Ambiguity Intolerance: An Impediment to Inferential Reasoning?

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Abstract

In an introductory statistics course, undergraduate students often struggle with the concepts and techniques of statistical inference. At the heart of inference is the inconvenient fact that we often need to make decisions or draw conclusions without benefit of all the relevant facts in ambiguous situations. There is reason to think that students vary in their attitudes and openness to ambiguity in general, and that an individual's discomfort with or intolerance of ambiguity could impede one's learning of inferential reasoning. Yet, little research has considered ambiguity tolerance as an explanatory or moderating factor in learning to apply the techniques of inference directly. This paper reports on empirical classroom research to investigate the extent to which intolerance of ambiguity is an impediment to learning about statistical inference.

Keywords: Statistics education, Ambiguity, Inferential Reasoning.

1. Introduction

In an introductory statistics course, many students struggle with the concepts and techniques of statistical inference: the process of forming judgments about a population or an ongoing process from a sample of observations drawn from the population or process. At the heart of statistical inference is the inconvenient fact that we often need to make decisions or draw conclusions without benefit of all the relevant facts. Statistical inference, then, represents an approach to decision-making in ambiguous or uncertain situations.
Research in statistics education is replete with investigations of techniques, technologies, pedagogical innovations, classroom activities, assignments and the like that may or may not improve student learning in the area of inference. Other research has focused on students' cognitive and affective characteristics vis a vis mathematics. A great deal of progress has been made, but little of the research has considered students' individual predisposition towards ambiguity itself as an explanatory factor in learning to apply the techniques of inference. This project seeks to address this gap.

1.1 Thinking About Statistics Education

This audience is very familiar with the calls for reform of statistics education since the early 1990's ((Cobb, 1993); (Hogg, 1991). Among the areas in which we've made great progress are enhanced use of technology, emphasis on the use of activities, group work, and real data, and adoption of a conceptual approach to the subject, particularly at the introductory level. (Ballman, 1997; Singer & Willett, 1990; Snee, 2003). Recently the ASA has recommended curricular and pedagogical guidelines. (The GAISE project: Statistics education guidelines for college courses, 2004).

The emphasis on a conceptual approach to statistics education has quite naturally raised discussions about precisely what the basic statistical concepts and conceptual skills are and how we can most effectively help students to learn them. [(Allen et al., 2005; McKenzie et al., 2005) As we think about how students learn statistical concepts, we have been able to draw on research about concept formation in general, and ways in which concept–building is facilitated or impeded. (Medin, 1989; Murphy & Allopenna, 1994; Pazzani, 1991).

Some of the work on student success in introductory statistics courses has focused on the learner, and in particular attitudinal or affective orientations towards statistics and mathematics (Schau et al., 1995; Tempelaar, 2003). Other research has concentrated on personality dimensions the might have implications for effective instruction. Seipel and Apigian (2005) focused on perfectionism and Whittingham (2006) has studied the impact of personality types on student performance in quantitative courses throughout the MBA curriculum.

The work described in this paper focuses on the development of inferential reasoning skills and one personality characteristic: one's general orientation towards dealing with ambiguity. In an introductory statistics course, many students struggle with the concepts and techniques of statistical inference: the process of forming judgments about a population or an ongoing process from a sample of observations drawn from the population or process. At the heart of statistical inference is the inconvenient fact that we often need to make decisions or draw conclusions without benefit of all the relevant facts. Statistical inference, then, represents an approach to decision-making in ambiguous or uncertain situations. It seems reasonable to ask if an individual's orientation towards ambiguity affects his/her development of inferential reasoning skill. On the one hand, an intolerance of or distaste for ambiguity in general might tend to enhance the appeal of statistical methods that offer a means of coping with ambiguity. On the other hand, intolerance of ambiguity itself might create a roadblock that impedes the learner from seriously engaging the study of inferential reasoning.

1.2 Tolerance of Ambiguity

Frenkel-Brunswick formally introduced the concept of ambiguity tolerance as a personality attribute (Frenkel-Brunswik, 1948). She suggested that when an individual is particularly intolerant of ambiguity, ambiguous situations are sources of conflict and anxiety. One coping strategy for such individuals is rigid adherence to preconceived notions or prejudices. Faced with evidence that is contrary to preconceptions, as a means of avoiding the conflict and anxiety, such individuals might not perceive or process the new evidence, continuing instead their rigid adherence to the initial conception.

MacDonald (1970) clarified the difference between a rigid personality and one intolerant of ambiguity in this way: "Once having accepted an answer, the former will tenaciously (i.e., rigidly) hold on to it, even in the face of new contradictory evidence. The latter, on the other hand, may easily exchange the held belief for a better one" (792).

Over the years there has been considerable work refining the construct, and extending it by suggesting contingency models or applying it to groups (Budner, 1962; Curley et al., 1986; Durrheim & Foster, 1997; Frenkel-Brunswik, 1948; Furnham & Ribchester, 1995). By 1995 Furnham & Ribchester summarized the concept in this way:

> Ambiguity tolerance (AT) refers to the way an individual (or group) perceives and processes information about ambiguous situations or stimuli when confronted by an array of unfamiliar, complex, or incongruent clues. AT is a variable that is often conceived on an unidimensional scale. The person with low tolerance of ambiguity experiences stress, reacts prematurely, and avoids ambiguous stimuli. At the other extreme of the scale, however, a person with high tolerance for ambiguity perceives ambiguous situations/stimuli as desirable, challenging, and interesting and neither denies nor distorts their complexity or incongruity. (179)

Some researchers think of AT as a personality trait while others conceive of it as a "cognitive and perceptual process favored by certain individuals." For example Durrheim and Foster challenge the view that AT is a generalized personality trait, finding evidence to suggest that manifestations of AT are related to the content of a particular situation (Durrheim & Foster, 1997). AT is also sometimes connected to psychological dimension of Openness in the "Big Five" structure, which also includes need for variety and preference for complexity, nontraditional attitudes and behavior flexibility. (Hogan et al., 2004)

Note that this understanding of ambiguity differs from that commonly used in decision theory. There, though not universally adopted, it tends to refer to decision situations in which the probability of success (or the appropriate distribution) is unknown to the decision-maker (Curley et al., 1986; Ellsberg, 1961; Keren & Gerritsen, 1999). The literature on this topic frequently describes and seeks to explain predictable avoidance of ambiguity.

As the concept of ambiguity tolerance has evolved, so have efforts at measurement. Budner (op. cit), with on-going refinements and alternative approaches. (Benjamin et al., 1996; Budner, 1962; Durrheim & Foster, 1997; Furnham, 1994; Furnham & Ribchester, 1995; Grenier et al., 2005; Keren & Gerritsen, 1999; Kirton, 1981; MacDonald, 1970; McLain, 1993; Norton, 1975). Furnham (1994) examined four commonly used scales to compare reliabilities and complexity. The four scales were those devised by Budner, Walk (preceded Budner—1952), Rydell (Rydell, Rydell/Rosen/MacDonald), and Norton. In terms of reliability, Budner's and Walk's scale were weakest, with reliabilities of 0.59 and 0.58, respectively. Norton had the highest reliability coefficient of the four (0.89) and RRM was reasonably high at 0.78. These four scales variously detect 3 to 6 factors related to ambiguity tolerance, with Walks having fewest. None of the four scales studied show a factor structure as simple as tolerance versus intolerance of ambiguity.

Nearly contemporaneous with Furnham's review of the available scales was McLain's MSTAT-I (Muliple Stimulus Types Ambiguity Tolerance) which represented an effort to address some of known problems and weaknesses in earlier scales (McLain, 1993). McClain reported a reliability of 0.86 and empirical support for a single factor of "general tolerance for ambiguity" (p. 186).

These scales have been applied in a wide variety of contexts, including the relationships of ambiguity tolerance and:

- course perfectionism in introductory statistics (Feinberg & Halperin, 1978);
- conceptual formation of causal relationships (Friedland & Keinen, 1991);
- magical thinking (Keinen, 1994);
- integrative processing of learning among undergraduates (Johnson et al., 1995);
- political orientation among university students in Israel (Filberg & Ressler, 1998);
- coping with uncertainty (Stoycheva, c2001);
- work satisfaction (Wittenburg & Norcross, 2001)
- academic success of undergraduates (Boyd, et al., 2003);
- need for course structure among students (deRoma, et al., 2003);
- leadership (Lane & Klenke, 2004);

2. Research Question and Hypotheses

Grenier et al. (2005) report Bhushan & Amal's (1986) summary as identifying three observable reactions as manifestations of ambiguity intolerance:

1. Cognitive reactions, which include such responses which indicate a tendency on the part of the individual to perceive an ambiguous situation rigidly in black or white.

2. Emotional reactions, which refer to expressions of uneasiness, discomfort, dislike, anger and anxiety in response to an ambiguous situation.

3. Behavioral reactions, which refer to responses which indicate rejecting or avoiding an ambiguous situation.

Inasmuch as inferential reasoning requires the adoption of a structured approach to integrating information in often ambiguous situations, it is plausible that the reactions cited here might interfere with mastery of inferential topics in introductory statistics. As noted above, the fundamental questions in this research revolve around the possible relationship an individual's tolerance for ambiguity and that same individual's success in building facility with inferential reasoning. The earlier discussion also noted that it is theoretically reasonable to anticipate that low tolerance for ambiguity could either impede or enhance the development of inferential reasoning. Therefore, the research hypotheses are non-directional.

H1: Students' tolerance for ambiguity will, other factors being equal, affect their success in tasks requiring inferential reasoning.

H2: Among students with low tolerance for ambiguity, effort expended during the course will have a significantly different impact on their success in tasks requiring inferential reasoning in comparison to students with high tolerance for ambiguity.

The study controls for several other factors including students' prior study of statistics, Math SAT scores, and the level of effort demonstrated throughout the course. Additionally, about one fourth of the subjects completed the introductory statistics course in conjunction with a Learning Community (described below), and the Learning Community environment may have had an impact on their development of reasoning skills.

Without laying out formal hypotheses about these variables, one should reasonably expect that prior study of statistics, Math SAT scores, and level of effort should also have a positive relationship to demonstrated skill in inferential thinking.

Methodology

2.1 Participants

The subjects in this study were 48 students enrolled in two sections of an introductory course in applied statistics for Business at Stonehill College in the spring semester 2006. Sixteen of the students elected the course as part of a Learning Community (LC) that consisted of two other courses: Epidemiology and an integrative seminar entitled "Calculated Risks." There were no prerequisites for any of the Learning Community courses. College-wide all sophomore students complete a Learning Community—a cluster of two related courses with a specially designed integrative seminar that treats themes common to both courses. The students simultaneously enroll in all three classes which are taught by two members of the faculty. The sixteen LC students encountered reading, assignments, instruction, and discussion touching broadly on statistical issues and thinking in both the epidemiology and seminar classes, as well as in the statistics course. The other 32 students were primarily first-year business students fulfilling a departmental quantitative reasoning requirement.

2.2 Measurements

All of the measurements and tasks were embedded within the course, either in the form of routine credit-bearing activities (e.g. homework assignments, quizzes, exam questions) or survey instruments completed in class and debriefed as examples of data collection and survey design. The research design was reviewed and approved by the College Institutional Review Board, and students were provided with the following disclosure both on the course syllabus and in class.

> Disclosure of Research Participation
> During the term, you will be asked to participate in some surveys or other data gathering activities as part of a larger research study that I am conducting. Participation in the study will not adversely affect your course grade; however there are incentives to participate. By the end of the course I will explain the nature of the study, but I cannot do so early in the course because that might bias the study.

2.2.1 Ambiguity Tolerance (AT) scale

Early in the term, students completed a paper-and-pencil form of McLain's MSTAT-I instrument (1993) as the operational measure of ambiguity tolerance. This is a 22-item questionnaire with each question eliciting a response on a seven-point Likert scale. Ten of the items are reverse-scored, and in this sample Cronbach's alpha was 0.897, quite similar to McLain's published alpha of 0.86. For the analysis reported in this paper the AT scale was dichotomized at its median score, and students are coded as being tolerant or intolerant of ambiguity.

In the first week of the term and in the final class sessions, students completed an on-line pre- and post-test of statistical thinking. These were the Comprehensive Assessment of Statistics (CAOS) scales developed by the ARTIST team at the University of Minnesota (delMas et al., 2003). This particular scale assesses a variety of skills and concepts in elementary descriptive and inferential statistics. For each student a difference score has been computed, and this score will serve as a 'third party' metric for the student's comprehensive achievement in the course.

2.2.2 Dependent variable

A review of the literature surfaced no standard instrument specifically designed to measure inferential reasoning, though the challenges of measurement of conceptual understanding in statistics have been documented (Konold, 1995). The CAOS improvement score cited above does not differentiate inferential reasoning from other forms of statistical thinking.

During the semester, students completed a series of tasks that require inferential thinking. These tasks were all embedded within both closed- and open-ended questions in credit-bearing quizzes and exams. Each of these tasks was scored independently with students' names blinded, and the scores were factor-analyzed into a single scale; that scale becomes the dependent variable in this study.

The CAOS difference score did not show a significant correlation with this Inferential Reasoning scale; however the IR scale does have significant correlations both with the CAOS pretest ($r = 0.472$) and posttest ($r = 0.566$). These correlations provide limited validation of the scale as a measure in this study.

2.2.2 Covariates

Effort: Naturally we expect performance differences to be affected by the level of effort students exert during a course. An effort scale was developed based on three variables: regularity of attendance, points earned on homework problem sets, and peer assessments of participation in a semester-long team project. These are small classes and attendance is recorded regularly (if not quite daily) by the instructor. Homework problem sets count as only five percent of the course grade, and are assigned as learning exercises. In general, a student's homework average largely reflects the care and effort devoted to the assignments more than it gauges ability or mastery. Finally, at the conclusion of the semester there is a problem on the final exam (worth 5 points) asking each student to provide a confidential assessment of the level of effort devoted by each member of their team during the major course project assignment. Students are informed that, based on the scores and intra-team agreement on scoring, individual student project grades are adjusted upward or downward. Therefore, there are incentives to be frank in their judgments. All of the effort components were factor analyzed and normalized to a scalar with mean 0 and standard deviation 1.

Controls: Finally, four variables were included as controls: Learning Community (LC) participation, Gender, prior college-level coursework in statistics and self-reported Math SAT scores. The LC control was introduced because of the special nature of the LC experience with common themes and examples occurring in three courses, as well as the fact that the two statistics sections used difference statistical software (SAS Learning Edition 2.0 in the LC and

Minitab 14 in the other section), and that most LC students were sophomores while the others were almost all freshmen. It was reasonable to expect that students in the LC section might have had an advantage over the others; at any rate their learning experience was different.

3. Analysis and findings

Table 1 reports the basic descriptive statistics for the variables used in this analysis. The two sections were evenly balanced between women and men. Two of the initial 48 students withdrew from the course during the semester, one male and one female. Both were in the non-LC section of the course. MSAT scores were not reported by 9 of the remaining 46 students. Somewhat surprisingly, 43% of the students reported some prior formal coursework in statistics.

Variable	N	N*	Mean	StDev	Median
InfScale (dependent)	46	2	68.54	13.82	71.12
AmbTolD (0-1)	46	2	0.50	0.51	0.50
PrevCourse (0-1)	46	2	0.43	0.50	0.00
MSAT	39	9	612.82	54.38	600.00
Effort	46	2	0.00	1.00	0.24
LC (0-1)	46	2	0.43	0.50	0.00
Female (0-1)	48	0	0.42	0.50	0.00

Table 1: Descriptive Statistics of Variables in Model

Examination of the bivariate correlations among the independent variables reveals no significant correlations at all; thus there is little potential for multicollinearity. Table 2 reports the correlations between the Inference Scale (dependent) and each of the independent variables described above.

Among the bivariate correlations, only the Effort scale and the binary Female variables have significant correlations with the Inference Scale at the 0.05 significance level, and the self-reported Math SAT score is significant at the 0.10 level. The other variables bear no direct linear relationship with the inferential reasoning scale.

To test the research hypotheses, two multiple regression models were fitted. The estimated parameters of these models are shown in Tables 3 and 4. Preliminary analysis revealed that neither the gender nor the LC controls were statistically significant, so they were dropped from the analysis.

	InfScale
AT	-0.172
	0.254
PrevCourse	0.104
	0.493
MSAT	0.300
	0.063
Effort	0.612
	0.000
LC	0.043
	0.776
Female	0.401
	0.006

Table 2: Correlations (p-values in second row)

Variable	Coeff	Signif
Intercept	9.700	0.580
AT	-5.201	0.086
PrevCourse	7.854	0.021
MathSAT	0.096	0.001
Effort	10.225	0.000
F	11.73	0.000
Adj R2	0.530	

Table 3: Results for H1 Regression

Recall the two research hypotheses:

H1: Students' tolerance for ambiguity will, other factors being equal, affect their success in tasks requiring inferential reasoning.

H2: Among students with low tolerance for ambiguity, effort expended during the course will have a significantly different impact on their success in tasks requiring inferential reasoning in comparison to students with high tolerance for ambiguity.

In the first regression we find support for H1 at the 10% significance level: students with low tolerance for ambiguity (AT = 0 condition), after controlling for prior coursework, level of effort and Math SAT score, tended to score higher on the inferential reasoning scale than did their peers who were classified as tolerant of ambiguity. The significant negative coefficient on the AT variable indicates that high ambiguity tolerance was associated with lower performance on the inferential reasoning scale items. Residual analysis revealed no concern with least-squares assumptions.

Due to the students who did not report SAT scores, the regression was rerun without the MathSAT variable thereby increasing *n*, and the result held up. The dichotomized AT variable showed a significant negative coefficient.

To test the second hypothesis, the following model was fitted:

$$\text{Infscale} = \beta_0 + \beta_1 \text{AT} + \beta_2\text{Prev} + \beta_3\text{MSAT} + \beta_4\text{Effort} + \beta_5\text{EffortxAT} + \varepsilon$$

Variable	Coeff	Signif
Intercept	7.340	0.654
AT	-5.307	0.062
PrevCourse dummy	8.025	0.012
MathSAT	0.100	0.001
Effort	6.655	0.004
Effort x AT	7.127	0.019
F	12.00	0.000
Adj R2	0.591	

Table 4: Results for H2 Regression

Once again, the LC and Gender control variables were dropped from the analysis owing to lack of significance, and again the AT variable has a significant (at the 10% level) negative coefficient. The interaction term is positive and significant as well: students with high tolerance who apply effort can overcome the initial "setback" expressed by the AT variable. Because the effort scale has a zero mean and standard deviation of 1 (but far from normal in shape), a full unit change in Effort is a tall order. Nonetheless, under the low AT condition Effort has a coefficient equal to 6.655; for high-AT students the impact of effort is more than doubled to a coefficient value of (6.655 + 7.127) = 13.782. This analysis also supports the proposition that effort has a differential impact for students high and low in ambiguity tolerance.

As in the case of the first regression graphical analysis of the residuals revealed no clear violations of the least squares assumptions.

4. Discussion and Future Research

This project has adduced some limited evidence that students with low ambiguity tolerance may more successful develop the skills related to inferential reasoning. The author's initial suspicion was counter to this result: that ambiguity intolerance would function as an impediment to inferential thinking because discomfort with incomplete information represented by a sample and with the very conventions of statistical inference that leave us with conditional conclusions. In this particular study though we find the opposite result, perhaps due to the fact that the methods of inference provide a "way out" of the ambiguity intolerance trap. Inferential cases are inherently uncertain and ambiguous, and these methods are established protocols for navigating through the uncertainty.

Surely there are areas for improvements to this study and extensions of the current research. This was reasonably small sample and the use of two different courses muddied the issues. The use of an untested scale for inferential thinking leaves open questions as to whether these results can be validated by others. Perhaps more importantly this study converted the McLain ambiguity intolerance scale into a binary variable with the attendant loss of information.

Further investigations should make use of alternative and more precise measures of performance in the realm of inferential reasoning as well as continuous ambiguity tolerance scale scores. Naturally a larger sample would be preferable paper using CAOS scale scores as dependent variable.

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