Reconsidering Cramér’s Measure of Association

Kaloyan Haralampiev[1, a)] and Dimitar Blagoev[1, b)]

[1]*Sofia University “St. Kliment Ohridski”, Department of Sociology, Faculty of Philosophy, Sofia, Bulgaria*

[a)] Corresponding author: k_haralampiev@phls.uni-sofia.bg
[b)] dblagoev@phls.uni-sofia.bg

Abstract. Although there is as a long history of application of different statistical measures of association in diverse fields of modern sciences, their inherent universality is very rarely questioned. One of the most commonly used measures of association between categorical variables is the well-established and universally applied Cramér’s coefficient, *V*. It is not until the 1980s, however, when the issues of subjectivity in the choice of proper sizes of association’s strength as well as interpretation of measures in contextual terms are risen. For instance, Cohen [1] discusses the need of particular caution regarding the qualitative conventions for „small“, „medium“, and „large“ effect size (ES) about the quantitative values for his ES index for contingency tables, w. Of particular importance in his argument is the extent of their aptness in a given substantive context, and particularly his idea that what is „subjectively the „same“ degree of association may yield varying w“ [1]. On the other hand, however, he uses three cutoff values regardless of the dimensionality of the table. Since it is contra-intuitive to use the same cutoff values for tables with different dimensions, the question arises whether Cohen's formula for w can be extended and generalized for tables with different numbers of cells, or is it just a special case. The purpose of the present paper is to answer this question in order to reconsider its corresponding frame of reference, the Cramér’s coefficient, *V*. We prove Cohen's formula for w is extendable and applicable in measuring the association strength in any contingency table, and our argumentation lies on a formula, particularly derived in this paper. Then it is used to reveal the relationship between Cohen’s effect size index, *w*, and Cramér’s coefficient, *V*. As a result, the cutoff values of Cramér’s coefficient for small, medium and large effect sizes were calculated for contingency tables with different numbers of rows and columns. These values were tabulated to facilitate their future use, given a particular substantive context and researchers’ qualitative conventions for „small“, „medium“, and „large“ effect size in their own scientific frame of reference.

INTRODUCTION

The scientific problem

Although Thomas Kuhn has posed more than a half a century ago the problem of scientific “development” as circular rather than progressively linear, subjective and dependable on perceptions rather than based on universal laws of the subject-matter [2], it was hardly the case of self-perception in the area of statistics and particularly in frequentist statistics. Yet, in the extent that comprehension of mathematics as a “pure science” has increasingly become intrinsic for the latter, it appeared as if statistics was escaping the Kuhn’s understanding of “scientific revolutions”. Statistics arose in the newly emerging modern society in the 17th century in the shape of demographic and population studies on the backdrop of emergence of probability as “a new system of thought” [3]. Probability theory evolved since then as dual and contradicting concept – as “a theory of consistent beliefs … what is now called Bayesian” and a “theory of stable relative frequencies to real-world prediction” [3].

It was not until the 19th century that statistics did become an undertaking based on universal mathematical rules. Mathematical statistics, rapidly maturing since then as a specialized scientific branch, spread to the natural sciences through its methods, indices and coefficients, and received there its true flourishing [4, 5]. Paradoxically, these indices and coefficients were perceived as universally applicable while natural sciences increasingly rediscovered their objective reality as less universal and deterministic, and more contextual and probabilistic.

With the rise of mass society – and especially after the WWII, of mass consumer society – the social and behavioral sciences were increasingly reincorporating the entire complex toolbox of mathematical statistics *as it was*. Similar process was seen also in the case of medicinal sciences at least from the 1960s onward. On the backdrop of extensive application of different statistical measures of association across diverse fields of modern sciences due to these measures’ usefulness, their inherent universality is very rarely questioned. One of the most commonly used measures of association between categorical variables was the well-established and universally applied Cramér’s coefficient, *V*. A need of a “complement to significance testing” slowly evolved [6] between 1960s and 1980s when statistical framework of effect size and later its notion have been introduced and developed during the first decade of this period [7]. Cohen was the one who particularly and firmly established it in his book *Statistical Power Analysis for the Behavioral Sciences* in 1969. It was not until the second edition of Cohen's book was published in 1988, however, that effect size has been identified as a fruitful tool precisely in behavioral sciences where the issues of subjectivity in the choice of proper sizes of association's strength as well as interpretation of measures in contextual terms were risen on the backdrop of increasingly perceived volatile character of their subject-matter. Cohen discussed the need of particular caution regarding the qualitative conventions for „small", „medium", and „large" effect size (ES) about the quantitative values for ES index for contingency tables, w [1]. Of particular importance in his argument is the extent of their aptness in a given substantive context, and particularly his idea that what is „subjectively the „same" degree of association may yield varying w" [1].

Since such a perspective is rather an exception within contemporary statistical developments, and, moreover, some of its applications miss its essence and omit firm grounds and argumentation (see e.g. [8]), here we propose a reconsideration of both Cohen's index, *w*, and consequently the cutoff values of its corresponding frame of reference, the Cramér's coefficient, *V*.

The statistical problem

In the fifth chapter of the second edition of his book, Cohen introduces the effect size index (g) when comparing observed and expected relative frequencies and proposes three values – $g = 0.05$ for small effect size, $g = 0.15$ for medium effect size and $g = 0.25$ for large effect size [1]. Then, in the seventh chapter, he introduces the effect size index (w) for contingency tables and proposes three values – $w = 0.10$ for small effect size, $w = 0.30$ for medium effect size and $w = 0.50$ for large effect size [1]. It can be seen that:

$$w = 2g \tag{1}$$

In doing so, Cohen uses these three cutoff values regardless of the dimensionality of the table. Other scholars (See e.g. Mangiafico [9]) cite Cohen and also use the same values for w regardless of the dimensionality of the table.

On the other hand, Cohen shows that $w = \sqrt{\frac{\chi^2}{n}} = \varphi$ [1], and φ is known to have an upper limit that is floating and depends on the number of rows and the number of columns of the contingency table; the larger the number of rows and/or the number of columns, the larger the upper limit of φ is. Therefore, it is contra-intuitive to use the same cutoff values for tables of different dimensions. Therefore, the question arose whether Equation (1) is a general formula that can be used for tables with a different number of cells, or is it a special case, only for tables with two cells.

The purpose of the present paper is to give an answer to this question and, if it turns out that Equation (1) is only a special case, to establish a general formula.

MODEL DERIVATION

A contingency table is used in the study of relationships between two categorical variables (Table 1).

TABLE 1. Contingency table

	x_1	x_2	…	x_c	**Total**
y_1	f_{11}	f_{12}	$\cdots$	f_{1c}	$f_{1\bullet}$
y_2	f_{21}	f_{22}	$\cdots$	f_{2c}	$f_{2\bullet}$
$\vdots$	$\vdots$	$\vdots$		$\vdots$	$\vdots$
y_r	f_{r1}	f_{r2}	$\cdots$	f_{rc}	$f_{r\bullet}$
Total	$f_{\bullet 1}$	$f_{\bullet 2}$	$\cdots$	$f_{\bullet c}$	n

Where:
x_j are the categories of the first variable;
y_i are the categories of the second variable;
c is the number of columns (number of categories of the first variable)
r is the number of rows (number of categories of the second variable)
f_{ij} is the frequency in row i and column j;
$f_{i\bullet} = \sum_j f_{ij}$;
$f_{\bullet j} = \sum_i f_{ij}$;
n is sample size.
From the frequencies in this table, the observed relative frequencies can be calculated:

$$p_{ij} = \frac{f_{ij}}{n} \tag{2}$$

These observed relative frequencies are matched with expected relative frequencies, which are obtained under the assumption of no relationship between x and y:

$$\pi_{ij} = \frac{f_{i\bullet} \times f_{\bullet j}}{n^2} \tag{3}$$

Then the differences between observed and expected relative frequencies are calculated:

$$p_{ij} - \pi_{ij} = g_{ij} \tag{4}$$

The differences g_{ij} can be both positive and negative. The only condition must be:

$$\sum_i \sum_j g_{ij} = 0 \tag{5}$$

which is a consequence of:

$$\sum_i \sum_j p_{ij} = \sum_i \sum_j \pi_{ij} = 1 \tag{6}$$

Since $w = \varphi$, from now on only φ will be used as a measure of effect size, respectively of measures of association for categorical variables:

$$\varphi = \sqrt{\sum_i \sum_j \frac{(p_{ij} - \pi_{ij})^2}{\pi_{ij}}} = \sqrt{\sum_i \sum_j \frac{g_{ij}^2}{\pi_{ij}}} \tag{7}$$

If instead of the absolute differences g_{ij} we work with the relative differences $k_{ij} = \frac{g_{ij}}{\pi_{ij}}$, then $g_{ij} = k_{ij}\pi_{ij}$ and:

$$\varphi = \sqrt{\sum_i \sum_j \frac{g_{ij}^2}{\pi_{ij}}} = \sqrt{\sum_i \sum_j \frac{k_{ij}^2 . \pi_{ij}^2}{\pi_{ij}}} = \sqrt{\sum_i \sum_j (k_{ij}^2 \pi_{ij})} \tag{8}$$

This is a weighted root mean square since $\sum_i \sum_j \pi_{ij} = 1$, i.e.:

$$\varphi = \sqrt{\sum_i \sum_j (k_{ij}^2 \pi_{ij})} = \bar{k} \tag{9}$$

In other words, φ is actually an average of the relative differences.

At the same time, the arithmetic mean of expected relative frequencies is:

$$\bar{\pi} = \frac{\sum_i \sum_j \pi_{ij}}{m} = \frac{1}{m} \tag{10}$$

Where $m = rc$ is the number of cells in contingency table.

Then, if $g_{ij} = k_{ij}\pi_{ij}$, it should[1] $g = \bar{k} \times \bar{\pi} = \varphi \frac{1}{m} = \frac{\varphi}{m}$, whence:

$$\varphi = g \times m \tag{11}$$

This proves that Equation (1) is not general formula, but it is a special case for $m = 2$. The general formula is Equation (11).

But even Equation (11) does not correctly measure effect size, since it averages the differences between expected and observed relative frequencies, while in social research relative frequencies *within rows and/or within columns* are calculated, compared and interpreted. Therefore, the effect size should reflect exactly the differences between the relative frequencies within rows and/or the relative frequencies within columns.

Comparing the relative frequencies within rows of two separate rows yields:

$$\Delta p_{r,cond} = p_{j|i} - p_{j|l} = \frac{p_{ij}}{p_{i\bullet}} - \frac{p_{lj}}{p_{l\bullet}} = \frac{\pi_{ij} + g_{ij}}{\pi_{i\bullet}} - \frac{\pi_{lj} + g_{lj}}{\pi_{l\bullet}} = \frac{\pi_{ij}}{\pi_{i\bullet}} + \frac{g_{ij}}{\pi_{i\bullet}} - \frac{\pi_{lj}}{\pi_{l\bullet}} - \frac{g_{lj}}{\pi_{l\bullet}} = \pi_{j|i} - \pi_{j|l} + \frac{g_{ij}}{\pi_{i\bullet}} - \frac{g_{lj}}{\pi_{l\bullet}}$$

Where:

$\Delta p_{r,cond}$ is the difference between the relative frequencies within rows in two different conditional distributions;

$p_{j|i}$ is the observed relative frequency in column j, given that row i is fixed;

$\pi_{j|i}$ is the expected relative frequency in column j, given that row i is fixed;

$p_{i\bullet} = \sum_j p_{ij}$;

$\pi_{i\bullet} = \sum_j \pi_{ij}$.

$p_{i\bullet} = \pi_{i\bullet}$ is a consequence of Equations (2) and (3), since:

$$p_{i\bullet} = \sum_j p_{ij} = \sum_j \frac{f_{ij}}{n} = \frac{\sum_j f_{ij}}{n} = \frac{f_{i\bullet}}{n}$$

[1] Since the mean of a product is not equal to the product of means, it is not correct to denote the obtained result as $\bar{g}$. Therefore g is used as a notation instead of $\bar{g}$.

$$\pi_{i\bullet} = \sum_j \pi_{ij} = \sum_j \frac{f_{i\bullet} \times f_{\bullet j}}{n^2} = \frac{f_{i\bullet}}{n^2} \sum_j f_{\bullet j} = \frac{f_{i\bullet}}{n^2} n = \frac{f_{i\bullet}}{n}$$

But once the expected frequencies are calculated under the assumption of no association, then $\pi_{j|i} = \pi_{j|l}$, whence $\pi_{j|i} - \pi_{j|l} = 0$, and then:

$$\Delta p_{r,cond} = p_{j|i} - p_{j|l} = \frac{g_{ij}}{\pi_{i\bullet}} - \frac{g_{lj}}{\pi_{l\bullet}}$$

If instead of the particular g_{ij} and g_{lj} we take the general $g = \frac{\varphi}{m}$, adding $\pm$, since g_{ij} and g_{lj} can be both positive or negative, and if instead of $\pi_{i\bullet}$ and $\pi_{l\bullet}$ we take their average, which for r rows is $\frac{\sum_i \pi_{i\bullet}}{r} = \frac{1}{r}$, we get[2]:

$$\hat{\Delta} p_{r,cond} = \frac{\pm \frac{\varphi}{m}}{\frac{1}{r}} - \frac{\pm \frac{\varphi}{m}}{\frac{1}{r}} = r\left[\pm \frac{\varphi}{m} - \left(\pm \frac{\varphi}{m}\right)\right]$$

There are two possibilities:

$$\hat{\Delta} p_{r,cond} = 0$$

Or

$$\hat{\Delta} p_{r,cond} = \pm 2r \frac{\varphi}{m}$$

Whence:

$$|\hat{\Delta} p_{r,cond}| = 2r \frac{\varphi}{m} \qquad (12)$$

Similarly, it is obtained by columns:

Comparing the relative frequencies within columns of two separate columns yields:

$$\Delta p_{c,cond} = p_{i|j} - p_{i|l} = \frac{p_{ij}}{p_{\bullet j}} - \frac{p_{il}}{p_{\bullet l}} = \frac{\pi_{ij} + g_{ij}}{\pi_{\bullet j}} - \frac{\pi_{il} + g_{il}}{\pi_{\bullet l}} = \frac{\pi_{ij}}{\pi_{\bullet j}} + \frac{g_{ij}}{\pi_{\bullet j}} - \frac{\pi_{il}}{\pi_{\bullet l}} - \frac{g_{il}}{\pi_{\bullet l}} = \pi_{i|j} - \pi_{i|l} + \frac{g_{ij}}{\pi_{\bullet j}} - \frac{g_{il}}{\pi_{\bullet l}}$$

Where:

$\Delta p_{c,cond}$ is the difference between the relative frequencies within columns in two different conditional distributions;

$p_{i|j}$ is the observed relative frequency in row i, given that column j is fixed;

$\pi_{i|j}$ is the expected relative frequency in row i, given that column j is fixed;

$p_{\bullet j} = \sum_i p_{ij}$;

$\pi_{\bullet j} = \sum_i \pi_{ij}$.

$p_{\bullet j} = \pi_{\bullet j}$ is a consequence of Equations (2) and (3), since:

$$p_{\bullet j} = \sum_i p_{ij} = \sum_i \frac{f_{ij}}{n} = \frac{\sum_i f_{ij}}{n} = \frac{f_{\bullet j}}{n}$$

$$\pi_{\bullet j} = \sum_i \pi_{ij} = \sum_i \frac{f_{i\bullet} \times f_{\bullet j}}{n^2} = \frac{f_{\bullet j}}{n^2} \sum_i f_{i\bullet} = \frac{f_{\bullet j}}{n^2} n = \frac{f_{\bullet j}}{n}$$

But once the expected frequencies are calculated under the assumption of no association, then $\pi_{i|j} = \pi_{i|l}$, whence $\pi_{i|j} - \pi_{i|l} = 0$, and then:

$$\Delta p_{c,cond} = p_{i|j} - p_{i|l} = \frac{g_{ij}}{\pi_{\bullet j}} - \frac{g_{il}}{\pi_{\bullet l}}$$

If instead of the particular g_{ij} and g_{il} we take the general $g = \frac{\varphi}{m}$, adding $\pm$, since g_{ij} and g_{il} can be both positive and negative, and if instead of $\pi_{\bullet j}$ and $\pi_{\bullet l}$ we take their average, which for c columns is $\frac{\sum_j \pi_{\bullet j}}{c} = \frac{1}{c}$, we get:

$$\hat{\Delta} p_{c,cond} = \frac{\pm \frac{\varphi}{m}}{\frac{1}{c}} - \frac{\pm \frac{\varphi}{m}}{\frac{1}{c}} = c\left[\pm \frac{\varphi}{m} - \left(\pm \frac{\varphi}{m}\right)\right]$$

There are two possibilities:

$$\hat{\Delta} p_{c,cond} = 0$$

Or

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[2] Once again, since g is not an average value, the resulting $\hat{\Delta} p_{r,cond}$ is also not an average value. Therefore, $\hat{\Delta} p_{r,cond}$ is used as a notation instead of $\bar{\Delta} p_{r,cond}$.

$$\hat{\Delta}p_{c,cond} = \pm 2c\frac{\varphi}{m}$$

Whence:

$$|\hat{\Delta}p_{c,cond}| = 2c\frac{\varphi}{m} \tag{13}$$

Our proposal is to use $|\hat{\Delta}p_{r,cond}| = 2r\frac{\varphi}{m}$ and $|\hat{\Delta}p_{c,cond}| = 2c\frac{\varphi}{m}$ as measures of effect size, which are actually:

$$\left|\hat{\Delta}p_{r,cond}\right| = 2r\frac{\varphi}{m} = 2r\frac{\varphi}{rc} = \frac{2\varphi}{c} \tag{14}$$

$$|\hat{\Delta}p_{c,cond}| = 2c\frac{\varphi}{m} = 2c\frac{\varphi}{rc} = \frac{2\varphi}{r} \tag{15}$$

These are the estimates of the absolute differences between the relative frequencies within rows and between the relative frequencies within columns respectively. And if these absolute differences are large, then the association can also be defined as strong.

A rule for the magnitude of φ can also be derived from this:

$$\varphi = \frac{c}{2}|\hat{\Delta}p_{r,cond}| \tag{16}$$

$$\varphi = \frac{r}{2}|\hat{\Delta}p_{c,cond}| \tag{17}$$

And from here we arrive to the magnitude of the Cramér's coefficient:

$$V = \frac{\varphi}{\sqrt{min[(r-1);(c-1)]}} = \frac{c|\hat{\Delta}p_{r,cond}|}{2\sqrt{min[(r-1);(c-1)]}} \tag{18}$$

$$V = \frac{\varphi}{\sqrt{min\ [(r-1);(c-1)]}} = \frac{r|\hat{\Delta}p_{c,cond}|}{2\sqrt{min\ [(r-1);(c-1)]}} \tag{19}$$

When the contingency table is a square table, i.e., $r = c$, then the two equations are the same:

$$V = \frac{c|\hat{\Delta}p_{r,cond}|}{2\sqrt{c-1}} = \frac{r|\hat{\Delta}p_{c,cond}|}{2\sqrt{r-1}} \tag{20}$$

But when the contingency table is a rectangular table, then either Equation (18) or Equation (19) should be chosen. In our opinion, decision should be based on the placement of the independent and dependent variables. If the independent variable is placed in rows, then relative frequencies within rows will be compared, and then Equation (18) will be used. If the independent variable is placed in columns, then relative frequencies within columns will be compared, and then Equation (19) will be used. For convenience and for unification of the formulas, new notations can be introduced:

IV is the number of categories of the independent variable;

DV is the number of categories of the dependent variable;

$\left|\hat{\Delta}p_{IV,cond}\right| = ES$ is the effect size.

Then the equation becomes only one:

$$V = \frac{\varphi}{\sqrt{min[(IV-1);(DV-1)]}} = \frac{DV \times ES}{2\sqrt{min[(IV-1);(DV-1)]}} \tag{21}$$

Finally, all that remains is to choose the ES values. If Cohen's suggestion is used, they would be 0.05, 0.15, and 0.25.

All this allows the cutoffs of Cramér's coefficient to be tabulated. We have prepared a table for $2 \leq IV \leq 10$ and $2 \leq DV \leq 10$ (Table 2). Contingency tables with more than 10 rows and/or columns are unlikely to appear very often in the social and behavioral sciences.

TABLE 2. Cutoff values of the Cramér's coefficient

DV	***ES***	***IV***								
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
2	0.05	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
	0.15	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150	0.150
	0.25	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250
3	0.05	0.075	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053
	0.15	0.225	0.159	0.159	0.159	0.159	0.159	0.159	0.159	0.159
	0.25	0.375	0.265	0.265	0.265	0.265	0.265	0.265	0.265	0.265
4	0.05	0.100	0.071	0.058	0.058	0.058	0.058	0.058	0.058	0.058
	0.15	0.300	0.212	0.173	0.173	0.173	0.173	0.173	0.173	0.173
	0.25	0.500	0.354	0.289	0.289	0.289	0.289	0.289	0.289	0.289
5	0.05	0.125	0.088	0.072	0.063	0.063	0.063	0.063	0.063	0.063
	0.15	0.375	0.265	0.217	0.188	0.188	0.188	0.188	0.188	0.188
	0.25	0.625	0.442	0.361	0.313	0.313	0.313	0.313	0.313	0.313
6	0.05	0.150	0.106	0.087	0.075	0.067	0.067	0.067	0.067	0.067

TABLE 2. Cutoff values of the Cramér’s coefficient

DV	***ES***	***IV***								
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	0.15	0.450	0.318	0.260	0.225	0.201	0.201	0.201	0.201	0.201
	0.25	0.750	0.530	0.433	0.375	0.335	0.335	0.335	0.335	0.335
7	0.05	0.175	0.124	0.101	0.088	0.078	0.071	0.071	0.071	0.071
	0.15	0.525	0.371	0.303	0.263	0.235	0.214	0.214	0.214	0.214
	0.25	0.875	0.619	0.505	0.438	0.391	0.357	0.357	0.357	0.357
8	0.05	0.200	0.141	0.115	0.100	0.089	0.082	0.076	0.076	0.076
	0.15	0.600	0.424	0.346	0.300	0.268	0.245	0.227	0.227	0.227
	0.25	1.000	0.707	0.577	0.500	0.447	0.408	0.378	0.378	0.378
9	0.05	0.225	0.159	0.130	0.113	0.101	0.092	0.085	0.080	0.080
	0.15	0.675	0.477	0.390	0.338	0.302	0.276	0.255	0.239	0.239
	0.25	-	0.795	0.650	0.563	0.503	0.459	0.425	0.398	0.398
10	0.05	0.250	0.177	0.144	0.125	0.112	0.102	0.094	0.088	0.083
	0.15	0.750	0.530	0.433	0.375	0.335	0.306	0.283	0.265	0.250
	0.25	-	0.884	0.722	0.625	0.559	0.510	0.472	0.442	0.417

Equation (21) can also be applied in the reverse order – from the Cramér’s coefficient calculated from the data, the effect size can be estimated:

$$ES = \frac{2V\sqrt{min[(IV-1);(DV-1)]}}{DV} \tag{22}$$

NUMERIC EXPERIMENT

Let's look at the example from page 219 of Cohen's book (Table 3).

TABLE 3. Observed relative frequencies in a joint distribution of sex and political preference

	Dem.	**Rep.**	**Ind.**	**Sex marginal**
Men	0.22	0.35	0.03	0.60
Women	0.23	0.10	0.07	0.40
Preference marginal	0.45	0.45	0.10	1.00

In this case, the independent variable is sex, which is placed in rows, so it is more appropriate to calculate the relative frequencies within rows (Table 4 and Figure 1).

TABLE 4. Political preference by sex (relative frequencies within rows)

	Dem.	**Rep.**	**Ind.**	**Total**
Men	0.367	0.583	0.050	1.000
Women	0.575	0.250	0.175	1.000
Preference marginal	0.450	0.450	0.100	1.000

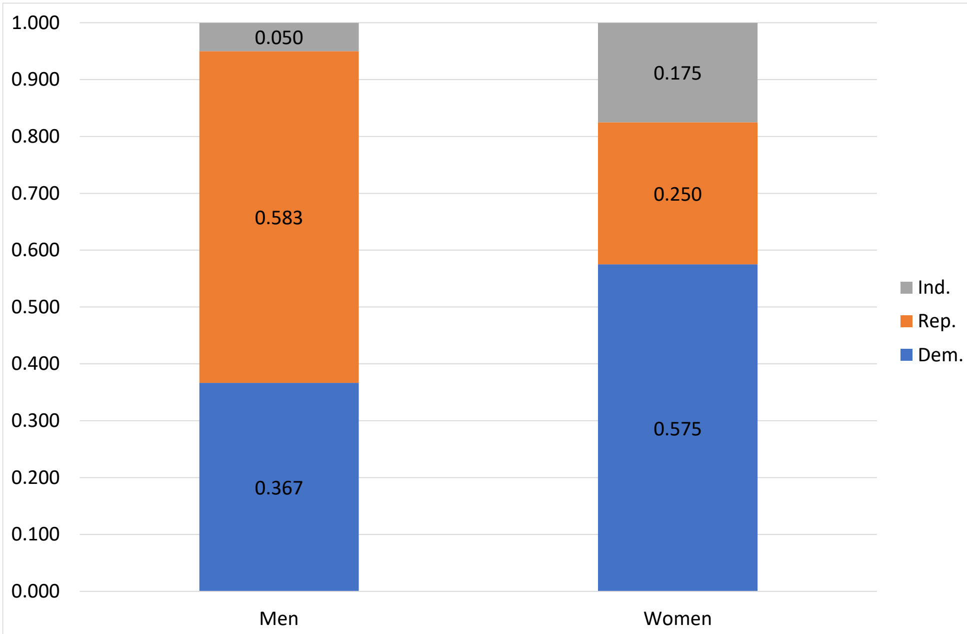

FIGURE 1. Political preference by sex

Since $IV = 2$ and $DV = 3$, from Table 2 the cutoffs for Cramér's coefficient are 0.075, 0.225 and 0.375, i.e.:

$0.000 \leq V \leq 0.075$ – very weak association;

$0.075 \leq V \leq 0.225$ – weak association;

$0.225 \leq V \leq 0.375$ – moderate association;

$0.375 \leq V \leq 1.000$ – strong association.

The calculated value of Cramér's coefficient is 0.346 [1], which is between 0.225 and 0.375, which means that the relationship is moderate.

And calculated in reverse order:

$$ES = \frac{2V\sqrt{min\,[(IV-1);(DV-1)]}}{DV} = \frac{2 \times 0.346 \times \sqrt{2-1}}{3} = \frac{0.692}{3} = 0.231$$

That is, the estimated absolute difference is 23.1 percentage points.

From Table 4, it can easily be calculated that the difference for Democrats is -20.8 percentage points, for Republicans it is 33.3 percentage points, and for independent candidates it is -12.5 percentage points. The average absolute difference is 22.2 percentage points, which is quite close to the estimation of 23.1 percentage points. The main reason for the difference between the averaged and estimated values is that the two groups (men and women) are unbalanced (in this case they are 60:40). If the two groups were more balanced (i.e., closer to 50:50), then the difference would be even smaller. Conversely, if the two groups were more imbalanced, then the difference would also be greater.

(FUTURE) APPLICATIONS

We would not claim that the proposed reconsideration of Cramér's measure of association can have a universal use. We agree that "determination of what constitutes an effect of practical significance depends on the context of the research and the judgment of the researcher, and the values… represent somewhat arbitrary cutoffs that are subject to interpretation" [6]. Moreover, any measure of association cutoffs should be regarded as not universally applicable mainly because in different scientific fields the specifics of both the notion of objective reality and epistemic patterns of its scientific understanding imply a variety of applications in narrower or wider limits and with different degree of freedom for reasoned conventions for these applications.

Depending on the relation „epistemological-ontological preconditions" one can provisionally sketch a typology of diverse scientific domains in their current state (leaving aside recent developments in increasingly evolving interdisciplinarity among scientific disciplines and fields), that varies alongside several dimensions. On the „subject-matter side" one can schematically posit the following comprehensions in form of axes: „*determinism – probabilism* *(non-determinism)*"; „*universalism – contextuality*", and „*mechanical causality – free will*" (i.e., degree of subjective construction). On the „epistemological side" we can posit the different levels of interpretative freedom as distinguishing the scientific fields in question. Depending on the particular scientific field's specificity in terms of the above typology, it is understandable that the levels of significance of Cramér's measure of association can be differently interpreted as regards the mutual intertwining between sciences' epistemological and ontological prerequisites.

CONCLUSION

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