTABS routine. At what point can one conclude that the χ^2 is sufficiently large to reject the null hypothesis of independence? The answer lies in a table of critical values for the χ^2 distribution that is associated with differing "degrees of freedom." In the generic case, degrees of freedom for a χ^2 test of independence are defined as the number of rows less one (r-1) multiplied by the number of columns less one (c-1). Since, in the 2x2 contingency table, r-1=1 and c-1=1, the critical values lie in the χ^2 distribution with 1 degree of freedom. To select the appropriate critical value the investigator must elect a level of risk of Type 1 error (α: the risk of mistakenly rejecting a true null hypothesis). Commonly used critical values for $\chi^2_{df=1,1-\alpha}$ are presented in table (3).

Table 3
Critical values of χ^2 with 1 degree of freedom at varied levels of 1-α:

P or (1-α) α	.95 *.05*	.975 *.025*	.990 *.01*	.999 *.001*
Critical $\chi^2_{1,1-\alpha}$	3.841	5.028	6.635	10.828

Thus, given a $\chi^2_{df=1}$ = 17.73, the chances of finding a $\chi^2_{df=1}$ that large is quite remote, less than 1 in 1000. The null hypothesis of independence is rejected. Therefore, it may be concluded that the intervention was an effective mechanism for altering the physicians' behavior.

In some instances, when sample sizes are small (less than 5), some statistics textbooks, especially older texts, suggest that the computed χ^2 be adjusted using the Yates Continuity Correction. The formula is adjusted by subtracting the value 0.5 from the absolute difference between the observed and expected value and squaring the result prior to dividing by the expected value.

$$\chi^2 = \sum \frac{\left(\left|O - E\right| - 0.5\right)^2}{E}$$

Were we to apply the Yates correction to the runaway data, the corrected $\chi^2_{df=1}$ would be 102.062, still significant at the .001 level. Some indicate that Yates correction should be applied generally (Everitt, 1977; Fliess, 1986; Rosner, 1986). However, other reviews (e.g., Brown, 1985; Conover, 1999; Overall, 1980) suggest that not only is the "correction" unnecessary, it may affect our risk of Type I error. I agree with Brown (1985) who concludes that if the results are so borderline that the conclusions would change by applying the Yates correction, "the research should be considered suggestive but not conclusive" (p. 414).

The existence of a statistically significant Pearson $\chi^2_{df=1}$ for a 2x2 contingency table justifies rejecting the null hypothesis of independence.

The $\chi^2_{df=1}$ does not, however, provide the investigator of a sense of the magnitude or the direction of the effect. One can look over the data and conclude from the example that those who received the reminder were more likely to request the blood test than those who did not receive the reminder. It would, however, be more instructive if we could have an index of the magnitude and the direction of the relationship. One such index that provides such assessments is the Odds Ratio (Everitt, 1977; Rosner, 1986; Conover, 1980; McNutt & Woolson, 1988; Morris & Gardner, 1988). The Odds Ratio is described below.

Suppose we were to ask the question: What is the relative likelihood that more adolescents with a history of running away are more likely to contemplate dropping out of school? An odds ratio or a risk ratio gives us a direct assessment of that question.

The Odds Ratio

The Odds Ratio (OR) index permits us to compare the odds in one group of displaying the targeted outcome to not displaying the outcome to the comparable odds in the second group. In this instance among those physicians who received the reminder, the ratio of the number who requested the test (a) to the number not requesting the test (b) or a:b is compared to the comparable ratio of those who did not get the reminder (c:d). The OR is thus:

$$OR = \frac{\left(a/b\right)}{\left(c/d\right)}$$

And, with some minor algebra

$$OR = \frac{\left(a/b\right)}{\left(c/d\right)} = \frac{a*d}{c*b}$$

If the likelihood of the outcome was the same for both samples runaways and non-runaways, the expected value of OR is 1.00. To the degree that the odds in sample 1 exceed the odds in sample 2, OR will be greater than 1.00. Alternatively, if the odds of the outcome in sample 1 are less than in sample 2, OR will be less than 1.00. Viewing the physician intervention data:

$$OR = \frac{a*d}{c*b} = \frac{33*14}{10*3} = \frac{462}{30} = 15.4$$

That is, physicians who received the reminder were 15.4 times as likely to request the test as those who did not receive the reminder. Practically, this communicated much more directly to hospital administrators than reporting the chi-square.

Relative Risk

The second alternative is a Relative Risk (RR) index. The use of RR allows us to compare the likelihood of our targeted outcome occurring in one sample relative to the likelihood of the outcome occurring in the other. The proportion of those who display the targeted outcome in sample 1: a/(a+b) is compared to the proportion of those who display the targeted outcome in sample 2: c/(c+d). RR is thus:

$$RR = \frac{a/(a+b)}{c/(c+d)}$$

If the likelihood of the outcome was the same in the two samples, the expected value of RR is 1.00. To the degree that the likelihood of the outcome in sample 1 exceeds sample 2, RR will be greater than 1.00. Alternatively, if the likelihood of the outcome in sample 1 is less than in sample 2, RR will be less than 1.00. Drawing on the example of the physicians educational intervention:

$$RR = \frac{a/(a+b)}{c/(c+d)} = \frac{33/(33+3)}{10/(10+14)} = 2.2$$

That is, the likelihood of administering the blood test among those physicians who received the intervention was 2.2 times as likely as those who did not receive the intervention.

Use of a 2x2 contingency table in a research context

In an earlier study (Ingersoll & Orr, 1989) various risk factors among middle school aged adolescents were examined. The sample consisted of 1418 students in grades 7, 8, and 9. For purposes of this discussion attention will be focused on students' responses to a question regarding one's intention to drop out of school. The item stated "I have thought about dropping out of school." To which a student could indicate "Never," "Once in a while," "Frequently," or "Nearly always." Responses were coded into a dichotomous variable (1 Low: Never or Once in a while, and 2 High: Frequently and Nearly always.) Response to dropout risk (low, high) will be assessed as it relates to two dichotomous variables, gender and a history of having ever run away from home. The resulting data for the two conditions can be summarized in 2x2 contingency tables (4&5) as follows:

Table 4
Dropout Risk for Males and Females

Dropout Risk		
Gender	High	Low
Male	43	669
Female	45	624

Table 5
Dropout Risk for Adolescents Who Have and Have Not Run Away From Home

Dropout Risk		
Runaway	High	Low
Ever	53	217
Never	33	1092

Odds Ratio

In the research context, the Odds Ratio (OR) index permits us to compare the odds in one group of displaying the targeted outcome to not displaying the outcome to the comparable odds in the second group. In this instance among those who have a history of running away, the ratio of intent to drop out of school (a) to not intending to drop out of school (b) is compared to the same ratio (a:b) of those without a history of running away (c:d). The OR is again:

$$OR = \frac{\left(a/b\right)}{\left(c/d\right)} = \frac{a*d}{c*b}$$

If the likelihood of the outcome was the same for both samples runaways and non-runaways, the expected value of OR is 1.00. To the degree that the odds in sample 1 exceed the odds in sample 2, OR will be greater than 1.00. Alternatively, if the odds of the outcome in sample 1 are less than in sample 2, OR will be less than 1.00. In the instance of the dropout risk relative to gender (see Table 4), the $\chi^2_{df=1}$ was .27, not statistically significant. The OR for that comparison was 1.1, not different from 1.00. In contrast, consider the runaway and dropout risk data (see Table 5):

$$OR = \frac{a*d}{c*b} = \frac{53*1092}{33*217} = 8.082$$

That is, adolescents who have a history of running away are 8.1 times as likely to contemplate dropping out of school. The $\chi^2_{df=1}$ was 104.93, suggesting statistical significance.

Hypothesis-testing using the Odds Ratio

The $\chi^2_{df=1}$ offers a direct test of the statistical significance of the relationship, but most writers encourage the establishment of confidence intervals around the index. The null hypothesis being tested is that OR = 1.00. The observed OR (OR_{obs}), is an estimate of the real OR, based on the available samples. A confidence interval provides a band within which the investigator can say, with a predetermined level of confidence, that the real OR is found. If the confidence interval includes the null hypothesis, that is, it overlaps 1.00, the null hypothesis is retained. The calculation of the confidence interval for OR requires the transformation of the data using natural logarithms.[1] The standard error of the $\log_e OR_{obs}$ (McNutt & Woolson, 1988, Morris & Gardner, 1988) is:

$$SE\left(\log_e OR_{obs}\right) = \sqrt{\frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}}$$

The lower and upper bounds of the confidence interval ($\log_e OR_L$, $\log_e OR_U$) are defined as:

$$CI_{1-\alpha} = \left\{\log_e OR_L ; \log_e OR_U\right\} = \log_e OR_{Obs} \pm Z_{1-\alpha/2} * SE\left(\log_e OR_{Obs}\right)$$

This can also be express as

$$P\left[\log_e OR_L \leq \log_e OR_{True} \leq \log_e OR_U\right] = 1-\alpha$$

where $Z_{1-\alpha/2}$ is the two-tailed critical value of Z, given a predetermined level of α. If α is established at .05, the two-tailed critical value is 1.96. Establishing a 95 percent confidence interval around the OR_{obs} for the runaway and dropout risk data:

1 The author has generated an Excel program that computes all these values and may be accessed at http://www.fedu.uaeu.ac.ae/main-pages/resources.html. To use the program one simply enters the four cell frequencies. The program produces all values referred to in this manuscript.

$$SE\left(\log_e OR_{obs}\right) = \sqrt{\frac{1}{a}+\frac{1}{b}+\frac{1}{c}+\frac{1}{d}} = \sqrt{\frac{1}{53}+\frac{1}{217}+\frac{1}{33}+\frac{1}{1092}} = .234$$

Computing the natural log of the observed OR:

$$\log_e OR_{obs} = \log_e(8.082) = 2.090$$

The 95 percent confidence interval is thereby established by

$$CI_{1-\alpha} = \left\{\log_e OR_L ; \log_e OR_U\right\} = \log_e OR_{Obs} \pm Z_{1-\alpha/2} * SE\left(\log_e OR_{Obs}\right)$$

$$CI_{1-\alpha} = 2.090 \pm 1.96 * .234 = \{1.631;2.548\}$$

Or

$$P\left[\log_e OR_L \le \log_e OR_{True} \le \log_e OR_U\right] = 1-\alpha$$

$$P\left[1.631 \le \log_e OR_{True} \le 2.548\right] = .95$$

However, we prefer to convert these values back to the normal metric upon which they are based. To do this we take the antilog of each of the limits. Since the base of the natural logarithm system is ***e*** (2.7182818),

$$\boldsymbol{e}^{1.631} = 5.11 \qquad \boldsymbol{e}^{2.548} = 12.78$$

Thus

$$P\left[OR_L \le OR_{True} \le OR_U\right] = 1-\alpha$$

$$P\left[5.11 \le \log_e OR_{True} \le 12.78\right] = .95$$

Since the lower limit of the confidence interval is greater than 1.0, we can reject our null hypothesis of no relationship.

Relative Risk

In the research context, the use of RR allows us to compare the likelihood of our targeted outcome occurring in one sample relative to the likelihood of the outcome occurring in the other. The proportion of those who display the targeted outcome in sample 1: a/(a+b) is compared to the proportion of those who display the targeted outcome in sample 2: c/(c+d). RR is again:

$$RR = \frac{a/(a+b)}{c/(c+d)}$$

If the likelihood of the outcome was the same in the two samples, the expected value of RR is 1.00. To the degree that the likelihood of the outcome in sample 1 exceeds sample 2, RR will be greater than 1.00. Alternatively, if the likelihood of the outcome in sample 1 is less than in sample 2, RR will be less than 1.00. Drawing on the runaway example:

$$RR = \frac{a/(a+b)}{c/(c+d)} = \frac{53/(53+217)}{33/(33+1092)} = 6.692$$

That is, among those adolescents who had a history of running away are 2.9 times as likely to plan to drop out of school as those who did not have a history of running away. It may be seen that in describing the relationships assessed through both in the use of $\chi^2_{df=1}$ and the odds ratio I have avoided using causal language. Much as I might like to conclude: Dropout risk is a function of having a history of running away", the analysis does not justify that level of inference. The same limits for the use of causal language for associational, categorical data apply as do with correlation analyses (Kraemer, 2006). In the research context, however, we also want to assess whether the relationship is statistically significant.

Hypothesis testing using the Risk Ratio

Like the OR, the null hypothesis being tested is that RR = 1.00. The obtained or observed RR (RR_{obs}), is an estimate of the real RR, based on the available samples. The standard error of the $\log_e RR_{obs}$ (McNutt & Woolson, 1988; Morris & Gardner, 1988) is:

$$SE\left(\log_e RR_{obs}\right) = \sqrt{\frac{1}{a} - \frac{1}{(a+b)} + \frac{1}{c} - \frac{1}{(c+d)}}$$

The lower and upper bounds ($\log_e RR_L$, $\log_e RR_U$) of the confidence interval for 1-∀ are defined as:

$$CI_{1-\alpha} = \{\log_e RR_L; \log_e RR_U\} = \log_e RR_{Obs} \pm Z_{1-\alpha/2} * SE\left(\log_e RR_{Obs}\right)$$

This can also be express as

$$P\left[\log_e RR_L \le \log_e RR_{True} \le \log_e RR_U\right] = 1-\alpha$$

where $Z_{1-\alpha/2}$ is the normal, two-tailed critical value of Z, given a predetermined level of α. If α is established at .05, the two-tailed critical value is 1.96. Establishing a 95 percent confidence interval around the RR_{obs} for the cognitive maturity data:

$$SE\left(\log_e RR_{obs}\right) = \sqrt{\frac{1}{a} - \frac{1}{(a+b)} + \frac{1}{c} - \frac{1}{(c+d)}}$$

$$SE\left(\log_e RR_{obs}\right) = \sqrt{\frac{1}{53} - \frac{1}{(270)} + \frac{1}{33} - \frac{1}{(1125)}} = .211$$

Computing the natural log of the observed RR:

$$\log_e RR_{Obs} = \log_e\left(6.692\right) = 1.901$$

The 95 percent confidence interval is thereby established by:

$$CI_{1-\alpha} = \left\{\log_e RR_L ; \log_e RR_U\right\} = \log_e RR_{Obs} \pm Z_{1-\alpha/2} * SE\left(\log_e RR_{Obs}\right)$$
$$CI_{1-\alpha} = 1.901 \pm 1.96 * .211 = \left\{1.487; 2.315\right\}$$

or

$$P\left[\log_e RR_L \le \log_e RR_{True} \le \log_e RR_U\right] = 1-\alpha$$
$$P\left[1.487 \le \log_e RR_{True} \le 2.315\right] = .95$$

However, we prefer to convert these values back to the normal metric upon which they are based.

$$e^{1.487} = 4.424 \qquad e^{2.315} = 10.122$$

Thus

$$P\left[RR_L \le RR_{True} \le RR_U\right] = 1-\alpha$$
$$P\left[4.424 \le RR_{True} \le 10.122\right] = .95$$

Since the lower limit of the confidence interval is greater than 1.0, we can reject our null hypothesis of no relationship.[2]

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[2] It is sometimes desirable to frame the question in the opposite form. That is, those with the presence of a condition are less likely to display an outcome. In that case, the process in the same but the resulting ratio is less than 1.0 and the limits of the confidence interval are also less than 1.0.

Cautions

Both the RR and OR indices convey information about the likelihood that one group displays a targeted outcome relative to a second group. The difference in interpretation of the two indices is reflected in their formulas.

In the case of the Relative Risk ratio, RR is the ratio of the proportion of all members of group 1 who display the targeted outcome [a/(a+b)] relative to the proportion of all members of group 2 who display the targeted outcome [c/(c+d)]. In the case of the Odds Ratio, OR is the ratio of the odds of those in Group 1 who display the targeted outcome to those who do not [a:b] relative to the odds of those in Group 2 who display the targeted outcome to those who do not [c:d]. The RR is a ratio of relative proportions; the OR is a ratio of relative odds.

Some cautions should be noted about the use of the 2x2 contingency table as a model of choice. In part, one caution has already been put forth. That is, the typical 2x2 implies independence of sampling. An investigator may wish to exert control over the sampling process by using matched pairs of subjects. Alternatively, an investigator may employ a pre-test post-test design. The resulting 2x2 table would look exactly like the 2x2 tables we have addressed. However, applying the assessments described in this article would be inappropriate; the McNemar test (Everitt, 1977; Fliess, 1986) would offer a more appropriate assessment of the results.

In a research model, there is an assumption that the samples which constituted the groups were independent and randomly selected from a larger parent population. To the extent that the samples are not random samples from a larger parent population, the ability of the researcher to generalize to the larger population is jeopardized.

There is some risk, in larger studies, of collapsing too much data into a single 2x2 table. First, if a continuous variable is compacted into a dichotomous variable, the choice of dividing points may have an effect on the character of the relationship. By and large, if stable, usable continuous variable data are available, they are usually preferable to dichotomous data. Similarly, a 2x2 table may be compiled over a third (or more) variable which covaries with the outcome of concern. For example, long-term risk of dropping out of school may be contaminated with the age of the group under study. It may be helpful under such circumstances to create multiple 2x2 tables across strata. That is, a 2x2 table for those in the age range 10 to 11 years old, a 2x2 table for those in the age range 12-13 to 50 years old, a 2x2 table for those in the age range 13-14 years old, etc. Still, what one wants from such a breakdown is a composite assessment. To accomplish that end, one needs to apply a somewhat more complex analysis, sometimes called the Mantel-Haentszel technique which produces an odds ratio across strata (Mantel & Haentzel, 1959; Davis, 1991).

Finally, it is often the case that an investigator has multiple outcomes toward which this model might be applied. It should be warned that the "experiment-wise" error rate across the several χ^2 or odds ratio analyses may no longer be the same as originally intended. The reader who wishes a more in-depth and advanced treatment of methods of analyzing 2x2 contingency tables is referred to Kraemer (2006).

Those cautions notwithstanding, the 2x2 contingency table offers a valuable addition to one's analytic arsenal.

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Note

1 If you were to read the output of a CROSSTABS analysis from SPSS, the uncorrected χ^2 is labeled the "Pearson" and the Yates corrected χ^2 is labeled "Continuity Correction." SPSS presents the <u>exact</u> probability of the

χ^2, thus, one compares the exact probability to the pre-established level of statistical significance (a). If the exact probability is less than a, then the null hypothesis is rejected.