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# An Extension and Further Validation of the Potential for Conflict Index

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*The Potential for Conflict Index (PCI) was developed to facilitate understanding and applicability of leisure, recreation, and human dimensions findings to managerial concerns. The PCI ranges from 0 (minimal potential for conflict) to 1 (maximum potential for conflict) and simultaneously describes a variable's central tendency, dispersion, and shape using a graphic display. This article (a) describes applications of the original formulation of the PCI ($PCI_1$) to illustrate the statistic's practical utility, (b) introduces the second generation of the PCI ($PCI_2$) and discusses enhancements incorporated in this version, (c) describes efforts to validate the $PCI_2$, and (d) offers suggestions for continuing the empirical validation process. Programs for calculating, graphing, and comparing $PCI_2$ values are freely available from http://welcome.warnercnr.colostate.edu/∼jerryv.*

**Keywords** consensus, disagreement, potential for conflict index, ratings

Many research studies in leisure, recreation, and human dimensions of natural resources apply survey methodologies and quantitative analytical techniques to improve understanding of complex concepts such as motivations, attitudes, and norms (Vaske, 2008). A primary goal of this research is to provide information that can inform and improve decision making. When communicating results to nontechnical audiences, however, researchers must clearly convey the meaning of the quantitative analyses and the statistical/practical implications of

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findings. Basic summary statistics, for example, describe a variable's distribution regarding central tendency (e.g., mean), dispersion (e.g., standard deviation), and shape (e.g., skewness). Although these statistics provide useful information, an accurate understanding of a distribution requires consideration of all three summary statistics simultaneously (Cramér, 1951). The challenge of communicating statistics to nontechnical audiences is compounded by the complexity of concepts investigated (e.g., value orientations, attitudes, norms) and measurement scales used.

The Potential for Conflict Index (PCI) and an associated graphic technique for displaying results were developed to facilitate understanding and interpretation of statistical information (Manfredo, Vaske, & Teel, 2003; Vaske et al., 2006). This approach requires little statistical training to understand results, minimizes effort required to process information, and improves comprehension.

Our article focuses on the PCI and has four objectives. First, the original formulation of PCI ($PCI_1$) is introduced and related to other social science measures (e.g., Tastle, Wierman, & Dumdum, 2005; Van der Eijk, 2001). Previous applications of PCI are presented to illustrate the statistic's practical utility. Second, we introduce the second generation of the PCI ($PCI_2$) and discuss enhancements that have been incorporated in this version. Third, the article describes ongoing efforts to validate $PCI_2$. Finally, we offer suggestions for continuing the empirical validation process.

## Original Formulation of PCI ($PCI_1$)

Surveys for obtaining information about respondent cognitions (e.g., beliefs, attitudes, norms) and behaviors frequently use response scales with an equal number of response options surrounding a neutral center point (Dillman, 2007; Vaske, 2008). Numerical ratings can be assigned with a neutral value of 0 (e.g., −3, −2, −1, 0, 1, 2, 3 where −3 = highly unacceptable, 0 = neutral or neither, and 3 = highly acceptable). The original $PCI_1$ (Equation (1)) was based on ratios of responses on either side of the response scale's neutral point (Manfredo et al., 2003). The greatest potential for conflict ($PCI_1 = 1$) occurred when responses were equally divided between the two extreme values on the scale (e.g., 50% highly unacceptable and 50% highly acceptable). A distribution with 100% at any one point on the response scale yielded a $PCI_1$ of 0 and suggested minimal potential for conflict. Computation of the $PCI_1$ used a frequency distribution and followed the formula:

$$PCI_1 = \left[1 - \left|\frac{\sum_{i=1}^{n_a} |X_a|}{X_t} - \frac{\sum_{i=1}^{n_u} |X_u|}{X_t}\right|\right] * \frac{X_t}{Z} \tag{1}$$

where

$\Sigma|X_a|$ = sum of positive values for responses for $n_a$ respondents giving "acceptable" (or "favor" or "like") responses;

$\Sigma|X_u|$ = sum of negative responses for $n_u$ respondents giving "unacceptable" (or "oppose" or "dislike") responses;

$X_t = \sum_{i=1}^{n_a} |X_a| + \sum_{i=1}^{n_u} |X_u|$

$n = n_a + n_u$ + number of neutral responses; and

$Z$ = the maximum possible sum of all scores = $n$ * *extreme score on a scale* (e.g., $Z = 2n$ for scale going from −2 to +2).

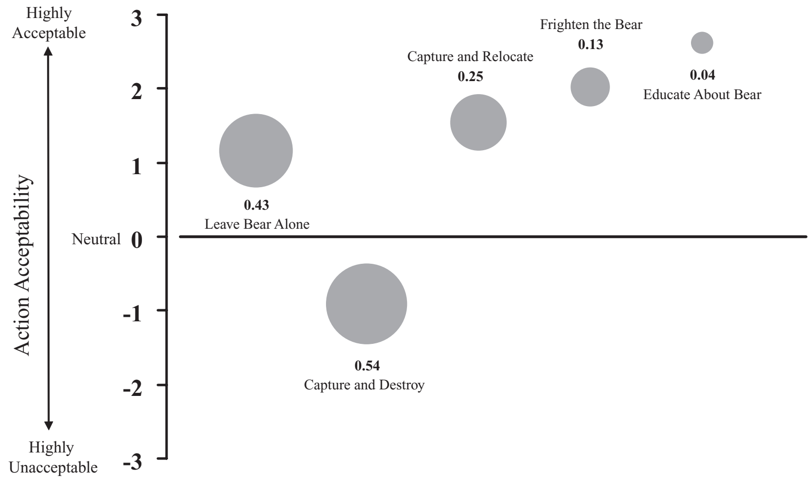


**FIGURE 1** Univariate measures using the PCI and the graphic technique: Alaskans' acceptance of bear management actions. *Note:* Numbers listed for each bubble in the graph represent the Potential for Conflict Index (PCI1). The middle of each bubble represents the mean acceptance of the action.

When using a 5-point scale, for example, if there were *n*/2 respondents at 2 and *n/*2 at $-2$, $PCI_1 = 1$. If all respondents gave the same response, substitution yields a $PCI_1 = (X_t - X_t)/Z = 0$. Thus, $PCI_1$ had boundary values of 1 and 0.

To facilitate visual understanding of this type of data, results can be displayed as bubble graphs that simultaneously describe a variable's form, dispersion, and central tendency (e.g., Figures 1 and 2). The size of the bubble depicts the magnitude of the PCI and indicates

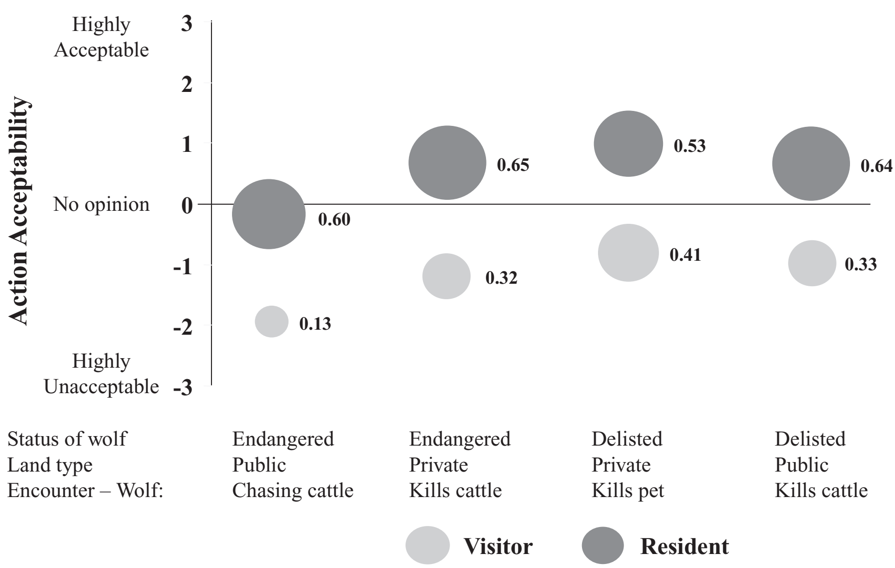


**FIGURE 2** Local residents' and National Park visitors' acceptance of destroying wolves under four hypothetical scenarios.

degree of dispersion (e.g., extent of potential conflict regarding acceptance of a management strategy). A small bubble (e.g., PCI = .04) suggests little potential for conflict; a larger bubble (e.g., PCI = .74) suggests more potential for conflict. The center of the bubble is plotted on the *y*-axis corresponding to the mean response (i.e., central tendency). Given a zero neutral point for a variable, the bubble's location shows whether respondents' average evaluations are above, below, or at the neutral point (i.e., an action is, on average acceptable, unacceptable, or neutral). Information about a distribution's skewness is conveyed by the position of the bubble relative to the neutral point. Bubbles at the top or bottom of the graph are more skewed than bubbles that are centrally located.

### *Applications of $PCI_1$*

Manfredo et al. (2003) illustrated computation and display of $PCI_1$ using data about Alaska residents' responses to wildlife species such as bears. Surveys presented respondents ($n$ = 342) with several scenarios such as the following and asked them to rate acceptance of five different management responses (e.g., leave the bear alone, capture and destroy the bear):

> In some areas and during certain times of the year, bears have been known to wander into residential areas where they get into trash cans, storage sheds, and bird feeders. They can destroy vegetation and pose a threat to both pets and humans. Some people feel the bears should be left alone or simply chased away. Others think the bears should be caught and relocated or destroyed. Still others feel that people who live near bear habitat should be educated about how to avoid problems with bears.

Figure 1 graphically displays the $PCI_1$ and mean acceptance of each management response. Visually, it is apparent that leaving the bear alone and capturing and destroying the bear have higher potential for conflict because the $PCI_1$ and associated bubbles are bigger than those for the other actions. Leaving the bear alone is, on average, acceptable, whereas destroying the bear is unacceptable. Among the other actions, public education and frightening the bear are much more acceptable, there is relatively little disagreement about the acceptance of these actions, and their distribution is positively skewed. Relocation of the bear is acceptable, but has a higher conflict potential than either public education or frightening the bear.

Vaske and Taylor (2006) used $PCI_1$ to understand public acceptance of possible management actions for addressing human conflict with wolves in the Greater Yellowstone Area. Surveys described four scenarios depicting possible encounters between humans and wolves. Factors that might influence acceptance of management actions were experimentally manipulated in these scenarios and included the location of encounter (on park property or private land), type of encounter (e.g., hikers see wolves on trail, wolves harass or prey on cattle), and endangered species status of wolves (listed as "endangered population" or delisted).

Local residents ($n = 604$) and park visitors ($n = 596$) evaluated several management options designed to remedy or prevent the conflicts described in each scenario (e.g., monitor the situation, frighten the wolves away, capture and relocate the wolves, destroy the wolves). Acceptance of management actions was measured on 7-point scales of –3 = "highly unacceptable" to +3 = "highly acceptable."

Across scenarios, visitor acceptance ratings of destroying the wolves were consistently below the neutral line, whereas local resident ratings were above the neutral line for three of the scenarios (Figure 2). The $PCI_1$ bubbles for visitors were consistently smaller (i.e., less conflict) than those for the local residents. The residents' $PCI_1$ value (.60) for the first scenario, for example, was approximately five times larger than the $PCI_1$ value for visitors (.13) and the resident bubble straddled the neutral line, suggesting that destroying the wolf in this situation would be controversial among local residents, but unacceptable among visitors.

These examples illustrate the utility of communicating findings using the $PCI_1$. Other research has applied $PCI_1$ to facilitate understanding of issues such as value orientations (Teel et al., 2005) and attitudes (Thornton & Quinn, 2009) toward wildlife, hunter behavior (Needham, Vaske, & Manfredo, 2004, 2006; Vaske et al., 2006), management of desert tortoises (Vaske & Donnelly, 2007a), perceived conflicts with off leash dogs (Vaske & Donnelly, 2007b), evaluations of wildfire management strategies (Vaske et al., 2004), national forest management (Shelby, 2005), ecotourism development (Mayer & Wallace, 2007), norms toward instream flows (Stafford, 2006), and scuba diver and snorkeler normative tolerances for other users (Heesemann, Vaske, & Loomis, 2009). Despite the breadth of these applications, $PCI_1$ had limitations (e.g., the formula limited analyses to bipolar scales with a neutral value and there was not a formal test of differences among the PCI values). The second generation of this statistic ($PCI_2$) addresses these shortcomings.

PCI was developed as an index for estimating the potential for conflict or the level of disagreement. Since PCI ranges from 0 (minimal potential for conflict) to 1 (maximum potential for conflict), it can also be considered as an index of consensus. No potential for conflict is equivalent to full consensus and maximum potential for conflict is equivalent to non consensus (i.e., 0 = full consensus; 1 = no consensus). Other measures of consensus and disagreement are introduced in the next section and discussed in relation to PCI.

## Measuring Consensus and Disagreement for Ratings

Concepts of consensus and disagreement are common in the information systems (Tastle et al., 2005), organization (Quigley, Tekleab, & Tesluk, 2007), ethics (Berk, Korenman, & Wenger, 2000), political science (Granberg & Holmberg, 1988; Miethe, 1984), economics (Gavin & Pande, 2008), sociology (Rossi & Berk, 1985; Scheff, 1967), and natural resources literature (Krymkowski, Manning, & Valliere, 2009; Twight & Paterson, 1979). Similar to PCI, for example, Tastle et al. (2005) measure response ratings for scales with a limited number of response options. In their formulation, as the number of categories responded to by participants diminishes, consensus/agreement increases, eventually approaching 1 when all responses are in a single category. When all participants place themselves in a single category, consensus is maximized and equals 1. A complete lack of consensus generates a value of 0. Other combinations of scale categories result in a value greater than 0 but less than 1. Similar to PCI, Tastle et al. (2005) imposed boundary conditions (i.e., 0, 1) and values between 0 and 1 for their $Cns(X_i)$ measure are determined by algebraic expression.[1] PCI and $Cns(X_i)$, however, differ conceptually in the way "neutral" respondents are treated. $PCI_2$ offers alternative approaches to considering neutral responses (see below); $Cns(X_i)$ contains no special provision for neutral respondents.

Van der Eijk (2001) proposed a distance-based measure of agreement ($A$). The $A$ statistic ranges between –1 (complete disagreement) and +1 (complete agreement). A value of 0 is assigned when responses are uniformly distributed. Consider a scale, however, with only two categories (positive–negative). If a uniform population is divided 50/50 into

[1]$Cns(X_i) = 1-0.5(\Sigma p_i \log_2((X_i-\mu)/d))$ where $X$ is any finite discrete random variable with probability distribution $p(x)$, the sum is over levels of $X$, $\log_2$ is log base 2, $d$ is the range of $X$ and $\mu$ is the mean of the random variable or some other measure "used as a strength" (Tastle et al., 2005).

these categories, measure $A$ should equal –1 (not 0) because there is complete disagreement about what is acceptable. As a result, Van der Eijk's arbitrary assignment of 0 to a uniform distribution appears to be flawed.

## The Second Generation of PCI ($PCI_2$)

### *The Logic of $PCI_2$*

Lack of consensus arises because people do not necessarily share similar value orientations, attitudes, or norms regarding what behaviors are acceptable. In responding to survey questions about cognitions (e.g., norms, attitudes), people may form their evaluations relative to where they perceive others are on the topic. The rating of person ($x$) relative to that of person ($y$) can be thought of as a function of the distance between their responses ($d_{x,y} = f(r_x, r_y)$). However, there are alternative ways to formulate $d_{x,y}$. For example, $d_{x,y}$ could be defined as the absolute value of $x$'s response ($r_x$) minus $y$'s response ($r_y$) (i.e., $d_{x,y} = |r_x - r_y|$).

Logic, however, suggests two issues with this formulation. First, the equal interval assumption (e.g., adopted by Van der Eijk, 2001, for the measure $A$) may not be satisfied. Two people with responses of –3 and –2 are not necessarily in conflict; they both find the situation unacceptable and differ only slightly in the degree to which their views are held. Second, people with negative or positive responses may perceive no conflict with a person who is neutral on the topic. Thus, a $d_{x,y} > 0$ may only exist between any negative response and any positive response. Using this logic, one formulation of $d_{x,y}$ (i.e., $D_1$) is:

$$\begin{aligned} D_1 = d_{x,y} = (|r_x - r_y| - 1) \;\; &\text{if } \operatorname{sign}(r_x) \neq \operatorname{sign}(r_y) \\ &(\text{e.g., } \operatorname{sign} \neq \text{ for } \mathrm{r}_x = -3 \text{ and } \mathrm{r}_y = +1) \\ &\text{otherwise } d_{x,y} = 0, \end{aligned} \tag{2}$$

where $d_{x,y}$ = distance between people on a variable, $r_x, r_y$ = response $x$ and response $y$, respectively, and sign = the sign for a positive or negative number (+ or −).

$D_1$ does not include "neutral" or "neither' responses in the calculation of distance. By subtracting 1, the distance from a person who has a negative evaluation to a person who has a positive evaluation is calculated as if there was no neutral category (e.g., distance from –2 to +1 is 2, not the algebraic difference of 3).

Alternatively, if circumstances associated with given research support believing that neutral ratings should affect distance, a second distance formulation, $D_2$, is defined by:

$$\begin{aligned} D_2 = d_{x,y} = |r_x - r_y| \;\; &\text{if } \operatorname{sign}(r_x) \neq \operatorname{sign}(r_y) \\ &\text{otherwise } d_{x,y} = 0, \end{aligned} \tag{3}$$

$D_2$ includes "neutral" responses in the calculation of distance. When using $D_2$, the distance from –1 to +1 is 2 and the distance from –2 to +1 is 3.

### *Calculating Distances for Other Types of Scales*

Not all researchers include a neutral category in bipolar scales. For example, a 4-point scale might be –2, –1, 1, 2, where –2 = highly unacceptable, and 2 = highly acceptable. $PCI_2$ can be computed for 2-, 4-, 6-, and 8-point bipolar scales using $D_1$ as the distance function for any power > 0. Other researchers use unipolar scales such as "not at all important" to "extremely important" (e.g., Beaman & Huan, 2008) or "not at all crowded" to "extremely crowded" (e.g., Vaske & Shelby, 2008). To accommodate these types of scales, a third distance function, $D_3$, was constructed:

$$D_3 = |r_x - r_y|^p \tag{4}$$

where $r_x$ and $r_y$ = ratings by person $x$ and person $y$ and p = a power (p > 0).

### *Powers of Distances*

Consistent with the Tastle et al. (2005) $Cns(X_i)$ measure, $D_1$, $D_2$, and $D_3$ need not be linear functions of responses. As argued by these researchers, powers of differences or some other nonlinear function of distance should be considered. For both PCI and $Cns(X_i)$, responses differing by 1 do not contribute half as much to conflict as responses differing by 2. In practical terms, someone with +1 may not see someone responding with –1 as being much in conflict. Someone responding –3, however, may be seen as threatening to what the +1 person wants because the –3 person may push strongly for change. To reflect these nonlinear perceptions, the difference scores can be raised to some power. If the initial difference scores were 1, 2, and 3 (i.e., power = 1), squaring the differences (i.e., power = 2) results in distances of 1, 4, and 9. A power of 2 gives more weight to larger differences between individuals. The greatest difference occurs between individuals who express the most extreme values on a scale (e.g., for a 7-point scale for $D_1$, –3 and +3 differ by 36). The $PCI_2$ estimation allows for alternative powers (e.g., 1, 1.5, 2). The general $PCI_2$ distance expression for distances with a power is:

$$Dp_{x,y} = d_{x,y} = (|r_x - r_y| - (m-1))^p \text{ if } \operatorname{sign}(r_x) \neq \operatorname{sign}(r_y) \text{ for } p > 0 \tag{5}$$
$$\text{otherwise } d_{x,y} = 0,$$

where $Dp_{x,y}$ = distance raised to some power, $m = D_1$, $D_2$ or $D_3$ and $p$ = power.

### *Calculating $PCI_2$*

A coefficient for person $x$ can be determined as the distance between $x$ and all other people. For example, if all people are in the same category, the coefficient for person $x$ is 0. For a sample of 101 and a maximum distance of 4 (i.e., a 5-point scale and $D_1$), a +2 person would make a 3/(4*100) contribution to a mean for a −1 person. The −1 person is at some distance from 100 people and the maximum total of distances would be 400 (100*4). The contribution to a mean for a –2 person would be 4/(4*100). If everybody but the +2 person was a –2, the sum would be 100*4/(4*100) = 1. These ideas are expressed by Equation (6):

$$\Delta_x = \frac{\sum d_{x,y}}{Max} = \frac{\sum f(r_x, r_y)}{Max} = \text{sum } x \text{ for } x \neq y \tag{6}$$

where $\Delta_x$ = normalized distance and $Max$ = maximum value of the sum.

Using $\Delta_x$ for individuals, $PCI_2$ can be calculated as a mean for a sample (Equation (7)). The approach is similar to computing $Cns(X_i)$ (see footnote 1). $PCI_2 = 1$ (maximum distance) if people divide into two groups with $\Delta_x = 1$. When $PCI_2$ is defined by a mean, when any person changes their response in such a way as to affect distance, $PCI_2$ will increase or decrease so the measure changes appropriately with any change in responses. Thus, $PCI_2$ changes based on a model of behavior; when all people are at a distance of 0, (i.e., all $\Delta_x = 0$), $\text{PCI}_2 = 0$. As defined by Equation (7), $\text{PCI}_2$ (and $Cns(X_i)$) changes based on algebraic formula that meet appropriate boundary conditions:

$$\text{PCI}_2 = Mean\ (\Delta_x)\ \text{ for all } x \tag{7}$$

Equation (7) can be described algebraically to facilitate understanding computation. Consider that there are $n_t$ respondents for valid values for a variable. For an $i$-value scale with $k$-levels (e.g., $k$ = –3 to +3), let $n_k$ be the number of respondents for each scale value and $n_h$ be the number of respondents at other scale values. For $k \neq h$, $n_k$ respondents are at some distance from $n_h$ respondents. Distances are assumed to be symmetric (i.e., $d_{h,k} = d_{k,h}$), therefore each of the $n_k$ respondents are a distance, $d_{h,k}$, from $n_h$ respondents. There are $n_h n_k$ distances from "$h$" to "$k$" and the same number from "$k$" to "$h$." Therefore, $2n_h n_k$ distances contribute to the total. Maximum distance, $d_{\max}$, occurs between extreme categories. Thus, for $n_t$ people when $n_t$ is an even number, a maximum total distance would occur for $\frac{n_t}{2}$ people at extreme responses. For $n_t$ when $n_t$ is an odd number, the maximum is for $\frac{n_t+1}{2}$ and $\frac{n_t-1}{2}$ people at extremes. This implies that:

$$\text{Maximum total distance} = \delta = \frac{d_{\max} n_t^2}{2} \text{ for } n_t \text{ even and}$$

$$\frac{d_{\max}\left(n_t^2 - 1\right)}{2} \text{ for } n_t \text{ odd} \tag{8}$$

The $\text{PCI}_2$ for an $i$-value scale, therefore, can be defined as:

$$\text{PCI}_2 = \frac{\sum n_k n_h d_{k,h}}{\delta} \quad \text{for} \quad k = 1 \text{ to } i \text{ and } h = 1 \text{ to } i \tag{9}$$

where $n_k$ = number of respondents at each scale value, $n_h$ = number of respondents at other scale values, $d_{k,h}$ = distances between respondents, and $\delta$ = maximum distance between extreme values multiplied by the number of times this distance occurs.

## An Initial Validation of $\text{PCI}_2$

Validation of a statistic typically requires vetting the statistic with researchers and using statistical techniques (e.g., modeling, experiments). In the case of PCI where interest was in developing an applied statistic, $\text{PCI}_1$ was also validated in the sense that nontechnical audiences indicated that they understood the findings (i.e., validity based on comments received from representatives of land management agencies and attendees at presentations and conferences in multiple countries). Since the original introduction of $\text{PCI}_1$ in 2003 (Manfredo et al., 2003), the statistic has been used in government reports (e.g., Teel et al., 2005; Vaske & Donnelly, 2007a, b), presented at public research forums (e.g., Heesemann et al., 2009; Shelby, 2005; Vaske et al., 2007), and published in journals (e.g., *Human Dimensions of Wildlife*, *Journal of Ecotourism*, *Wildlife Society Bulletin*), which has enabled the scientific community to apply $\text{PCI}_1$ and expose it to scientific critique.

After statistics are introduced and vetted, validation research can be conducted by the research community (see Grissom & Kim, 2005; Stigler, 1986, for the historical development and validation of statistics). Validation efforts for $\text{PCI}_2$ have included simulations, experiments (e.g., Vaske et al., 2007), and logical analysis.

**TABLE 1** Observed and Simulated $PCI_2$ Statistics[1]

| | | | Simulated $PCI_2$ | | | | |
|---|---|---|---|---|---|---|---|
| Sample size | Number of Repetitions | Observed $PCI_2$ | Mean | Median | Mode | Standard deviation | Skewness |
| 100 | 1,000 | .351 | .351 | .351 | .351 | .061 | .213 |
| 200 | 1,000 | .353 | .350 | .349 | .350 | .043 | .114 |
| 300 | 1,000 | .350 | .349 | .349 | .350 | .035 | .090 |
| 400 | 1,000 | .351 | .351 | .351 | .351 | .031 | .168 |
| 500 | 1,000 | .352 | .351 | .351 | .352 | .027 | .081 |
| 600 | 1,000 | .351 | .351 | .351 | .352 | .025 | .069 |
| 700 | 1,000 | .352 | .351 | .351 | .352 | .024 | .036 |
| 800 | 1,000 | .351 | .350 | .350 | .351 | .024 | .043 |
| 900 | 1,000 | .350 | .350 | .350 | .351 | .021 | .065 |
| 1000 | 1,000 | .350 | .350 | .350 | .350 | .020 | .056 |

[1]Simulations based on a 5–point scale.



### *Boundary Conditions and Effect Sizes*

Cohen (1988) described effect sizes as the degree to which a phenomenon is present in the population (i.e., a value of zero implies absence; a nonzero value suggests presence). "The larger the value, the greater the degree to which the phenomenon under study is manifested" (pp. 9–10). PCI is consistent with this definition of effect sizes. It represents the degree of potential conflict present in the population, satisfies the lower boundary requirement of 0, and increases in value based on the degree of potential for conflict in a population (upper boundary of 1). Accepting the argument that PCI is an effect size, in addition to the bubble graphs that facilitate interpretation, allows PCI to be used as a measure of practical significance for applied research in leisure, tourism, recreation, and human dimensions.

### *Simulations and $PCI_2$ Statistical Properties*

Simulation routines were developed in SAS, SPSS, Microsoft Excel, and a stand alone ($PCI_{2sa}$) version of the statistic.[2]Using the actual distribution of responses for a given variable, these programs generate observations based on probabilities associated with the number of people reporting a particular response (e.g., –2, –1, 0, 1, 2).

*Normality assumption simulations.* A desirable property of the distribution of estimates for a coefficient is approximate normality. Observed and simulated $PCI_2$ statistics for a 5–point scale are presented in Table 1. These simulations calculated the $PCI_2$ for samples sizes of 100, 200, 300, 400, 500, 600, 700, 800, 900, and 1,000. The number of repetitions for each simulated sample size was 1,000. Based on Q–Q plots for the simulated distributions and on location of $n$-tiles, estimates of $PCI_2$ were approximately normally distributed centrally but depart from normality in the tails. When using the $PCI_2$ in actual applications, skewness should also be examined to determine if normality can be assumed.

[2]The stand alone version, $PCI_{2sa}$, was written in PHP (a scripting language). This version requires an Internet connection, but does not require any additional software to calculate the observed $PCI_2$ or generate the simulation statistics.

If skewness is more than +1.0 or less than –1.0, the distribution is markedly skewed (Vaske, 2008). The skewness for a distribution of simulated PCI values relevant to an estimate is produced by the SAS, SPSS, Excel, and $PCI_{2sa}$ routines.

When $PCI_2$ is adequately close to normality, the standard deviations calculated using simulations can be used to test differences between observed $PCI_2$ values using the following formula:

$$d = \frac{ABS(PCI_a - PCI_b)}{\sqrt{(PCI_{aSD})^2 + (PCI_{bSD})^2}} \text{ where } d \text{ is considered to be N(0, 1)} \quad (10)$$

where ABS = absolute value, $PCI_a$ = observed $PCI_2$ for the first sample or group, $PCI_b$ = observed $PCI_2$ for a second sample or group, $PCI_{aSD}$ = standard deviation of the simulated $PCI_2$ distribution for the first sample or group, and $PCI_{bSD}$ = standard deviation of the simulated $PCI_2$ distribution for the second sample or group.

To use this formula to test for a statistical difference between two observed PCI values based on normality, compare $d$ to the critical value for a normal distribution. If $d$ is greater than 1.96, the difference is statistically significant ($p < .05$).

*Sample size simulations.* Table 1 suggests that $PCI_2$ is not substantially influenced by sample size; all of the observed and simulated $PCI_2$ means were approximately .35. The simulation shows that $PCI_2$ can be biased by an amount that is small compared to its standard deviation except for extremely large samples (tens of thousands of cases). Figure 3 displays this simulation graphically and compares results to a 7-point simulation. The $PCI_2$ values for the 7-point scale ranged from .479 to .497 and were consistently greater than the 5-point simulation. In general, $PCI_2$ values are not expected to be constant across scale widths.

### *Logical Analysis*

Logic proves that the $PCI_2$ values need not be constant and should not be forced to be constant when scale widths change. Assume, for example, that a researcher used a 9-point

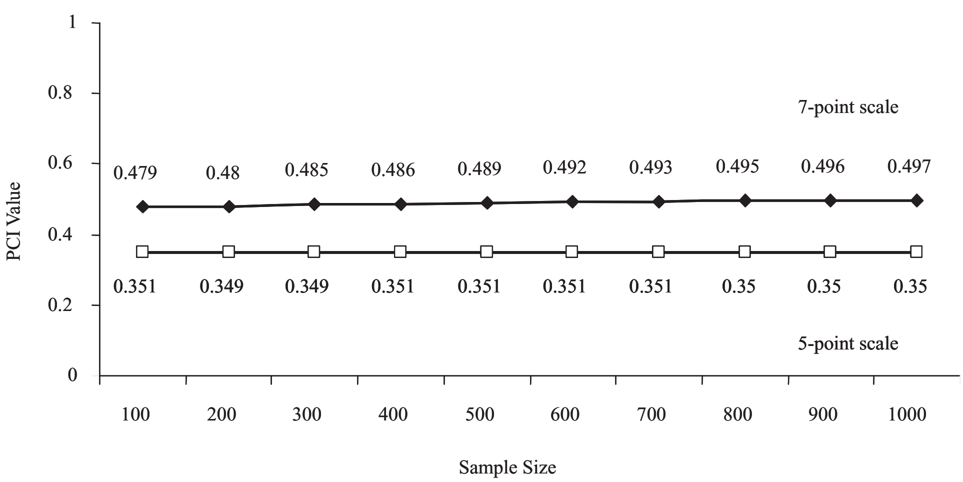


**FIGURE 3** Mean simulated $PCI_2$ values for different sample sizes. *Note:* Each sample size is based on 1,000 simulated repetitions.

scale. If there were an equal number of negative and positive responses at –4, –3, +3, and +4 on a 9-point scale, $PCI_2 < 1$. Using a 7-point scale in this example may have resulted in responses equally divided between –3 and +3, and $PCI_2 = 1$. For these scale widths (i.e., 7 and 9), individuals who report a +3 on a 7-point bipolar scale may not respond with +4 on a 9-point scale. Ipsative influences (i.e., individual variation in response patterns) may alter frequencies sufficiently to change the calculated value of $PCI_2$ (Beaman & Vaske, 1995). For scales of width 2 or 3, the ability to express any strength of feeling within the negative or positive responses is lost. Logically, then, changing scale width impacts values of $PCI_2$. The $PCI_2$ values for 5- and 7-point scales may or may not differ depending on the evaluation context.

### *Experimental Evidence*

Vaske et al. (2007) experimentally manipulated the number of response options to examine the influence of scale width on the $PCI_2$. A 3 × 3 × 3 experimental design included three predictors with three levels for each predictor: (a) response options (3-, 5-, 7-point scales), (b) species (bear, raccoon, mountain lion), and (c) severity of human-wildlife interaction (animal present, nuisance, caused human death). Respondents ($n = 364$) were presented with nine human-wildlife interaction scenarios and rated their acceptance of six management actions (e.g., destroy the animal) for each scenario. Subjects were randomly assigned to a survey containing 3-, 5-, or 7-point responses for all scales. The simulated $PCI_2$ means for acceptance of destroying the animal for all nine scenarios are presented in Table 2. For bears and mountain lions (both charismatic megafauna), the $PCI_2$ values were statistically equivalent across all three levels of severity of human-wildlife interaction (presence, nuisance, human death). Differences in the $PCI_2$ mean values, however, were observed for raccoons in both the presence and nuisance scenarios. Slightly less conflict (i.e., smaller $PCI_2$ values) was found for the 5- and 7-point scales. Given experimental results, it is recommended that 5- or 7-point scales be used in most surveys.

**TABLE 2** Mean Simulated $PCI_2$ Values for Different Scale Widths, Wildlife Species, and Severity of Human-Wildlife Interactions for Acceptance of Destroying the Animal

| Species | Severity of interaction | Scale width[1] | | |
|---|---|---|---|---|
| | | 3-point scale | 5-point scale | 7-point scale |
| Bear | Presence | .09 | .03 | .09 |
| | Nuisance | .26 | .15 | .12 |
| | Human death | .57 | .43 | .52 |
| Mt. Lion | Presence | .26 | .14 | .16 |
| | Nuisance | .25 | .23 | .24 |
| | Human death | .55 | .51 | .60 |
| Raccoon | Presence | .26[a] | .25[a] | .11[b] |
| | Nuisance | .47[a] | .38[ab] | .26[b] |
| | Human death | .47 | .48 | .49 |

[1]Cell entries are simulated $PCI_2$ means.
Entries with different row superscripts differ statistically at $p < .05$.

## Discussion

The $PCI_1$ and its associated graphic technique for displaying results were introduced to facilitate communicating and understanding a variable's distribution for nontechnical audiences. This approach has proven useful for communicating statistical findings associated with sociological and psychological concepts (e.g., value orientations, attitudes, norms) within contexts such as endangered species, national forest and wildland fire management, recreation behavior, and instream flows in rivers. Despite this applied utility, $PCI_1$ had limitations that prompted developing $PCI_2$. For example, the $PCI_1$ formula (Equation (1)) limited the statistic to bipolar scales with a neutral value. In addition, there was not a formal test for differences among the $PCI_1$ values. The second generation of this statistic ($PCI_2$) addresses these shortcomings, expands researchers' analytical capabilities, and raises questions for further investigation. This section summarizes these improvements and highlights avenues for future research.



### *Summary: $PCI_1$ versus $PCI_2$*

$PCI_2$ (Equation (9)) and associated enhancements offer multiple advantages compared to the initial formulation (Equation (1)). First, $PCI_1$ required bipolar scales (e.g., –3 to +3) with a neutral point (0) and scale widths were constrained to 3, 5, 7, and 9. $PCI_2$ can be used with scale widths of 2, 3, 4, 5, 6, 7, 8, and 9, and can be applied to bipolar scales (i.e., with or without a neutral value) and unipolar scales (e.g., not at all important to extremely important). This expanded flexibility of $PCI_2$ allows researchers to use the statistic with virtually all fixed length scales used in survey research.

Second, $PCI_2$ formulation allows for an indefinite number of distance functions. Current implementation includes two distance formulations ($D_1$ and $D_2$) for bipolar scales and a distance function for unipolar scales ($D_3$). Given that people with negative or positive responses may perceive no disagreement or conflict with a person who is neutral on a topic, $D_1$ does not include neutral responses in the calculation of distance. The second distance function, $D_2$, includes neutral responses when calculating the $PCI_2$. To illustrate where $D_2$ may be appropriate, consider an off-highway vehicle (OHV) enthusiast who staunchly believes that OHV's should be allowed on all public lands. A wilderness purist, on the other hand, may hold equally strong beliefs in the opposite direction. If a bill was introduced into Congress that either allowed or prohibited OHV access to public lands, individuals at both ends of the spectrum might be in conflict with those who were noncommittal (i.e., neutral). The size of this neutral group could swing the vote in favor of one decision over the other (Browne-Nuñez & Vaske, 2006). Although $D_1$ is recommended for bipolar scales, $PCI_2$ allows researchers to experiment with impacts of excluding ($D_1$) or including ($D_2$) "neutral" or "neither" values when calculating the $PCI_2$. For unipolar scales, $D_3$ should be used.

Third, as argued by Tastle et al. (2005), distances need not be linear functions of responses. $PCI_2$ allows for powers of distances. Because distributions of $PCI_2$ can be generated, researchers can examine the impact of linear and nonlinear response patterns. Power 1 (i.e., $P_1$, the unsquared version) is currently recommended for use unless there is a rational for increasing weight as differences between responses become more extreme (i.e., $P_2$, the squared version). Given that any power $> 0$ can be used, options for transforming a distance function are infinite.

Fourth, the original formulation of the $PCI_1$ required users to calculate a variable's frequency distribution in a statistical program (e.g., SAS, SPSS) and then type or copy the distribution into Microsoft Excel. The second generation of this statistic allows researchers to produce the statistic directly from SAS or SPSS, use an Excel spreadsheet or the standalone version ($PCI_{2sa}$). Programs for calculating, graphing, and comparing $PCI_2$ values can be downloaded at http://welcome.warnercnr.colostate.edu/∼jerryv.

Fifth, the SAS, SPSS, Excel, and $PCI_{2sa}$ programs also generate a simulation based on a variable's actual distribution of $PCI_2$; $PCI_1$ did not include such routines. This simulation produces a mean and standard deviation for the estimated $PCI_2$. The standard deviations from the simulated $PCI_2$ is critical in testing for a significant difference from a value (e.g., from 0 or 1) and for testing for significant differences between $PCI_2$ values. The simulation is based on 400 repetitions, but this default can be changed to any number.

### *Toward a Validation of the $PCI_2$*

Efforts to validate $PCI_2$ have included logical analysis, simulations, and experiments. $PCI_2$ satisfies logic based boundary conditions; the statistic produces values of 0 and 1 when it should. Using a series of simulations, the observed $PCI_2$ values only differed slightly from the simulated $PCI_2$ values. Distributions for the simulated statistic were approximately normally distributed, implying that standard deviations generated from simulations can be used to compare the observed $PCI_2$ values using common tests for differences. The simulations also showed that bias in the statistic is relatively small compared to the standard deviation except for extremely large samples (i.e., tens of thousands of cases). Finally, the $PCI_2$ is not substantially influenced by sample size.

As anticipated, an experiment showed that different scale widths can produce slightly different values of the $PCI_1$ and $PCI_2$. Logically, it must not be assumed that individuals who report the most extreme value (+3) on a 7-point scale, for example, will always report the most extreme value (+4) on a 9-point scale. Ipsativity or individual variation in response patterns for different scale widths can influence both the mean responses and values of the $PCI_1$ and $PCI_2$. Although more research on scale width is necessary, the following guidelines are recommended. First, 5- and 7-point scales probably allow for sufficient variation in most evaluation contexts. Second, unless the goal is to replicate previous studies (e.g., 9-point perceived crowding scale, see Vaske & Shelby, 2008, for a review), the use of 9-point scales may not be necessary.

### *Future Research*

This article raises several unanswered research questions. First, $PCI_2$ assumes that distance is symmetric (i.e., $d_{h,k} = d_{k,h}$). Although this assumption is a reasonable starting point, distance may not be symmetric when operationalized in terms of perceptions. A person at –1 may or may not perceive a person at +2 as being as distant as the person at +2 sees the person at –1. Modeling nonsymmetric distance functions remains a topic for further investigation.

Second, guidelines for interpreting the relative size of the PCI should be established. Does a PCI of .80 for a 7-point scale, for example, imply that a manager needs to take immediate action to reduce the potential for conflict? Does a PCI of .30 for a 5-point scale suggest that a situation should be monitored? Researchers working with other indicators of "practical significance" have offered guidelines for interpreting effect sizes. For example, some researchers (e.g., Cohen, 1988; Gliner, Vaske, & Morgan, 2001; Vaske, 2008) have suggested that a Pearson's $r$ correlation of .10 could be interpreted as a "small" or "minimal" effect size, .30 as a "medium" or "typical" effect, and .50 as a "large" or "substantial" effect. Although others have noted that "small" effect sizes can sometimes have more practical importance than "large" effect sizes (Rosnow & Rosenthal, 1996), Cohen (1988) argued that more is to be gained than lost by offering a common frame of reference for evaluating these types of indices, especially when no better alternative exists for making a judgment. A similar set of guidelines for interpreting the PCI values would be useful for interpreting results and comparing findings within and across studies.

Third, a variety of "practical significance" indicators (e.g., odds ratios, confidence ratios) and consensus measures (e.g., $Cns(X_i)$ Tastle et al., 2005; Measure *A*, Van der Eijk, 2001) have been suggested in the literature. Establishing the relationships between these statistics and the PCI is likely to enhance the utility of all measures. If all of the statistics suggest that a problem situation exists, a manager could have more confidence in taking action.

Development of any statistic should be based on and supported by logic, theory, and empirical evidence. Given the research avenues opened by $PCI_2$, it is hoped that more innovative research will continue to result. Such research can help to shed new light on measuring the potential for conflict (or consensus) across multiple leisure, recreation, and natural resource issues.



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