

## STATISTICAL LITERACY CURRICULUM DESIGN

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**Abstract:** A specially-designed statistical literacy course is needed for college students in majors that don't require statistics or mathematics. The goal of this course is to show the power of randomized experiments, the pitfalls of using a statistical association to infer causation in observational studies, and ways to discriminate between stronger and weaker arguments using statistics as evidence. This paper suggests that key topics in conditional probability, multivariate regression and the vulnerability of statistical significance to confounding should be included and presents some new ways to teach these ideas based on field trials in the W. M. Keck Statistical Literacy project at Augsburg College. This paper argues that whatever literacy means, it must entail utility or perceived value. Statistical literacy should give students a lasting appreciation of the value of statistics in their everyday, civic and professional lives. By that standard the W. M. Keck Statistical Literacy program may be succeeding. After studying statistical literacy, 43% of Augsburg students "strongly agree" that it "helped me develop critical thinking skills, 33% said it is "practical and relevant to my major or work" (33%), 28% said it is "practical and relevant to my personal or civic life" and 18% said it should be "required of all students for graduation."

### 1. Focus and Philosophy of a Statistical Literacy Curriculum

Moore (1998a, 2001) distinguished *statistical literacy*<sup>1</sup> ("What every educated person should know about statistical thinking") from *statistical competence*<sup>2</sup> ("roughly the content of a first

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<sup>1</sup> Moore outlined "the new statistical literacy": (1) "Think broadly: Is this the right question? [Who is unemployed?]" (2) "Think broadly: Does the answer make sense? [Only 15% of entrants into the work force will be native white males.]" (3) "Communication: Can you read a graph? [France in a population pyramid]" and (4) "Filters for Nonsense: Triage on the information flood. [Does the Bible code predict the future?]"

<sup>2</sup> (1) "statistical thinking (ASA/MAA): [The need for data, The importance of data production and The omnipresence of variation.]" and (2) "the quantification and explanation of variability" [Randomness and distributions, Patterns and deviations (fit and residual), Mathematical models for patterns, and Model-data dialogs (diagnostics)]."

course for those who must deal with data in their work” or “what we hope a statistics student will retain five years later”). For Moore, statistical literacy involves two clusters of “big ideas.” #1: “The omnipresence of variation, Conclusions are uncertain, Avoid inference from short-run irregularity, and Avoid inference from coincidence.” #2: “Beware the lurking variable, Association is not causation, Where did the data come from?, and Observation versus experiment.” Statistical literacy is for data consumers; statistical competence is for data producers.

### 1.1 Kinds of Data in the 21st Century

A sound curriculum should be based on the subject matter of the discipline. The subject of statistics is data. Not just data as numbers studied by mathematics but data in context. Several wide-spread and important changes are occurring in the forms and kinds of data available.

- Sample sizes are getting larger, so smaller differences are becoming statistically significant.

In the National Longitudinal Study of Youth (NLSY) with 12,000 subjects, a difference of 0.4 points of IQ<sup>3</sup> between men and women is statistically significant at a 5% level.

- Population data are becoming more common for both governments and for businesses.
- Observational studies are becoming more common in research. In medical journals, articles involving observational studies (34%) were 50% more prevalent than those involving randomized trials (25%). Among related news stories, those involving observational studies (60%) were 10 times as common as those involving randomized trials (6%).<sup>4</sup>
- More so-called experiments have the properties of observational studies. In education,

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<sup>3</sup> Standard error is 0.207 with samples sizes of 6,000 when IQ has a mean of 100 and a standard deviation of 16.

<sup>4</sup> *Scientific American* (2002) reported that “Researchers from the University of Bristol and the University of Bern looked at 1,193 medical journal articles and determined which ones were accompanied by press releases and subsequently picked up by two newspapers. Notably, the papers were not inclined to describe results from randomized trials, which generate the strongest kind of scientific evidence.” The journals were the *British Medical Journal* and *Lancet*; the newspapers were the *Times* and the *Sun*. Among these medical-journal articles, researchers found that those based on observational studies (37.2%) were about 1.5 times as prevalent as those based on randomized trials (24.7%). Among the related news stories, researchers found that those involving observational studies (58%) were almost 10 times as prevalent as those involving randomized trials (6.2%). *British Medical Journal*, July 13, 2002.

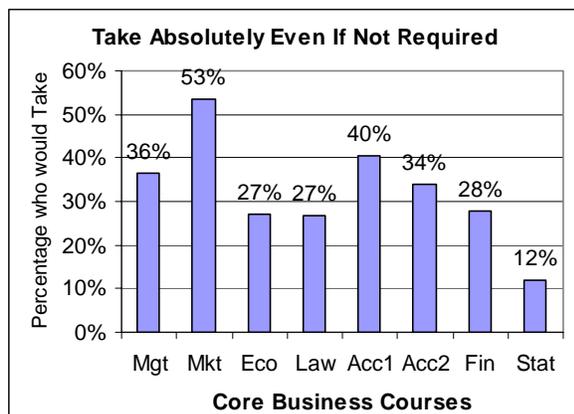
Chance (2001) noted that teachers and students can be randomly assigned to classes or teaching methods, but it is difficult to blind either as to which teaching methods are being used.

- Observational studies are becoming a basis for policy decisions. Using US longitudinal crime data, John Lott's *More Guns; Less Crime* supported states passing concealed-carry gun laws.
- Statistics based on observational studies are becoming politically significant. Participation in the National Assessment of Educational Progress (NAEP) is now a basis for Title 1 funds.
- Simpson's Paradox (a reversal of an association after accounting for the influence of a lurking variable or confounder) is no longer a rarity. Terwilliger and Schield (2004) found 52 statistically-significant reversals of state NAEP scores in one data set using one confounder.

Students should be taught to distinguish statistical experiments from observational studies. A controlled medical study involving random sampling is not a randomized experiment.

## 1.2 Motivation of Students to Study Statistics

A sound curriculum should take into account student motivation toward the subject. During the first week, 47 Augsburg business students taking statistics were asked "Would you take the following core business courses even if they were not required?" Figure 1 shows the percentage by course who answered 'Absolutely' (rather than Almost Certainly, Likely, Unlikely or Absolutely Not). For statistics, 24% said 'Absolutely Not' while 52% said it was 'Unlikely.'



**Figure 1: Willingness to Take the Course**

Business Students	Attitude Toward Math			
	MAJOR	ALL	Like	Dislike
ALL	22%	29%	16%	
Acc/Fin/Econ/MIS	28%	38%	21%	
Mgmt/Mktg	7%	12%	0%	

**Table 1: Percentage who would Absolutely or Almost Certainly take Statistics as Elective**

These students<sup>5</sup> were also asked about their major and their attitude toward mathematics.<sup>6</sup> Binary groups were formed from all three variables: willingness to take statistics as an elective, major and attitude toward math.<sup>7</sup> As shown in Table 1, those who would absolutely or likely take statistics if it were an elective are 22% of these business students, 16% of those who dislike mathematics, and 0% among the less-quantitative majors (marketing and management) who dislike mathematics: a combination that describes many of those majoring in the liberal arts.

This lack of perceived value for statistics has been documented by Schau (2003) who conducted the Survey of Attitudes toward Statistics (SATS). After completing a traditional course, student's attitudes were more polarized (increased standard deviations) than before and there was a statistically significant 8% decrease in the value they perceived in the subject.<sup>8</sup> Schau noted, "Many of us believe that attitudes impact students' achievement, [their] course completion, [their] future course enrollment, and [their] statistical thinking outside of the classroom." The less value students see in what they are learning, the less motivated they are to participate, to learn, to remember what they learned, and to use what they learned. Robert Hayden (private communication) noted, "Students will not use what they learn in a statistics course (of any kind) unless they believe they learned something usable. So we have to both provide something useful AND sell them on it." This lack of value for statistics was evidenced when 190 students at Pomona College (1999) ranked Critical Thinking first in value among 10 core competencies, but ranked Data Analysis last. Macnaughton (2004) has argued that the primary goal of an introduc-

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<sup>5</sup> One alternate explanation for this difference is that prospective judgments are lower than retrospective. Most students are seniors so their judgments on other courses are retrospective while those on statistics are prospective.

<sup>6</sup> Choices: Like Very Much (4), Like Somewhat (3), Neutral (2), Dislike Somewhat (1), and Strongly Dislike (0).

<sup>7</sup> Like Very Much (4) and Like Somewhat (3) were combined into Like; the rest were combined into Dislike.

<sup>8</sup> Attitudes involve affect, cognitive competence, value and difficulty. The survey involved 287 undergraduates in 11 sections of the introductory statistics course offered by a Math-Stats Department. Increase in standard deviations: Difficulty (46%), Affect (28%), Value (25%) and Cognitive (16%). Of the changes in the mean scores, only the 8% decrease in Value was statistically significant. Alternate explanations for this decrease include a fatigue effect (post scores are generally lower than pre) and a delayed recognition effect (it takes time to appreciate the value).

tory statistics course should be to give students “a lasting appreciation for the value of statistics.” By that criterion, the traditional course may not be achieving the Macnaughton goal. One explanation for this is a lack of focus on observational studies and causation. About 70% of those studying statistics are in majors that focus on using observational data to infer causation.<sup>9</sup>

### 1.3 Role of Statistics in Everyday, Business and Civic Life

A sound statistical literacy curriculum should be based on the role of statistics in a student’s daily, civic or professional life. Table 2 presents the prevalence of published articles using statistical terms. Articles involving confidence or significance are as high as 18% of all articles in *Nature* but no more than 0.1% of all articles in *The Economist*.<sup>10</sup> The following data involves Business majors, but if statistical topics are over-emphasized for business majors, it seems that such topics would definitely be over-emphasized for liberal arts majors. Table 3 summarizes the percentage of young workers (18-25) in business who use a particular statistics topic (Holmes, 1981). While 54% read and interpret tables of data and 37% make decisions using data, only 6% use a statistical test of significance. Stroup and Jordan (1982 & 1983) surveyed 151 business statistics teachers and 1,495 business managers. Figure 2 illustrates (a) the percentage of these statistics teachers who teach a given topic versus (b) the percentage of those teaching a topic who teach it extensively. While both data sets are over 20 year old, we are unaware of anything more recent. Based on our experience in business, these data appear to be fairly accurate.

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<sup>9</sup> This percentage is estimated by relating the kind of data to the major. Randomized experiments are the hallmark of modern psychology and the health sciences; observational studies are the hallmark of business and the social sciences. Assume that all students receiving Bachelor’s degrees in these four disciplines study statistics. In 1995 that involved 234,000 in business, 125,000 in the social sciences, 84,000 in the health sciences, and 74,000 in Psychology per Table 287, 2001 US Statistical Abstract. If all students studying statistics are in these disciplines, then of the US students studying statistics (517,000), 70% are in majors that focus primarily on observational data (359,000

<sup>10</sup> Search 12/14/2003 within each source. Rates were calculated by dividing hits by the total number of articles in that source. The total number of articles was obtained by searching on ‘the’: a word common to all articles.

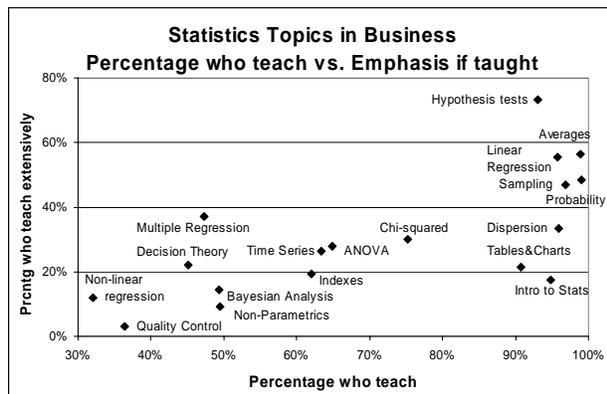
<sup>11</sup> Teachers were asked how much they taught the topic: extensive, moderate or none. Their answers generated two scales. (a) The horizontal *frequency scale*: the percentage of all respondents who said “Moderate” or “Extensive”. (b) The vertical *emphasis scale*: the percentage who said “Extensive” of those who said “Moderate” or “Extensive.”

STATISTICAL TERM	Nature Magazine	USA Today	The Economist	Yahoo Search
Mean/Median/Mode	36,456	7,996	890	316
Rate	31,763	7,647	22,870	1,837
Sample	29,263	778	1,598	807
Risk	20,962	4,003	16,474	837
Percentage	14,968	3,234	3,745	260
Random	12,592	662	1,243	458
Probability	7,685	109	481	134
Chance	6,306	7,550	13,096	586
Standard deviation	4,058	3	0	19
Random Sample	686	10	15	11
Percentage Points	64	717	1,849	13
<b>CONFIDENCE</b>				
Standard Error	2,164	0	0	7
Confidence Interval	1,817	0	0	9
Confidence Level	336	26	0	6
Level of Confidence	62	9	9	4
Margin of Error	32	359	44	4
<b>SIGNIFICANCE</b>				
Statistically significant	6,512	14	47	12
Statistical significance	3,474	1	3	6
P-value	2,982	0	12	7
Level of Significance	449	0	0	2

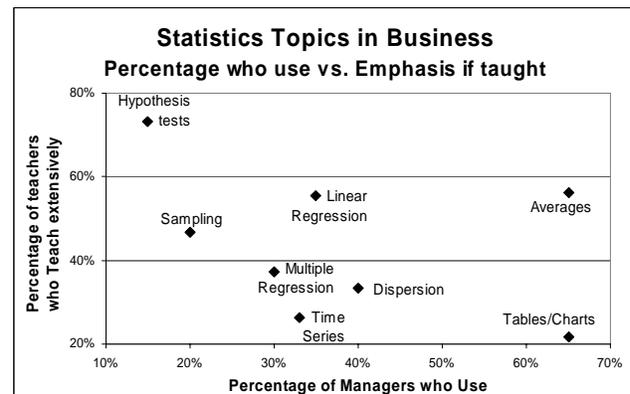
**Table 2: Prevalence of articles using the term per 100,000 articles by source.**

60%	draw up tables of data
54%	read and interpret tables of data
53%	assess the accuracy of someone else's data
53%	write reports based on data for others
52%	decide what data to collect
51%	calculate the mean
40%	detect and estimate trends
38%	simplify tabulated data
37%	allow for variability in data
37%	make decisions using data
35%	make projections
27%	draw bar charts and time series graphs
20%	use words such as likely and uncertain
19%	calculate variance or standard deviation
19%	use logarithm or other specialist scales
19%	draw trend lines; read/interpret histograms
17%	calculate median and quartiles
17%	assign probabilities to events
15%	allow for non-response to questionnaires
14%	select the questions on questionnaires
14%	read and interpret scatter diagrams
13%	use statistical tests to compare sets of data
13%	use probability as a measure of uncertainty
12%	read and interpret results of simulations
9%	calculate correlation coefficients
8%	calculate moving averages
6%	use a statistical test of significance
4%	use the normal distribution
2%	calculate index numbers

**Table 3: Usage in Business**



**Figure 2: Topics taught in business statistics**



**Figure 3: Statistics topics used in business**

Figure 3 illustrates topics in introductory business statistics courses classified by (b) how extensively they are taught and (c) their usage in business.<sup>12</sup> Note the negative association. This

<sup>12</sup> (c) The horizontal scale is the percentage of business managers who use this topic. Stroup & Jordan (1982, 1983).

mismatch may contribute to the lower level of motivation among business majors. It seems that college statistics is not tested on the GMAT.<sup>13</sup> If business use is the standard then hypothesis tests are over-taught while multiple regression, time series, dispersion and tables/charts are under-taught. If we look at the use of statistics as evidence in public policy<sup>14</sup> or historical analysis<sup>15</sup> it appears that multivariate analysis is used more often than statistical significance.<sup>16</sup>

#### 1.4 Key Topics in Statistical Literacy

A sound curriculum should reflect the key topics, tools and principles in that discipline.<sup>17</sup> Since the subject of statistics is data, the key statistical ideas can be organized in terms of data. One way is to see what statistical factors dominate the reasoning in different kinds of studies. Chance (random error) dominates in small-sized, well-designed experiments: treatments with random assignment. Bias (systematic error) can dominate in poorly-designed studies regardless of size. Confounding (the influence of a lurking variable) dominates in populations or large-scale, well-designed observational studies. As these observational studies become increasingly common, the study of confounding becomes increasingly important.<sup>18</sup>

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<sup>13</sup> GMAT questions presume one is familiar with basic statistical concepts such as “% of”, “% change”, “average”, etc. (1) Sample questions in Quantitative Problem Solving: 1a Arithmetic: discount on discount (cumulative), 1b. Percents: basis points, percentage point differences, 1c. Geometry: conversion from area to perimeter, 1d. Algebra: roots of equations, 1e. Algebra: solve two simultaneous linear equations. (2) Sample questions in Quantitative Data Sufficiency: 2a. Percentages: commission and net proceeds, 2b. Percentages: salary increase; percent comparison, 2c. Arithmetic: identifying mileage on trip, 2e. Arithmetic: identifying operator/operation, 2f. Arithmetic: prime numbers, 2g. Geometry. Some questions focus on the distinction between necessary and sufficient.

<sup>14</sup> In the US, the Kinsey Report presented findings on sexual practices; the “Moynihan” Report warned about increasing problems among black families; the “Coleman” report analyzed different forms of urban education; Julian Simon and “The Skeptical Inquirer” argued that environmental concerns were often unwarranted.

<sup>15</sup> In “*The Great Breakthrough and Its Causes*”, Julian Simon used historical data to argue that the size of population (the free, skilled population) is the fundamental cause of the dramatic improvements in human welfare.

<sup>16</sup> In “*The Bell Curve*” Herrnstein and Murray used multivariate analysis to argue that low IQ had a stronger association with various social problems than did low socioeconomic status. In “*More Guns; Less Crime*”, John Lott used multivariate analysis to argue that passing concealed-carry laws for handguns was associated with reduced crime.

<sup>17</sup> One way to identify key topics in a field is to identify what the leaders in that field actually do. This approach may work for deciding what to teach statistics majors (statistics is what statisticians do) but this may not work for deciding what to teach data consumers in a statistics service course.

<sup>18</sup> Holmes (2003) put it this way. “*When you have huge data sets, which are essentially populations, it isn’t the sampling variability that’s important. It is, the actual figures themselves and what are the connections between them.*”

A second way of organizing topics is by the kind of data required whether univariate, bivariate or multivariate. Chance and inference apply to all three kinds of data as does modeling. But confounding requires multivariate data. Multivariate data are seldom studied in the introductory course but are generally the focus of a second course on regression. Note that most observational data is multivariate. The results may be presented one predictor at a time (pair-wise using bivariate techniques), but the underlying data is multivariate. One thing is clear: while an estimated 60% of college students take an introductory statistics course, very few take a second course.<sup>19</sup> As a result, the understanding of those taking just the introductory course is biased towards inference and against confounding as compared with the understanding of those taking both courses.<sup>20</sup> The emphasis on statistical inference rather than on multivariate thinking in the introductory course may reflect the difficulty students have with conditional reasoning<sup>21</sup> or the difficulty of teaching multivariate thinking without teaching multivariate regression.

The controversy over hypothesis tests is longstanding. (Morrison and Henckle, 1970 and Harlow et al, 1997). A reduced emphasis on hypothesis testing has been recommended by a business statistics association ([www.MSMESB.org](http://www.MSMESB.org)) with more emphasis on confidence intervals<sup>22</sup>) and by the American Psychological Association with more emphasis on effect sizes.<sup>23</sup>

The use of multivariate summary data is more common in the social sciences and business. Podelhl (2003) advocates using official statistics to assist students in dealing with current social issues. Bregar (2003) shows how Economic Statistics can be taught using official statistics.

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*That is an important part of what I would now put in statistical literacy – which I wouldn't have put in 20 or 30 years ago, because there wasn't so much of this sort of stuff around."*

<sup>19</sup> For justification of the 60%, see Schield (1999a). At the University of St. Thomas in St. Paul, Minnesota with at least 14 sections of introductory statistics per year there is generally just one section a year on regression.

<sup>20</sup> Note that the new MAA two-semester Curriculum in Business Statistics focuses more on modeling and less on chance and inference. See [www.maa.org/pubs/busmath.html](http://www.maa.org/pubs/busmath.html) or <http://business.math.arizona.edu/MBD/mbd.html>.

<sup>21</sup> E.g., "How likely is this outcome *if* due to chance?" versus "How likely is this outcome *to be* due to chance?" "This outcome is very unlikely *if* due to chance" versus "This outcome is very unlikely *to be* due to chance."

<sup>22</sup> MEMESB members Cryer and Miller (1994) wrote such a textbook but added hypothesis testing in a later edition.

<sup>23</sup> 1996 report at [www.apa.org/science/tfsi.html](http://www.apa.org/science/tfsi.html) and the 1999 report at [www.apa.org/monitor/may99/task.html](http://www.apa.org/monitor/may99/task.html).

## 1.5 Statistical Thinking and Informal Reasoning

A sound curriculum should reflect the kinds of reasoning used in the discipline. As a branch of mathematics, statistics uses deductive logic and conditional reasoning in the reasoning from a population to random samples. There are disagreements on the importance of conditional reasoning. A business statistics association, MSMESB,<sup>24</sup> argued that there should be less emphasis on conditional probability. Rossman and Short (1995) raised concerns while Dawes (2001) advocated more emphasis on informal uses of conditional probability. While Berry (1997) argued persuasively that students should be exposed to Bayesian thinking<sup>25</sup> in the first course, Moore (1996) argued conversely noting that students lacked the required skill in conditional reasoning.

As an art, statistics must deal with data-related questions internal to the data: what outliers to ignore, what transformations to make, what level of non-response to ignore, which model is best, what interactions to model, and how sensitive is the model to a change in the data. In addition to these, statistical literacy must also deal with data-related questions external to the data. How do the following relate to the argument at hand: the choice of the population and the outcome of interest, the choice, definition and connotation of each variable, and the vulnerability of both the value and the statistical significance of an observed association to an unknown confounder?

In reasoning ‘beyond’ the data, statistical literacy should be concerned with informal, inductive, pre-inferential, reasoning as well as with formal, deductive, inferential reasoning. Erickson and Finzer (2004) support a stronger focus on pre-inferential reasoning by claiming that “many students have trouble with “real” statistics later because they do not have enough experience interpreting these more obvious quantitative arguments and displays.” Pfannkuch and Horning (2004) called for more attention to “informal inferences” to help school teachers teach statistics.

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<sup>24</sup> For a history, see [www.MSMESB.org](http://www.MSMESB.org).

<sup>25</sup> Bayesian thinking focuses on the ‘chance’ of the alternate hypothesis being true given the data. For example, as the p-value decreases, does the evidence increase for saying the null hypothesis is false and the alternate is true?

## 1.6 Curriculum Determinants

A sound curriculum should reflect the time available during the course in relation to the time required to present the underlying concepts necessary to properly understand a topic of interest. To include more advanced topics within a given time limit, educators must find ways to do so without giving a detailed presentation of all the supporting topics: teaching about the binomial distribution without a detailed study of combinations and permutations, teaching conditional probability without teaching algebra, teaching logistic regression without a full exposition of maximum likelihood, teaching multivariate thinking without teaching multiple regression, and teaching statistical inference without deriving the sampling distribution from the binomial. The time required to cover the underlying concepts for each topic may determine which topics can be effectively presented within a single course.

## 1.7 Thinking and Experience of Leading Statistical Educators

A sound curriculum should relate to the current thinking of the leaders in that field. Statistical educators agree on the importance of statistical literacy.<sup>26</sup> There are many suggestions on the definition and nature of statistical literacy<sup>27</sup>, but at present there is no general agreement on the relation between statistical literacy, reasoning and thinking<sup>28</sup> much less between statistical liter-

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<sup>26</sup> Statistical literacy was the theme of the 2001 IASE Satellite Conference in Seoul and of the 2002 ICOTS-6 conference in Cape Town. See [www.swin.edu.au/math/iase/statlit.html](http://www.swin.edu.au/math/iase/statlit.html) and <http://icots6.haifa.ac.il/icots6.html>.

<sup>27</sup> Reviews that focus directly on statistical or quantitative literacy include Steen (2001), Scheaffer (2001), Moore (1998a, 2001), Macnaughton (2004), Best (2003), Holmes (2003), and Stroup, Goodman and Scheaffer (2004). For materials, see the ASA-NCTM Quantitative Literacy series by Gnanadesikan et al. (1987).

<sup>28</sup> Garfield (2002), Chance (2002), Rumsey (2002), del Mas (2002a and b) and others are working at distinguishing statistical reasoning, statistical thinking and statistical literacy. The March 2003 issue of *The American Statistician* contained articles by Utts (2003), Gal (2003) and Sowe (2003) on this topic. Gal (2000) and Groenestijn (2002) have reviews on adult numeracy. For more background, see websites maintained by the IASE International Statistical Literacy Project (<http://course1.winona.edu/cblumberg/islplist.htm>), by the Statistical Reasoning, Thinking and Learning (SRTL) project ([www.stat.auckland.ac.nz/~iase](http://www.stat.auckland.ac.nz/~iase)) or by the W. M. Keck Statistical Literacy project ([www.StatLit.org](http://www.StatLit.org)). Note that this statistical literacy curriculum is proposed as an supplement to – not as a replacement of – the current introductory curriculum as described by Garfield et al (2002).

acy<sup>29</sup>, numeracy (Crockhoft, 1982) and quantitative literacy (Steen's "*Everybody Counts*" published by the Mathematics Science Education Board, 1988 and Steen, 2001).

## **1.8 Conclusion**

Many of the key topics needed for statistical literacy are currently taught in the first two college statistics courses on inference and regression. Most students do not take the second course which contains important ideas involving confounding that are essential to evaluating the strength of evidence provided by statistics obtained in observational studies. This is the dilemma of statistical education today: the choice between statistical inference and multivariate thinking in a single course. Statistical educators are not willing to argue for two required courses even though the MAA is supporting a two-semester statistics-modeling course for business majors.<sup>20</sup>

## **2. Background and Development Process**

### **2.1 Background of the W. M. Keck Statistical Literacy Curriculum**

The statistical literacy course at Augsburg College originated in the Department of Business Administration in 1993. A second course in General Studies was initiated in 1997. In 2001, the W. M. Keck Foundation gave Augsburg College a grant to develop tools and materials for teaching statistical literacy. In the W. M. Keck Statistical Literacy curriculum, statistical literacy is defined as "critical thinking about statistics used as evidence in arguments." See Schield 1999a, 2000a and 2002. Burnham (2003) noted that the purpose of statistical literacy is "to improve the quality of the student's decisions about issues for which statistical information is available." Augsburg's program has strong similarities with those described by Steen (2001), Scheaffer

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<sup>29</sup> Li Jun (2004) noted that statistical literacy is described by the China Ministry of Education (MOE, 2001) as follows: "1. Be familiar with using statistical thinking to deal with problems containing data. 2. Appreciate the role statistics plays in decision making by going through the process of collecting, displaying, analyzing data, and making reasonable decisions. 3. Be able to read critically data resources, data analyses, and summarized information."

(2001), Moore (2001), Best (2004), and Stroup et al. (2004).<sup>30</sup> Whatever literacy means, it must mean utility or perceived value. Statistical literacy should give students a lasting appreciation of the value of statistics in their everyday lives as decision makers and citizens.<sup>31</sup>

## 2.2 W. M. Keck Statistical Literacy Curriculum: Statistical Perspective

From a statistical perspective, the goal of Statistical Literacy is “to teach students how to read and interpret data.”<sup>32</sup> To be of value to data users, a sound course in statistical literacy should instruct students about the big ideas of statistical significance (statistical inference) and confounding (multivariate reasoning). While teaching statistical inference may have been more critical in the past where the focus was on experiments with small size samples, statisticians cannot afford to withhold the value of multivariate thinking from data consumers who must deal primarily with large scale observational studies where confounding typically has a greater effect on related inferences than does sampling variability. The real question is how to do all of this within a single semester course where the students have limited mathematical skills and have little motivation to study the subject. The next sections present new tools used in the W. M. Keck Statistical Literacy curriculum to present the ideas of statistical significance and the influence of confounding within a single-semester course. To teach less is akin to educational negligence given the changes in data and the uses of statistics in commerce and in social policy.

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<sup>30</sup> Holmes (2003) said, “*The Augsburg course [in Statistical Literacy] is different. It has a different emphasis from many other courses to establish statistical literacy. It comes from a different background, but it has a lot of overlaps. And in many ways it reflects better the amount of the data that comes as part of every day life, certainly from large observational studies.*” *What the Augsburg course “puts together is unique. That’s not to say that the individual things are necessarily unique. But the package as a whole comes off as a very different package. It draws on ideas from areas which have not been in the traditional mainstream of statisticians. But they are there and they are statistical and we should be drawing on them.”* The Augsburg “*approach to statistical literacy goes beyond numeracy by focusing on reading and communicating those topics studied in numeracy.*” *The emphasis of this course “is much more in line with the sort of statistical literacy needed by most people in everyday life to read the news, by those who are in business commerce or management and by policy makers.”*

<sup>31</sup> Of course, not all students may see the full utility of a course by the end of the course. But the fewer the students seeing utility by that time, the weaker the evidence for saying that the course teaches statistical literacy.

<sup>32</sup> Dr. John Cerrito, Chair of Business Administration at Augsburg College, has argued consistently and persuasively since 1994 that statistics should teach students “how to read and interpret data!”

### 3. Description

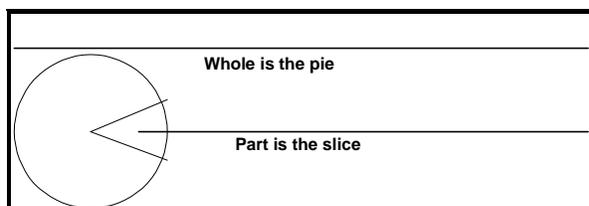
A curriculum is determined by the goals, the tools, the time available and the motivation, background and interests of the students. The W. M. Keck Foundation has developed and/or tested new tools involving graphs for use in teaching statistical literacy. Figures 4, 6 and 8-12 illustrate some of these tools. With these simple tools, one can focus clearly on the big ideas at hand in ways that students can readily understand. For more details consult the associated reference(s). A common feature is the ability to measure both the strength and the influence of a confounder so that students can work numeric problems on the influence of confounding.

#### 3.1 Teaching Conditional Probability using Ordinary Language

Conditional probability is taught using natural language to describe ratios (percentages and rates). Table 4 illustrates a two-way half table of percentages. [10% of male smokers (whole) are runners (part).] These rate-style half tables convey more information in a smaller space.

<b>PERCENTAGE WHO ARE RUNNERS</b>			
	Non-smoker	Smoker	Total
Female	50%	20%	40%
Male	25%	<b>10%</b>	20%
Total	37%	15%	30%

**Table 4: Two-way Table of Percentages**



**Figure 4: Part-whole Pie**

Figure 4 is a device for analyzing the underlying data into the components of a part-whole ratio. Schield (2000b) indicates how to describe ratios in percent grammar and percentage grammar. Schield (2001) presents techniques needed to read tables of rates and percentages.<sup>33</sup> Students find these activities surprisingly challenging and are self-motivated to master them. Since all the margin values in Table 4 are averages, both indexes are wholes and the part is in the title: runners. In percent grammar, “10% of male smokers are runners.” In percentage grammar, “The

<sup>33</sup> Some statisticians have felt such tables of percentages are improper because they lack a 100% sum. These rate-style tables of percentages are found in government publications in the US and UK, and in business publications.

percentage of male smokers who are runners is 10%” or “Among male smokers, the percentage of runners is 10%.” Studying this part-whole ratio grammar helps students realize that  $P(A|B) \neq P(B|A)$ . Utts (2003) identified this “confusion of the inverse” as one of seven key statistical ideas commonly misunderstood by citizens. See also Dawes (2001) and Gigerenzer (2002).

### 3.2 Measuring Associations using Ordinary Language Arithmetic Comparisons

Arithmetic comparisons are a powerful form of association. See Schield (1998 and 2000b). Expressing comparisons of ratios takes more factors into account, but doing so in ordinary language is not a trivial matter. Two diagrams are used to analyze these comparisons of ratios. Figure 5 displays a common-part comparison of ratios: “*Girls grades 9-12 in Wyoming are 10 times as likely to chew tobacco as those in New York.*”

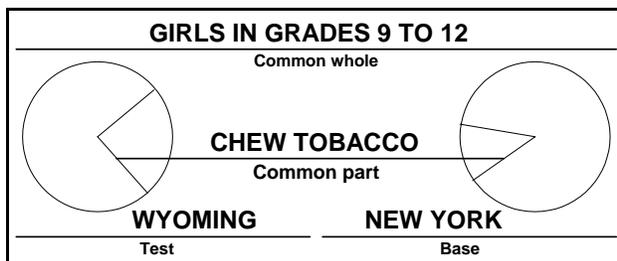


Figure 5: Common-part Comparison

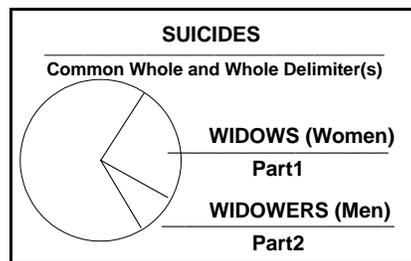


Figure 6: Distinct-parts Comparison

Figure 6 displays a distinct-part comparison of ratios: “*Widows are more likely among suicides than are widowers.*” This diagram helps students recognize that ‘suicide’ is a whole – not a part.

### 3.3 Diagramming Confounding

Statisticians typically focus on what is “in” the data and on the proper design of studies to ensure that plausible confounders are included. But data analysts must think “outside” the data. What unmeasured variables could influence the observed association? A commonly-used diagram, Figure 7, can illustrate the associations between three variables. Students generally see the importance of the relationship between the confounder and the outcome of interest but take longer to see the importance of the relation between the confounder and the predictor. They see

alternate causes for an outcome but cannot see alternate explanations for an association.

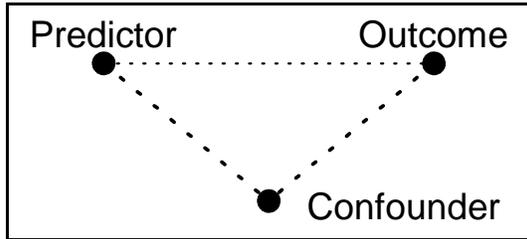


Figure 7: Three-Factor Diagram

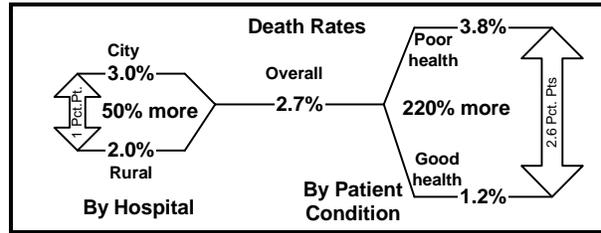


Figure 8: Outcome-Difference Diagram

### 3.4 Measuring the Strength of a Confounder

Schild (1999c) introduced the outcome comparison diagram in Figure 8 to help students compare the strengths of associations involving a binary predictor and a binary confounder. The link between the confounder and the outcome must be stronger (greater difference or ratio) than that between predictor and outcome in order for a confounder to nullify or reverse an observed association between predictor and outcome. Since the relative prevalence of death is greater for patient condition than for hospital in Figure 8, taking into account patient condition could reverse the association of death rates (Simpson’s Paradox).

### 3.5 Standardizing for the Influence of a Confounder

Figure 9 and Figure 10 illustrate a new graphical technique to standardize associations for the influence of a binary confounder. See Schild (2004a) and Wainer (2004) for details.

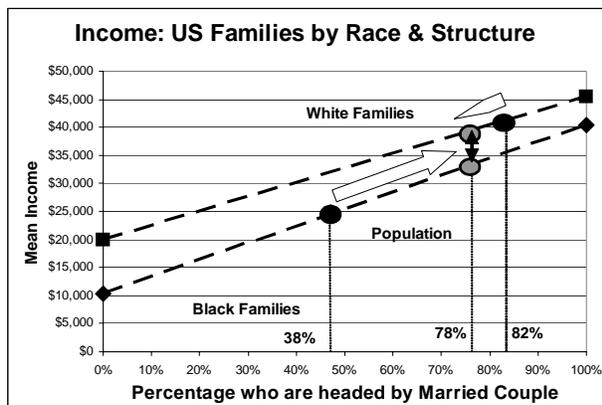


Figure 9: Family Income by Race

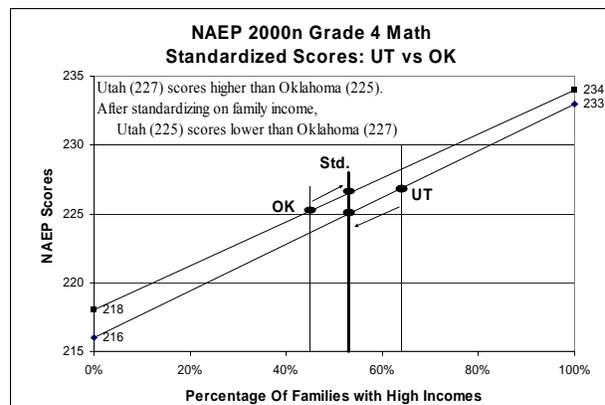


Figure 10: NAEP Scores by State

This outcome-mixture graph helps students see confounder influence as a change in mix in a weighted average. The binary confounder is on the horizontal axis; the outcome of interest is the on the vertical axis, and the binary predictor groups are the two weighted-average lines. A vertical line is the confounder prevalence for the group in question. The weighted average for each predictor group depends on the confounder prevalence for that group: the vertical lines on the left and right. The vertical line in the middle is the confounder prevalence for both groups taken as together. The standardized values are obtained by using this common confounder prevalence: the vertical line in the middle. By focusing on binary predictors and confounders so that an interactive multivariate model is fully-saturated, there is no need to focus on the adequacy of the model or on model diagnostics, although one must still focus on assuming independence between the outcome and the confounder prevalence.

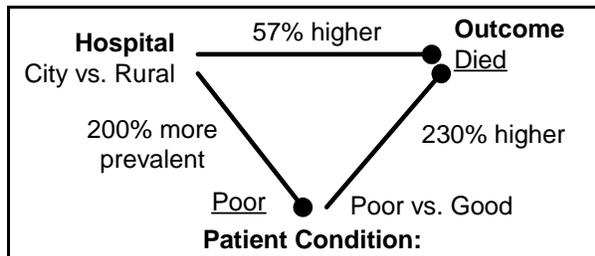
In Figure 9, family income is 64% (\$16K) greater among whites (\$41K) than among blacks (\$25K). After standardizing on their common family structure (78% of all these families are headed by a married couple), family income is 18% (\$6K) greater among whites (39K) than among blacks (\$33K). Thus, 62% (\$10K) of the original black-white family-income gap (\$16K) is accounted for or explained by family structure.

This graph links quantitative literacy (Steen 2001) and statistical literacy (Moore 2001).

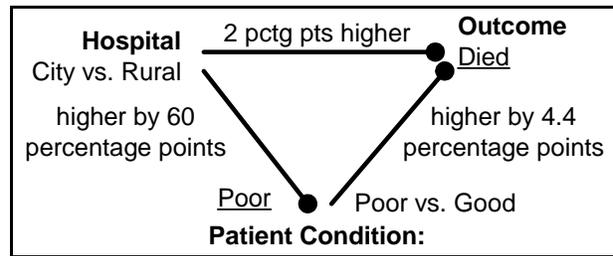
### **3.6 Confounder-based Estimates**

At this point students become aware that a confounder can either increase or decrease an observed association – and in some cases can actually reverse it (Simpson’s Paradox). Using a non-interactive model, some results can be inferred. See page 5 of Schield and Burnham (2003) or D5 in Abramson (1994) on the Exclusion Test and Direction Rule. When students are given numeric comparisons between two or three factors (Figure 11 or Figure 12), they are expected to

infer the relation between the *whole effect* (57% higher or 2 percentage points higher) and the *direct effect* (the partial slope): the effect that would be obtained after taking into account the influence of a confounder in a non-interactive model.



**Figure 11: Percentage Difference Triangle**



**Figure 12: Simple Difference Triangle**

Will the direct effect be greater, smaller or the reverse of the whole effect? Given the data in Figure 11 students should conclude that a Simpson's Paradox is possible (not impossible). Given the data in Figure 12 they should conclude that a Simpson's Paradox reversal must occur after taking patient condition into account. Being able to reach these conclusions without actually doing the multivariate regression is a useful skill in reading and interpreting data. See Schield and Burnham (2003) for a complete discussion of these data and an indication of how "direct" and "whole" effects relate to the standardization graphs shown previously.

### 3.7 Statistical Significance using Confidence Intervals

Even though statistical significance is not common in the everyday press, it is an important statistical concept. But as typically taught, it takes many class hours to cover all the underlying machinery. Giere (1996) utilized a short cut approach using just binary data (difference in proportions). This short cut bypasses the problem of distinguishing the standard deviations of the population, the sample and the sampling distribution. By using just the most conservative confidence intervals, the standard error depends only on the confidence level ( $Z$ ) and the sample size ( $n$ ). And by using the lack of overlap for confidence intervals as a sufficient condition for statistical significance, the teaching of statistical significance is shortened considerably.

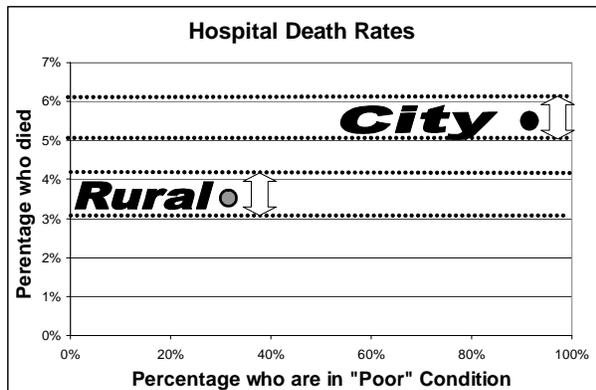


Figure 13: Statistically Significant

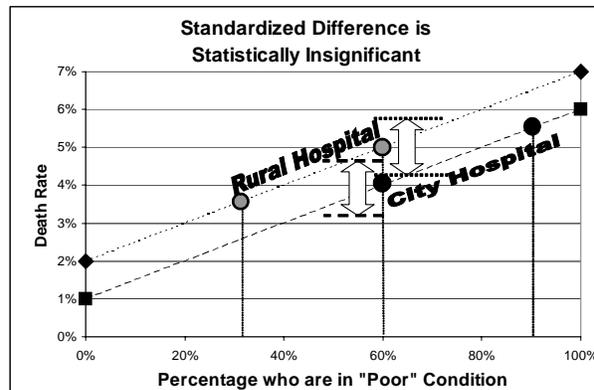


Figure 14: Statistically-Insignificant

Given a random sample of patients from two hospitals, students calculate the confidence intervals associated with the associated death rates as shown in Figure 13. Since these intervals do not overlap, they conclude that the observed difference is statistically significant at 5% level.

### 3.8 Vulnerability of Statistical Significance to Confounding

Figure 14 illustrates the crown jewel of a complete course in statistical literacy: showing the vulnerability of statistical significance to confounding in observational studies. (Schield, 2004a) Confidence intervals are generated around the standardized value. Since these intervals overlap, this standardized difference in death rates may not be statistically significant.

We are unaware of any other introductory course that teaches this topic. If 517,000 U.S. college graduates study statistics each year<sup>9</sup> then all too many students may be leaving with the mistaken impression that statistical significance is absolute regardless of the kind of study. Statistical educators at the IASE 2004 Roundtable support remedying this situation. After reading and discussing this paper, they were asked if students should be shown “*that statistical significance can be influenced by a confounder in all introductory statistics courses?*” In an anonymous survey, eight circled ‘strongly agree’, seven circled ‘generally agree’, and one circled ‘indifferent.’ The real issue is the cost. When these same people were asked, “*Should introductory statistics teach stu-*

*dents more about confounding even if that means less time for statistical significance?”*, seven circled ‘generally agree,’ four circled ‘indifferent’ and five circled ‘disagree.’

#### **4. Pilot and Implementation Results**

A goal of this project is to develop teaching materials that are “useful to students and usable by other teachers.” Due to the continual design and infusion of new tools and topics, the teaching materials are still under development. It takes time to integrate these new techniques into a coherent curriculum and much trial and error is required. Student surveys indicate the progress.

Sixty-six students taking the general studies course in statistical literacy at Augsburg College were surveyed after completing this course. The data in Table 5 indicates the percentage of students who agree strongly or agree at least moderately with the following statements.

<b>Agree Strongly</b>	<b>Agree at least Moderately</b>	<b>STATEMENT</b>
43%	81%	Developed critical thinking skills
33%	77%	Practical/relevant to major or work
33%	75%	Practical/relevant to personal/civic life
18%	57%	Should be required of all students

**Table 5: Percentage who agree with these statements**

Note that ‘at least moderately’ includes ‘strongly agree.’ There is no comparable data for those taking other courses, so any conclusion is disputable. Still, these percentages are encouraging – especially since many of these students started the course saying they would not take statistical literacy unless it was required. Since respondent credibility is always an issue, the last question is perhaps the most telling. It is easy for students to agree with nebulous outcomes (e.g., developed critical thinking skills). It is much harder for them to agree with an outcome involving very definite costs unless the student truly agrees.

What explains these higher percentages? The unrelenting focus on context is a prime candidate. Students may recognize this is an essential element of critical thinking (Schield 2004b).

## **Toward Statistical Literacy**

In “More Damned Lies and Statistics,” Best (2004) titled his last chapter, “Toward Statistical Literacy?” He questioned whether statistical educators will take responsibility for this area. Yet Scheaffer (2003) in talking about Quantitative Literacy argued that statistics could and should take responsibility for such matters. *“Some of the QL leaders tend to see statistics as only the small part of QL that deals with chance. I see statistics as much broader than that; in fact, I see it as encompassing much of the QL litany of topics that deal with data and its practical use in everyday situations. Thus, there is an important role for statisticians to play in this expanding interest in QL, .... Statistics is the branch of the mathematical sciences that deals with numbers in context – data – and makes systematic study of how to reason under uncertainty. Statistics must be a key part of QL!”* Scheaffer concluded by saying, *“Over the years, statistics has lost out on many initiatives that should have been its province because of lack of interest or lack of foresight. Isn't it time we wholeheartedly embrace one that we can see coming?”*

### **4.1 Conclusion**

Statistical educators should develop a college-level statistical literacy course for students in majors that do not require a math or statistics course. This statistical literacy course should focus on statistics as evidence in arguments. It should highlight the difference between causation and association, and between experiments and observational studies. It should uphold the power of randomized experiments and identify some specific pitfalls of observational studies in using statistical associations as evidence of causal connections. By adding a graph-and-language based course focusing on context alongside the math-based course focusing on statistical inference, statistical educators can serve a greater variety of students, and in the process help them think more critically about the role of statistics as evidence in the arguments they will encounter in daily life.

## 5. Sources and References

- Abramson, J. H. (2002). *Making Sense of Data*. Second Edition, Oxford University Press.
- Berry, Donald A (1997). *Teaching elementary Bayesian statistics with real applications in science* (with discussion). *The American Statistician* 51:241-274.
- Best, Joel (2001). *Damned Lies and Statistics*. University of California Press.
- Best, Joel (2004). *More Damned Lies and Statistics*. University of California Press.
- Bregar, Lea (2003). *Teaching Economic Statistics in the Internet Era*. IASE Satellite Conference on Statistics Education and the Internet in Berlin, Germany.<sup>34</sup>
- Burnham, Tom (2003). *Purpose and Definition of Statistical Literacy*. Spring 2003 Keck Statistical Literacy Project Review Conference at Augsburg College.
- Chance, Beth (2000). *Components of Statistical Thinking*. AERA.<sup>35</sup>
- Chance, Beth (2001). *What Can We Learn? Classroom-Based Research in Statistics*. 2001 ASA Proceedings of the Section on Statistical Education
- Crockhoft, W. H. (1982). *Mathematics Counts. Report of the Commission of Inquiry into the Teaching of Mathematics in Schools*. Her Majesty's Stationary Office.
- Cryer, Jonathan D. and Robert Miller (1994). *Statistics for Business: Data Analysis and Modeling*. Duxbury Press.
- Dawes, Robyn (2001). *Everyday Irrationality*. Westview Press
- del Mas, Robert (2002a). *Statistical Literacy, Reasoning and Learning*. *Journal of Statistical Education*, Vol. 10, No. 2.<sup>36</sup>
- del Mas, Robert (2002b). *Statistical Literacy, Reasoning and Learning: A Commentary*. *Journal of Statistical Education*, Vol. 10, No. 3.<sup>36</sup>
- Finzer, William and Tim Erickson (2004). *Curriculum Innovations Using Census Microdata: A Meetings of Statistics, Mathematics and Social Science*. IASE Curriculum Design Roundtable.
- Gal, Iddo (2000). *Adult Numeracy Development: Theory, Practice and Research*. Hampton Press

<sup>34</sup> Available at [www.stat.auckland.ac.nz/~iase/publications.php](http://www.stat.auckland.ac.nz/~iase/publications.php). Link at [www.StatLit.org](http://www.StatLit.org) under "Teaching Stat Lit."

<sup>35</sup> Available at [www.rossmanchance.com/papers/aera.html](http://www.rossmanchance.com/papers/aera.html).

<sup>36</sup> Available directly at [www.amstat.org/publications/jse/](http://www.amstat.org/publications/jse/). Web link at [www.StatLit.org](http://www.StatLit.org) under "Teaching Stat Lit."

Gal, Iddo (2003). *Teaching for Statistical Literacy and Services of Statistics Agencies*. The American Statistician, Vol. 57, No. 2. Pg. 80-84.

Garfield, Joan (2002). *The Challenge of Developing Statistical Reasoning*. Journal of Statistical Education, Vol. 10, No. 2.<sup>36</sup>

Garfield, Joan, Bob Hogg, Candace Schau and Dex Whittinghill (2002). *First Course in Statistics: The Status of Educational Reform Efforts*. Journal of Statistical Education, Vol. 10, No. 2.<sup>36</sup>

Giere, Ronald (1996). *Understanding Scientific Reasoning*. 4<sup>th</sup> ed., Holt, Rinehart and Winston.

Gigerenzer, Gerd (2002). *Reckoning With Risk: Learning to Live With Uncertainty*. Penguin. See Amazon.com in the UK.

Gnanadesikan, M., R. L. Scheaffer, J.M. Landwehr, A.E. Watkins, P. Barbella, J. Kepner, C.M. Newman, T.E. Obremski, J. Swift (1987). *The Quantitative Literacy Series*. Dale Seymour.<sup>37</sup>

Groenestijn, Mieke van (2002). *A Gateway to Numeracy: A Study of Numeracy in Adult Education*. Utrecht Press.

Harlow, Lisa, Stanley Julaike and James. Steiger (Eds). (1997). *What If There Were No Significance Tests?* Lawrence Erlbaum Associates

Holmes, Peter (1981). *Statistical Needs of Young Non-Specialists*. Available at <http://science.ntu.ac.uk/rsscse/publications.htm>.

Holmes, Peter (2003). *Statistical Literacy, Numeracy and the Future*. Talk, Augsburg College.<sup>38</sup>

Jun, Li (2004). *Statistics Education for Junior High Schools in China*. IASE Roundtable 2004.

Macnaughton, Donald (2004). *The Introductory Statistics Course: The Entity-Property Approach*. Posted at [www.MatStat.com/teach](http://www.MatStat.com/teach).

Mathematical Sciences Education Board, National Research Council (1989). *Everybody Counts: A Report to the Nation on the Future of Mathematics Education*. National Academies Press.<sup>39</sup>

Moore, David (1996). Reply to Donald A Berry on “*Teaching Elementary Bayesian Statistics*.” The American Statistician 51, p. 275.

<sup>37</sup> See [www.pearsonlearning.com/dalesey/dalesey\\_default.cfm](http://www.pearsonlearning.com/dalesey/dalesey_default.cfm). Exploring Probability, The Art and Techniques of Simulation, Exploring Data, Exploring Surveys and Information from Samples and Exploring Measurements.

<sup>38</sup> Accessible at [www.StatLit.org](http://www.StatLit.org) under “*Teaching Stat Lit*.”

<sup>39</sup> Available at [www.nap.edu/books/0309039770/html/index.html](http://www.nap.edu/books/0309039770/html/index.html).

Moore, David (1998a). *Statistical Literacy and Statistical Competence in the 21<sup>st</sup> Century*. Abstract of talk at 1998 Making Statistics More Effective in Schools and Business (MSMESB). [www.stat.uiowa.edu/~jcryer/dmooreabstract.htm](http://www.stat.uiowa.edu/~jcryer/dmooreabstract.htm).<sup>38</sup>

Moore, David (1998b). *Statistics Among the Liberal Arts*. ASA Presidential Address. Journal of the American Statistical Association, Vol. 93, No. 444, pp. 1253-1259. December 1998.<sup>38</sup>

Moore, David (2001). *Statistical Literacy and Statistical Competence in the New Century*. (Power Point Slides.) IASE Satellite Conference on Statistical Literacy in Seoul, Korea.<sup>38</sup>

Morrison, D.E. and Henckle, R.E. (1970). *The Significance Test Controversy*. Chicago: Aldine.

Podehl, Martin (2003). *Statistics in the Classroom: Learning to Understand Societal Issues*. IASE Satellite Conference on Statistics Education and the Internet in Berlin, Germany.<sup>34</sup>

Pfannkuch, Maxine and Julia Horring (2004). *Developing Statistical Thinking in a Secondary Girls School: A Collaborative Curriculum Development*. IASE Curriculum Design Roundtable.

Pomona (1999): <http://pom-oit-nt6.pomona.edu/gened/Files/PACs%20Evaluation%201999.pdf>.

Rumsey, Deborah J. (2002). Statistical Literacy as a Goal for Introductory Statistics Courses. Journal of Statistical Education, Vol. 10, No. 3.<sup>36</sup>

Rossmann, Allan J. and Thomas H. Short (July 1995) *Conditional Probability and Education Reform: Are They Compatible?* Journal of Statistical Education.<sup>36</sup>

SATS: Survey of Attitudes Toward Statistics. See [www.unm.edu/~cschau/satshomepage.htm](http://www.unm.edu/~cschau/satshomepage.htm)

Scheaffer, R. L. (2001). *Quantitative Literacy and Statistics*. *Amstat News* 293, Nov. 2001, 3-4.<sup>38</sup>

Schau, Candace (2003). *Students Attitudes: The "Other" Important Outcome in Statistics Education*. ASA Proceedings of the Section on Statistical Education. Pg. 3673 - 3681.<sup>38</sup>

Schild, Milo (1998). *Statistical Literacy and Evidential Statistics*. 1998 ASA Proceedings of the Section on Statistical Education.<sup>38</sup>

Schild, Milo (1999a). *Statistical Literacy: Thinking Critically about Statistics*. *Of Significance* journal. The Association of Public Data Users, Volume 1.<sup>38</sup>

Schild, Milo (1999b). *Common Errors in Forming Arithmetic Comparisons*. *Of Significance* journal. The Association of Public Data Users, Volume 1.<sup>38</sup>

Schiold, Milo (1999c). *Simpson's Paradox and the Cornfield Conditions*. 1999 ASA Proceedings of the Section on Statistical Education.<sup>38</sup>

Schiold, Milo (2000a). *Statistical Literacy and Mathematical Reasoning*. University Working Group, International Conference on Mathematics Education (ICME-9), Tokyo.<sup>38</sup>

Schiold, Milo (2000b). *Statistical Literacy: Describing and Comparing Rates and Percentages*. 2000 ASA Proceedings of the Section on Statistical Education.<sup>38</sup>

Schiold, Milo (2001). *Statistical Literacy: Reading Tables of Rates and Percentages*. 2001 ASA Proceedings of the Section on Statistical Education.<sup>38</sup>

Schiold, Milo (2002). *Three Kinds of Statistical Literacy*. 2002 ICOTS-6.<sup>38</sup>

Schiold, Milo and Tom Burnham (2002). *Algebraic Relationships between Relative Risk and Phi in 2x2 Tables*. 2002 ASA Proceedings of the Section on Statistical Education.<sup>38</sup>

Schiold, Milo and Tom Burnham (2003). *Confounder-Induced Spuriousity and Reversal: Algebraic Conditions Using a Non-Interactive Model for Binary Data*. 2003 ASA Proceedings of the Section on Statistical Education.<sup>38</sup>

Schiold, Milo (2004a). *Three Graphs To Promote Statistical Literacy*. ICME-10.<sup>38</sup>

Schiold, Milo (2004b). *Statistical Literacy and Liberal Education at Augsburg College*. Peer Review, September 2004. American Association of Colleges and Universities.<sup>38</sup>

Scientific American (2002). *Data Points Fit to Print*. News Scan Section, p. 34.

Sowey, Eric (2003). *The Getting of Wisdom: Educating Statisticians to Enhance Their Clients' Numeracy*. The American Statistician, Vol. 57, No. 2. Pg. 74-79.

Steen, Lynn (2001). *Mathematics and Democracy: The Case for Quantitative Literacy*. National Council on Education and the Disciplines.

Stroup, Donna and Eleanor W. Jordan (1982), *The Organizational Context of Statistics*. Graduate School of Business, University of Texas at Austin, Working Paper Series, 81/82-3-7.

Stroup, Donna and Eleanor W. Jordan (1983). *Statistics: Monster in the University*. ASA Proceedings of the Section on Statistical Education, pp. 135-138.

Stroup, Donna, Richard Goodman, Ralph Cordell, and Richard Scheaffer (2004). *Understanding Populations, Teaching Statistical Principles Using Epidemiology*. American Statistician, Feb.

Terwilliger, James and Milo Schield (2004). *Frequency of Simpson's Paradox in NAEP Data*. Presented at the national meeting of the American Educational Research Association.<sup>38</sup>

Utts, Jessica (2003). *What Educated Citizens Should Know About Statistics and Probability*. The American Statistician, Vol. 57, No. 2. Pg. 74-79.

Wainer, Howard (2004). *Three Paradoxes*. Draft submitted to the American Statistician.<sup>38</sup>

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