EXPANDING THE HORIZONS OF EDUCATIONAL PAIR PROGRAMMING:

A METHODOLOGICAL REVIEW OF PAIR PROGRAMMING

IN COMPUTER SCIENCE EDUCATION RESEARCH

by

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ABSTRACT

Expanding the Horizons of Educational Pair Programming:

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Educators and researchers continue to explore the benefits, real or imagined, of implementing pair programming as part of the computer science pedagogy. Current reviews of computer science educational research practices do not focus on educational pair programming. This thesis presents a review of the research methods used in recent educational pair programming research. The primary purpose of this review is to inform the ongoing dialogue about and to provide evidence-based recommendations for improving educational pair programming research.

Replicating the design of a previous computer science education methodological review, this study inspected a sample of 108 articles from a population of 129 of articles related to educational pair programming published from 2000 to 2008. Articles were

classified using a 112-variable taxonomy, identifying report elements, research methodology, research design, kinds of variables inspected, and statistical practices.

Major findings include several differences between the methodological characteristics of educational pair programming research when compared to general computer science education research, including: (a) an increased proportion of studies involving human participants, (b) a decreased proportion of quantitative methodologies, and (c) an increased proportion of controlled research designs. There exists some minor evidence that researchers affiliated with institutions in the United States are more likely than their counterparts outside of the United States to inspect only student attitudes and implement a posttest-only research design, and less likely to implement an experimental or quasi-experimental methodology.

(127 pages)

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INTRODUCTION

As the practice of pair programming gathers popularity in industry, educators increasingly explore the benefits, real or imagined, of implementing pair programming into *computer science education* (CSE). Because research results about educational pair programming have the potential to affect policy regarding the use of pair programming as a pedagogical tool, and because changes in policy affect the lives and educational quality of human students, it is important to ensure high quality research methodology. A review of research methods in the current body of literature, called a *methodological review* (Randolph, 2007, pp. 1-2), can identify areas of improvement to the science and inform dialogue about the scope, quality, and direction of current research efforts.

Pair programming research is a young field, and pair programming in CSE even younger. This author found no published review that evaluates the methods used in educational pair programming research. Hence, this study is the first of its kind. While some related reviews exist, they are either of a different kind, such as meta-analysis, or of a different scope, such as general computer science education. In an effort to fill the gap in the current research, and promote the improvement of research practices in the field, I conducted a thorough methodological review on a representative sample of all the pair-programming-related research articles published in major computer science education research journals and conferences from 2000-2008.

This thesis builds upon the work of Randolph (2007), who conducted a rigorous methodological review sampling articles from all areas of CSE research. I modeled this study after Randolph's in an effort to achieve the same goals stated by Randolph: To

"make a contribution to the field by supplying a solid ground on which to make recommendations for improvement and to promote informed dialogue about computer science education research" (Randolph, p. 2).

The results of this methodological review promote improvement of educational pair programming research practices, the natural consequence of which is improvement in computer science instructional methodology, and ultimately improvement in student success.

Pair Programming in Computer Science Education

Pair programming is a relatively new practice that extends the concept of collaborative development by assigning two developers to a single workstation. Programmers actively collaborate using a role-based protocol (Williams, 2007). In industry, the practice of pair programming was popularized by agile programming methodologies such as extreme Programming (XP) (Beck, 2001). The application of pair programming to computer science education began to appear in the literature in the late 1990's (Keefe, Sheard, & Dick, 2006).

Recent studies explore the use of pair programming in a variety of situations, for example, by implementing variations in pair selection methods, pair trading strategies, paired task characteristics, and combinations of other software development methodologies. The diversity of contexts combined with the tendency for reports to contain positive results from the application of pair programming strengthen the case for its use in computer science pedagogy. Benefits reported include:

- Increased student success (Williams, Wiebe, Yang, Ferzli, & Miller, 2002),
- High confidence, enjoyment, and perception of learning (Williams, 1999),
- Improved retention, confidence, and program quality (McDowell, Werner, Bullock, & Fernald, 2006),
- Improved success for women (Werner, Hanks, & McDowell, 2004), and
- Improved student grades, and improved success rates on solo exams in courses that used pair programming on assignments (Williams, McDowell, Nagappan, Fernald, & Werner, 2003).

There exist some doubt and disagreement among researchers regarding the value of pair programming in computer science education despite the broad spectrum of measured benefits. Notwithstanding the evidence in favor of the practice, some researchers, such as Hulkko and Abrahamsson (2005) and Reges (2006), have reported contradictory results or doubt the validity and general applicability of the practice. It is reasonable to speculate that this doubt arises from one of two causes, namely that current empirical evidence favoring pair programming may be insufficient, or that it may be the case that the quality of empirical evidence is inadequate.

Heany and Daly (2004) described the current condition of pair programming research, claiming that current studies "fail to conclusively show that pair programming improves learning, but our hunch is that it does when used correctly" (p. 117). Valentine (2004) echoed the sentiment that current research methods are inadequate when describing so-called "Marco Polo" papers, which he described as "a staple at the [SIGCSE] Symposium," in which "reasoning is defined, the component parts are

explained, and then… a conclusion is drawn like 'Overall, I believe the [topic] has been a big success'" (p. 256).

Anecdotal papers such as these are not without value to the community, as they can encourage the reader to consider and explore new ideas, and even stimulate ideas for empirical research; however, as research they are susceptible to nearly every threat to internal validity, and often lack reliable analysis, replicability, and appropriate application of the scientific method.

Applying Methodological Review to Improve Practice

When research has the potential for affecting changes in policy or practice, researchers must bear the responsibility of ensuring high quality in research practices. Krippendorff (2004) describes the ethical requirement of ensuring high research quality, stating that when findings can "aid business decisions…, categorize people, or affect the lives of individual human beings in other ways, wrong conclusions may have costly consequences" (p. 316). He calls for the use of content analysis, arguing, "Validation reduces the risk of making decisions based on misleading research findings" (p. 316).

Thus, uncertainty in the findings of researchers regarding the educational quality of pair programming invites content analysis practices such as methodological reviews to validate and provide direction for the current research.

Krippendorff (2004) identifies the characteristics of effective content analysis, describing it as a scientific technique "learnable and divorceable from the personal authority of the researcher," that must be reliable and "should result in findings that are

replicable" (p. 18). For these reasons, well-designed methodological reviews do not require extensive experience or expertise in the field in order to yield valid and convincing results.

Methodological reviews differ in kind from typical content analyses, which generally focus on aggregating or comparing results across a body of research. Methodological reviews, instead, focus on "the research process, that is, the methods by which a research topic is addressed, including research design and statistical analyses issues" (Keselman et al., 1998, p. 350). Methodological reviews have the capability of informing editorial decision making and influencing methodological practice. Furthermore, methodological reviews can provide guidance to educators who mentor student researchers to ensure that "students have adequate skills to interpret the published literature of a discipline and to carry out their own projects" (Keselman et al., 1998, p. 351).

Randolph (2007) described two conditions under which a methodological review can provide valuable recommendations for process and policy improvement:

> …The first is when there is consensus among experts for "best practice" but actual practice is expected to fall far short of best practice. The methodological review can identify these shortcomings and suggest policies for research funding and publication. For example, in the Keselman and colleagues (1998) review, they found that there was a difference between how statisticians use ANOVA and how social science researchers use ANOVA. Thus, the rationale for the Keselman and colleagues review was that the recommendations given by the statisticians could benefit the research practices of the social science researchers. The second condition is when there are islands of practice that can benefit from exposure to each other—for example, when there are groups that practice research in different ways or at different levels. (pp. 15-16)

CSE researchers do not overlook the need to reach across islands of practice and determine best practices. Indeed, Goldweber and colleagues have urged drawing upon, when possible, existing methodologies, stating (emphasis added):

> To date much of what is published as [computer science education research] (called "research" or not) has been concerned with noticing phenomena: "This is what happens when I teach x in this way." What moves recognition of phenomena to evidence is *purposeful investigation and a relationship to theory*….
>
> …We need to go beyond "this works for me" to *draw upon - even develop - theories of action, and report studies designed to illuminate them.* (Goldweber, Clark, Fincher, & Pears, 2004)

Insofar as research of pair programming in computer science education is a subset of general CSE research, the need to draw upon existing, interdisciplinary strategies and best practices is essential to advancing the field.

A Review of Related Methodological Reviews

Methodological reviews are not new to CSE research or to pair programming research; however, there do not appear to be reviews specifically addressing the intersection of the two fields. Here, I summarize the findings of several methodological reviews closely related to research of either computer science education or of pair programming. For a more comprehensive summary of computer science education methodological reviews, see Randolph (2007, p. 24).

Valentine (2004) presented a methodological review of articles published as part of the annual SIGCSE Technical Symposium. He evaluated two criteria for each article, namely, whether or not the article dealt with first-year college students, and which of

six defined content categories best describes the report style. With a little humor, Valentine defined the content categories as:

- Experimental, or applying any kind of scientific analysis,
- Tool presentation or evaluation,
- Philosophical, or initiating a discussion or debate,
- Marco Polo, the label for most non-experimental case studies,
- John Henry, the tall tales of the Symposium, and
- Nifty, the so-called "icing on the cake" of the Symposium. (pp. 256-257)

Of the 444 articles in the sample reporting research on first-year undergraduate students, Marco Polo papers, experimental studies, and tool descriptions comprised most of the articles in Valentine's (2004) sample. The proportions of articles for each category grouped by year provides evidence of a decreasing yearly trend in the proportions of Marco Polo papers and an increasing yearly trend in the proportions of experimental papers. As a result of this methodological review, Valentine issued a challenge to SIGCSE members to "push their presentations [to the] next step", that is, expend at least the minimal level of effort to upgrade a Marco Polo case study to an experimental study (p. 259). He argued that the level of effort necessary should be small in comparison to the effort already spent on the tool or the intervention that must otherwise be presented as a Marco Polo paper.

Perhaps the most rigorous and comprehensive review of computer science education research is the study conducted by Randolph (2007) as a doctoral dissertation, which evaluates characteristics and relationships in the kinds of research generally accepted by computer science education journals and conferences. The scope of this work is both large, including 352 research articles from a collection of 1306 articles and conference publications, and broad, utilizing a 111-point scale (of which,

Valentine's content category was one) for evaluating and research publications and defining the taxonomy. For convenience in comparison later, listed below is Randolph's summary of results.

- About one third of articles did not report research on human participants.
- Most of the articles that did not deal with human participants were program descriptions.
- Nearly 40% of articles dealing with human participants only provided anecdotal evidence.
- Of the articles that provided more than anecdotal evidence, most articles used experimental/quasi-experimental or explanatory descriptive methods.
- Questionnaires were clearly the most frequently used type of measurement instrument. Almost all of the measurement instruments that should have psychometric information provided about them did not have psychometric information provided.
- Student instruction, attitudes, and gender were the most frequent independent, dependent, and mediating/moderating variables, respectively.
- Of the articles that used an experimental research design, the majority used the one-group posttest-only design.
- When inferential statistics were used, the amount of statistical information used was inadequate in many cases (pp. 128-129).

Additionally, Randolph analyzed and compared several subgroups in the sample, finding quantitative evidence of the following:

- There was a decreasing yearly trend in the number of anecdotal-only articles and in the number of articles that used explanatory descriptive methods.
- First authors affiliated with North American institutions tended to publish papers in which experimental/quasi-experimental methods were used; first authors affiliated with Middle Eastern or European institutions tended to not publish papers in which experimental or quasi-experimental methods were used.
- First authors affiliated with Middle Eastern institutions strongly tended to publish explanatory descriptive articles.
- First authors affiliated with Asian-Pacific or Eurasian institutions tended to publish articles in which attitudes were the sole dependent variable; and
- First authors affiliated with North American institutions tended to publish more anecdotal-only articles than their peers in other regions. However this proportion had been decreasing linearly over time. (p. 130)

True to the promise that methodological review can promote informed dialogue and effect change, Randolph's dissertation sparked discussion and action in the SIGCSE community. Lister (2007) published an invited column that both criticized an inadequate analysis of qualitative methods, and generally agreed with most of Randolph's findings while urging the SIGCSE community to improve the quality and image of the research. Simon, and colleagues, conducted a classification of CSE literature published in the first three years of the International Workshop on Computing Education (Simon et al., 2008). Sheard, Simon, Hamilton, and Lönnburg (2009) recently reported a methodological review with results that validate some of Randolph's findings, and that explore in more detail the methodological characteristics of qualitative studies published in six major forums.

In a predecessor to the methodological review cited above, Randolph, Bednarik, and Myller (2005) examined research articles published in the Koli Calling conference held near Helsinki in an effort to improve the quality of research published in that forum. Because the Koli Calling conference was very young (4 years) at the time, a methodological review could carry exceptional influence to shape and direct the future of the conference. Like the journal articles and conference proceedings Randolph reported on in 2007, empirical studies in Koli Calling extensively used exploratory descriptive and quasi-experimental methodologies. Unlike Randolph's 2007 report, findings in the Koli conference consisted mostly of program or project descriptions, and deviated "sharply from structures that are expected in behavioral science papers"

(2005, p. 107). With this information, Randolph provided credible and informed recommendations to improve the quality of the conference.

More recently, Randolph (2008) reported an evaluation of methods used in 29 program evaluations for K-12 classrooms published between 1971 and 2005. The intent of the review was to promote improvement of instruction for young computer science students. Using a scale similar, though smaller, than the one described above, Randolph identifies several strengths and weaknesses in the current body of program evaluations.

Strengths reported include the following: first, most program evaluations preferred the use of tests and direct observation over surveys with self-reports of learning; second, experimental designs exhibited good design characteristics and adequate controls; and, third, the research exhibited a broad spectrum of methodologies, including exploratory, experimental and qualitative designs. Weaknesses reported include lack of reliability measures in the data, underrepresentation of studies measuring computer science achievement, gender factors, and lack of the level of detail necessary for evaluations to be replicated using only information available in the report. As with his other reviews, Randolph provides recommendations for research improvement with potential to affect the success of K-12 computer science students positively.

Hulkko and Abrahamsson (2005) reported a small methodological review of pair programming research. They identified an increasing trend in yearly publication rates from 1998 to 2004, and evaluated two methodological characteristics, namely:

- Type of study, any of survey, experiment, case study, or experience report, and
- Context under which pair programming research took place, for example, as a component of extreme programming, pair programming effects on a software development project, or pair programming educational topics. (pp. 496-497)

Educational pair programming represents the second largest pair programming context reported in the study; however, the sample size was sufficiently small that the authors only conclude that "studies focused on using pair programming for educational purposes in university settings have not been thoroughly explored" (p. 496). The product of the review consists of a family of research questions classified as having or not having empirical evidence.

Purpose, Questions, and Hypotheses

The intent of this thesis is to analyze the state of pair-programming research in CSE and make credible recommendations toward improving research methods. To do so, I answered the following research question, adapted from Randolph (2007, pp. 39-41): *What are the methodological properties of research reported in articles in major computer science education research forums related to pair programming from the years 2000-2008?* Following Randolph's model, the question contains the following sub-questions:

1. What is the proportion of articles that reported research on human participants?
2. Of the articles that did not report research on human participants, what types of articles are being used and in what proportions?
3. Of the articles that did report research on human participants, what proportion provide only anecdotal evidence for their claims?
4. Of the articles that reported research on human participants, what types of methodologies are used and in what proportions?
5. Of the articles that report research on human participants, what measures were used, in what proportions, and was psychometric information reported?
6. Of the articles that report research on human participants, what are the types of independent, dependent, mediating, and moderating factors examined and in what proportions?
7. Of the articles that used experimental methodologies, what types of designs were used and in what proportions, and were participants randomly assigned or selected?
8. Of the articles that reported research on human participants, what are the characteristics of the articles' structures?
9. Of the articles that reported quantitative results, what kind of statistical practices were used and in what proportions?

Supplementing these eight descriptive questions are additional questions about associations, or islands of practice, within the data. The intent of these questions is to provide insight into trends in practice, and identify with greater precision areas requiring improvement.

The three associative questions, each of which requires inspection of four associations, are as follows:

1. Is there an association between type of publication (whether articles are published in conferences or in journals) and frequency of articles providing only anecdotal evidence, frequency of articles using experimental/quasi-experimental research methods, frequency of articles in which the one-group posttest-only design was exclusively used, and frequency of articles in which attitudes were the sole dependent variable?
2. Is there a yearly trend (from 2000-2008) in terms of the frequency of articles providing only anecdotal evidence, frequency of articles using experimental/quasi-experimental research methods, frequency of articles in which the one-group posttest-only design was exclusively used, and frequency of articles in which attitudes were the sole dependent variable?
3. Is there an association between the region of the first author's institutional affiliation and frequency of articles providing only anecdotal evidence, frequency of articles using experimental/quasi-experimental research methods, frequency of articles in which the one-group posttest-only design

was exclusively used, and frequency of articles in which attitudes were the sole dependent variable?

These questions specify 12 contrasts, which is fewer than the fifteen analyzed by Randolph. The reason for this is that the data are inadequate to inspect associations related to rates of explanatory descriptive articles.

Because pair programming pedagogy is a subcomponent of computer science pedagogy, it seemed reasonable to predict that there would be no significant difference between results obtained by this sample and the sample reported by Randolph (2007, pp. 128-129). Expected results are as follows:

1. About one third of articles will not report research on human participants.
2. Most articles not dealing with human participants are program descriptions.
3. Many articles dealing with human participants provide only anecdotal evidence.
4. Of empirical articles, most use experimental, quasi-experimental or explanatory descriptive methods.
5. Questionnaires will be the most frequently used type of measurement instrument. Nearly all instruments will lack psychometric information,
6. Student instruction, attitudes, and gender will be the most frequent independent, dependent, and mediating/moderating variables, respectively.
7. Most experimental studies will use the one-group posttest-only design,
8. When reporting inferential statistics, the amount of statistical information will usually be inadequate.

Also, I predicted that there would be small, but significant trends in the types of articles published yearly and that associations exist between region of first author's affiliation and the types and quality of articles published by the author.

Biases

As a professional developer, I advocate the use of pair programming to improve program understanding, code quality, process adherence, and team cohesion. I believe that when used properly, pair programming can enhance computer science instruction; however, I acknowledge that the meaning of "used properly" has not been fully explored.

This study inherits most of its design from the work of Randolph (2007) and, consequently, it inherits many of his biases, which Randolph describes as the "biases of a quantitatively trained behavioral scientist" (p. 45). I recognize that this research design favors and emphasizes quantitative methods. I do not have the opinion that quantitative methods are necessarily superior to qualitative methods; however, I believe that exercising forethought and methodological rigor is the ethical duty of contributors to science, regardless of methodology.

I once had a conversation with a student who, after I described to him the topic of this thesis, remarked while gesturing toward the university, "If they did that [pair programming], I would still be in Computer Science." I believe this student's sentiment represents the sentiments of a nontrivial proportion of students having potential in

computer science, and warrants serious consideration by educational institutions worldwide.

METHOD

The model for this study is Randolph's (2007) thorough methodological review. Most of the variables of the study, their corresponding operationalization, the coding form and coding book, are derived from it, with modifications as seemed appropriate for a population of research articles focused on Pair Programming in CSE.

This research represents both a replication and an extension of Randolph's study: a replication because many of the core components and analyses of Randolph's study are repeated, and an extension due to the application of the current study to a different population.

This section, describes the process used to obtain the sample, code each variable, and analyze the resulting data set.

Sample

I collected a random sample, without replacement, from a representative body of peer-reviewed literature articles addressing pair programming in CSE. Collecting the representative body of literature involved a combined search from the following databases: the ACM digital library, IEEE digital library, and Ebsco Host.

Table 1 presents a summary of the search results, wherein only unique entries are reported for each subsequent query.

A precursor to the main study was an initial review of the complete sample literature to remove irrelevant articles and ensure the quality of the sample. I operationalized relevance as having the following characteristics: (1) the article was

Table 1

Description of the Electronic Search for Representative Population

Search	Date	Term(s)	Database	Records
1	6-8-2008	"pair programming"	IEEE Library	74
2	6-8-2008	"paired programming"	IEEE Library	3
3	6-8-2008	"pair programming"	Ebsco Host (Computer Source)	21
4	6-8-2008	"paired programming"	Ebsco Host (Computer Source)	0
5	6-13-2008	"pair programming" "computer science education"	ACM Library	165
6	6-13-2008	"pair programming"	ACM Library	4

published between 2000 and 2008; (2) the topic of pair programming receives more attention in multiple paragraphs or sections; and (3) the authors discuss pair programming in the context of CSE or use a student sample. The rationale for including articles not explicitly CSE-oriented, but use a student sample, is because the classroom environment differs significantly from industry (Bryant, 2004, pp. 55-56). Of 267 articles, only 129 qualified under this definition of relevance.

I estimated the size of the population expected after a single-level hand branching search of references to be 150. To enable statistical analyses and promote generalizability of results, determining an appropriate sample from the population was necessary. Selecting a random subsample of the discovered population decreases the risk of the external threat to validity caused by convenience sampling (Cohen, 2001, p. 9). The size of the sample, 108 articles, was determined using an online tool (Sample Size Calculator, 2008), configured with the estimated population size of 150, confidence interval 5%, and confidence level $\alpha = .05$. These 108 were subsequently drawn without

replacement and coded in the order they were drawn. Appendix A lists the articles selected for the sample.

It was necessary to remove two articles from the sample due to incorrect classification during the initial review, resulting in a final sample size of 106. This resulted in a trivial weakening of the confidence interval, 5.17%, as calculated using the online tool, assuming that the true population size contains 150 articles.

Table 2 presents the number of articles collected and the number of articles randomly selected, grouped by year of publication. Note that the random sample omits the two incorrectly classified articles while the total sampling frame includes all 129 articles. The total numbers of articles discovered before screening for relevance are not reported. Note that the year 2008 had not completed at the time of the sampling.

Table 2

Number of Articles Sampled by Year

Year	Random Sample	Sampling Frame
1999	1	1
2000	2	3
2001	5	6
2002	3	6
2003	14	15
2004	12	14
2005	22	28
2006	23	28
2007	11	13
2008[a]	13	15
Total	106	129

[a] Because the sample was selected in June, 2008, this row does not accurately represent the proportion of articles published in 2008.

Coding

As with Randolph's study, the instrument rates articles for "demographic characteristics, type of article, type of methodology used, type of research design used, independent variables examined, measures used, and statistical practices" (2007, p. 52). I adapted some parts of Randolph's instrument as seemed appropriate, mostly where changes involved customizing the format of the coding book, correcting typographical errors, or adapting categories to reflect those expected from pair programming research.

The adapted code sheet and coding book, listed in Appendices B and C, include detailed instructions on how to encode each variable. Randolph provides a thorough discussion of the instrument, to which the reader can refer for the background and derivation of each variable (2007, pp. 233-262). This section provides a brief summary of changes to the original instrument.

Adaptations to variables describing article demographics include the following:

- No case number category as assigned,
- No volume number for the publication forum was collected, except as accounted in the references (Appendix A), and
- No issue number for the publication forum was collected, except as accounted in the references (Appendix A).

Adaptations to the variables describing article types include the following:

- Some of Kinnunen's categories, which were not relevant to the study of pair programming, were modified accordingly, and

- Type of abstract was replaced with an indication of whether the abstract was present.

Adaptations to the variables describing independent variables or interventions included:

- Whether the use of pair programming, pair designing, or pair testing, was an intervention.

Variables describing report structure, methodology type, experimental research designs, factors, or statistical practices, are unmodified. Not reported here are details for any typographical or formatting modifications.

Analysis

To answer the research questions, I performed several kinds analysis on the data, modeled after the analyses reported by Randolph. Randolph reported three general kinds of analyses: first, aggregate statistics of the probabilities of each variable; second, association tests for each of the 15 planned contrasts; and, third, logistic regression for discovering predictive models for certain characteristics. This study includes replications only of the first two kinds of analyses.

I selected C#.NET 3.5 SP1 as the language to take advantage of the rich predicate logic capabilities and LINQ for filtering or transforming the data. The original statistics code listing is available in Appendices D and E. To create a data store compatible with the LINQ technology required that data be transferred from handwritten coding forms

to a SQL Server 2008 database, with intermediate migrations to an OpenOffice.org spreadsheet, a Microsoft Office spreadsheet, and a Microsoft Office Access database.

To answer the primary research question, I computed frequencies of responses for each variable, along with confidence intervals using the following resampling strategy:

> We assume that the population is distributed exactly as is the sample. We randomly draw one score from the sample. We record it, replace it, and draw another…. We compute the median of the obtained resample and record it. We repeat this process, obtaining a second sample… and computing and recording a second median. We continue until we have obtained a large number (10,000 or more) of resample medians. We obtain the probability distribution of these medians and treat it like a sampling distribution. From the obtained sampling distribution, we find the .025 and the .975 percentiles. These define the confidence limits. (Wuensch, 2007)

Original code for computing the confidence intervals is reported in Appendix D.

To answer the second research question, I cross tabulated each of the planned contrasts and analyzed standardized Pearson residuals, as described by Simonoff (2003, pp. 215-298). For the categorical comparison variables, I also inspected Pearson's chi-square test of association as described by Cohen (2001, pp. 642-650). For ordinal comparison variable, I inspected the M^2 statistic described by Agresti, due to its increased sensitivity to correlational data (Agresti, 2007, pp. 41-42). Original code for computing residuals, χ^2, and M^2 is available in Appendix E.

It happened to be the case that too few empirical articles reported explanatory descriptive methodologies to provide credible analysis in the cross tabulations. As a result, I omitted the three planned contrasts using explanatory descriptive methodologies. Consequently, this study contains only the remaining 12.

RESULTS

To facilitate comparison between the result of this study and Randolph (2007) wherever possible, this section contains aggregated results and twelve predetermined cross tabulations using a similar organization and structure. Compare Randolph (2007, pp. 65-126).

Aggregated Results

General Characteristics

Forum in which article was published. Figure 1 presents the relative representation of each forum, adjacent to the equivalent metric from Randolph et al. (2005, p. 49). Table 3 contains full forum names listed by label. Also listed is the forum classification as either a journal or a conference. Note that some articles published in *Bulletin*, *JCSC*, and *CSE* are classified as journals, while it is true that some articles published in those forums were once conference proceedings.

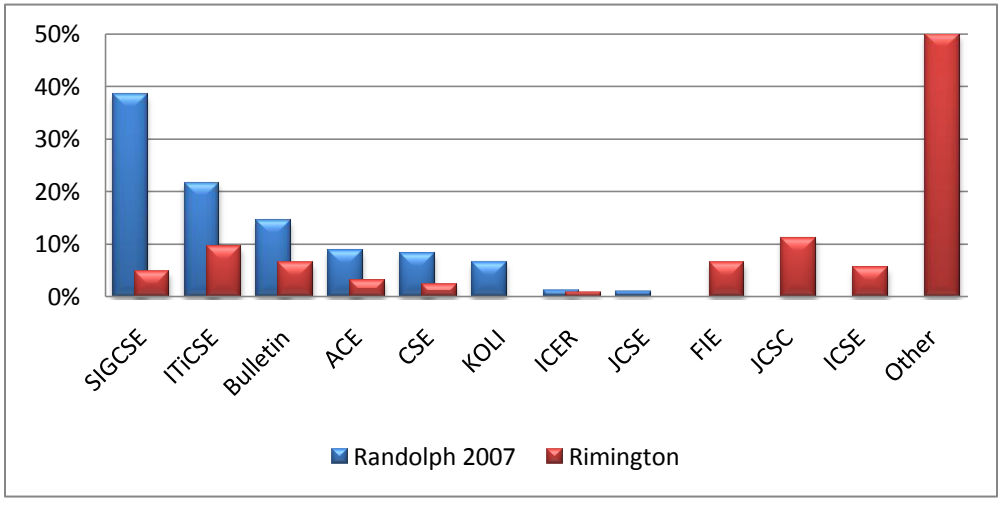


Figure 1. Proportions of articles published in each forum.

Table 3

Labels for Forums with the Greatest Number of Articles

Label	Forum Name	Classification
Bulletin	SIGCSE Bulletin	Journal
CSE	Computer Science Education	Journal
JCSE	Journal of Computer Science Education Online	Journal
SIGCSE	SIGCSE Technical Symposium	Conference
ITiCSE	Proceedings of the Innovation and Technology in Computer Science Education Conference	Conference
Koli	Coli Calling: Finnish/Baltic Sea Conference on Computer Science Education	Conference
ACE	Proceedings of the Australasian Computing Education Conference	Conference
ICER	International Computer Science Education Research Workshop	Conference
FIE	ASEE/IEEE Frontiers in Education Conference	Conference
ICSE	International Conference on Software Engineering	Conference

Classification of the random sample by forum type resulted in the following: 63 (59.4%) were published in conference proceedings, 40 (37.7%) were published in journals, and three (2.8%) were published via other means. These proportions differ substantially from the sample obtained by Randolph for conferences and journals, which were 76.4% and 23.6%, respectively.

First authors whose articles were most frequently sampled. The first authors most frequently sampled by this study were Laurie Williams with thirteen articles, Gerardo Canfora and Brian Hanks with five articles each, Matthias Müller with four articles, and Charlie McDowell and Shaochun Xu with three articles each. All other authors were sampled two or fewer times. A total of 69 first authors contributed to the sample.

First authors' affiliations. The first authors of the sample represent 61 distinct institutions. Table 4 presents the quantity of articles from the most frequently represented institutions and the proportion of sample represented by each institution.

Table 4

Institutions with Greatest Number of Articles

Content category	Number of articles in the sample	Proportion
North Carolina State University	20	18.9
University of California, Santa Cruz	6	5.7
University of Sannio	5	4.7
Universität Karlsruhe	4	3.8
Fort Lewis College	4	3.8
Fayetteville State University	3	2.8
Other Institutions	64	60.3
Total	106	100.0

Median number of authors per articles. The median number of authors on the selected articles was 2, with a minimum of 1, maximum of 8, with first and third quartiles of 2 and 5. The 2.5th and 97.5th percentiles of the median from 10,000 samples of size 106 were 2 and 3. Figure 2 presents the distribution of articles in the sample grouped by number of authors.

Median number of pages per article. The median number of pages in the sample was 7, with a minimum of 2 and a maximum of 30, first quartile of 5 and third quartile of

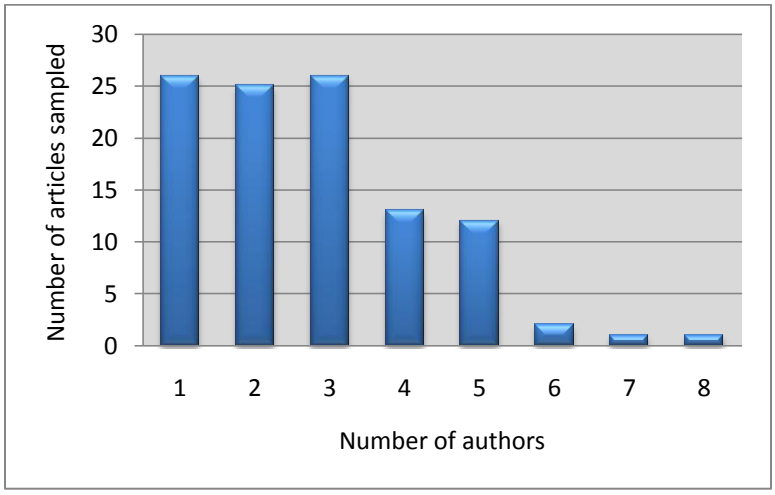


Figure 2. Frequency of articles published by number of authors

10. The 2.5th and 97.5th percentiles of the median from 10,000 samples of size 106 were 6 and 8.

Report elements. Table 5 presents the proportion of articles dealing with human participants having elements considered necessary by the American Psychological Association for empirical publications (American Psychological Association, 2001, pp. 10-29). Figure 3 visualizes a comparison between report structure reported in this study to report structure reported by Randolph (2007, p. 75). Note that Randolph reported low levels of inter-rater reliability for some of the variables that appear to have the greatest difference, such as literature review present, purpose stated, setting described, procedure described, and results and discussion separate.

Kinnunen's content categories. Table 6 presents the proportions of articles falling into each of several content categories adapted from the Kinnunen's Content Category

Table 5

Proportions of Report Elements

Report element	*n* (of 91)	%	Lower CI 95%	Upper CI 95%
Abstract present	89	97.8	94.5	100.0
Problem is introduced	90	98.9	94.5	100.0
Literature review present	72	79.1	70.3	86.8
Purpose/rationale stated	83	91.2	84.6	96.7
Research questions/hypotheses stated	42	46.2	36.3	56.0
Participants described	79	86.8	79.1	93.4
Setting adequately described	85	93.4	87.9	97.8
Instrument adequately described	43	47.3	37.4	57.1
Procedure adequately described	50	54.9	45.1	64.8
Results and discussion separate	56	61.5	51.6	71.4

Note. Column marginals do not sum to 91 (or 100%) because more than one methodology type per article was possible.

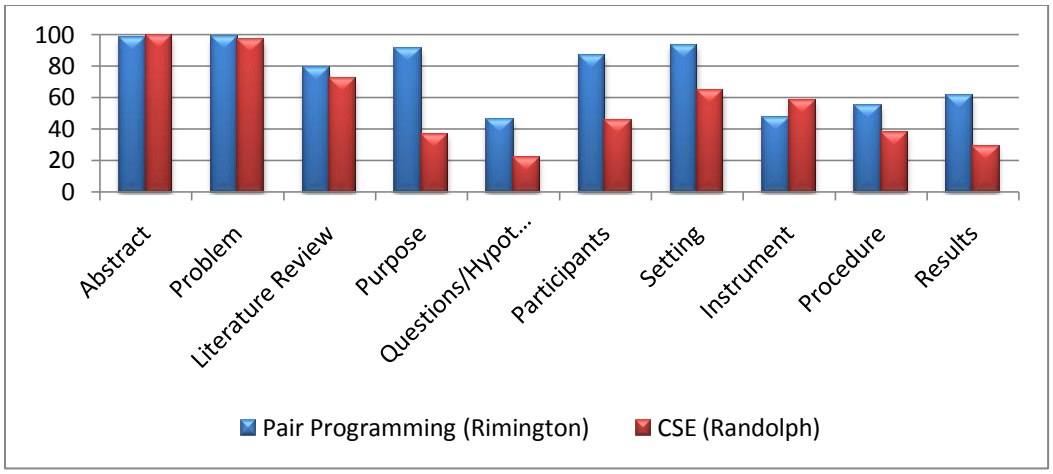


Figure 3. Comparison of proportions of report elements between studies

Table 6

Proportions of Articles Falling into Each Adapted Kinnunen Category

Content category	*n*	%	Lower CI 95%	Upper CI 95%
SE methodologies in CSE	64	60.4	50.9	69.8
New way to organize a course	17	16.0	9.4	23.6
SE methodology in industry	15	14.2	7.5	20.8
Tool	8	7.5	2.8	13.2
Other	1	0.9	0.0	2.8
Curriculum	1	0.9	0.0	2.8
Total	106	100.0		

(Randolph, 2007, pp. 246-247). The table shows that most articles from this sample addressed the application of some software engineering principle to CSE. Note that my confidence in the correctness of this variable is low because some of the categories selected were not mutually exclusive. Due to the adaptation of this variable, comparisons cannot be drawn to results reported by Randolph.

Valentine's research categories. Table 7 presents the proportions of articles distributed among Valentine's research categories. Experimental and Marco Polo studies comprised over 82% of the sampled literature. A greater proportion (48.1%) of

Table 7

Proportions of Articles Falling into Each of Valentine's Categories

Content category	*n*	%	Lower CI 95%	Upper CI 95%
Experimental	51	48.1	38.7	57.5
Marco Polo	36	34.0	25.5	43.4
Philosophy	12	11.3	5.7	17.9
Tools	6	5.7	1.9	10.4
Nifty	1	0.9	0.0	2.8
John Henry	0	0.0		
Total	106	100.0		

articles in this sample reported on experimental studies than in the sample reported by Randolph (40.9%), while a lesser proportion (5.7%) of articles in this sample reported on tools than in the sample reported by Randolph (12.5%). Differences in the proportions of others of Valentine's categories were negligible. Note that confidence intervals for all of Valentine's categories reported in this overlap confidence intervals reported by Randolph.

Human participants. As shown in Table 8, of 106 articles in this study, the majority (85.8%) dealt with human participants. Randolph's sample contained a substantially lesser proportion (66.3%) of articles dealing with human participants. Also note that the 95% confidence interval reported in this study (79.2% - 92.5%) does not overlap the confidence interval reported by Randolph (62.2% - 70.1%), indicating that, in this human participants dimension, each study inspected a different population of research articles.

Grade level of participants. Table 9 presents the grade level of participants in the 91 human-related studies. Note the near-absence of pre-collegiate research, contrasted to Randolph's results in which 8% of the articles dealt with pre-collegiate participants.

Table 8

Proportions of Articles Dealing with Human Participants

Human Participants	*n*	%	Lower CI 95%	Upper CI 95%
Yes	91	85.8	79.2	92.5
No	15	14.2	7.5	20.8
Total	106	100.0		

Table 9

Proportions of Grade Level of Participants

Grade Level of Participant	*n*	%	Lower CI 95%	Upper CI 95%
K-12	1	1.3	0.0	3.8
Undergraduate	67	84.8	77.2	92.4
Graduate	11	13.9	6.3	21.5
Total	79	100.0		

Also, note that this study reports the grade level by selecting the participant subgroup with the largest sample size, while Randolph classified articles reporting on a mixed participant grade level using a dedicated category.**Error! Not a valid bookmark self-reference.** further subdivides the 67 studies reported using undergraduate participants. When compared to Randolph's sample, the proportion of studies involving mostly first-year students is much less (43.3% compared to 70.9%), and the proportion of studies involving mostly second-year students is much more (25.5% compared to 5.5%), with non-overlapping confidence intervals. Almost no difference can be observed in the proportion of studies reported using fourth-year students (10.4% to 9.1%). For both third- and fourth-year undergraduate levels, confidence intervals overlap those reported by Randolph.

Table 10

Proportions of Undergraduate Level of Computing Curriculum

Year of undergraduate level of computing curriculum	*n*	%	Lower CI 95%	Upper CI 95%
First Year	29	43.3	31.3	55.0
Second Year	17	25.4	14.9	35.8
Third Year	14	20.9	11.9	31.3
Fourth Year	7	10.4	3.0	17.9
Total	67	100.0		

Table 11

Proportions of Articles Providing Only Anecdotal Evidence

Anecdotal	*n*	%	Lower CI 95%	Upper CI 95%
Yes	23	25.3	16.5	34.1
No	68	74.7	65.9	83.5
Total	91	100.0		

Table 12

Proportions of Types of Articles Not Dealing with Human Participants

Type of Article	*n*	%	Lower CI 95%	Upper CI 95%
Theory, methodology, or philosophical paper	7	46.7	20.0	73.3
Program description	4	26.7	6.7	53.3
Panel summary[a]	3	20.0	0.0	40.0
Literature review	1	6.7	0.0	20.0
Total	15	100.0		

[a]*This item not part of the original coding categories*

Anecdotal evidence only. As shown in Table 11, of 91 articles dealing with human participants, 25.3% presented only anecdotal evidence. The confidence interval for this measure (16.5% - 34.1%) is nearly non-overlapping with Randolph's (33.1% - 43.3%).

Types of articles that did not deal with human participants. Table 12 presents the types of articles represented by the 15 that did not deal with human participants, of

which approximately half reported a theoretical, methodological, or philosophical viewpoint, and approximately a fourth reported a course or program description.

Types of Research Methods and Research Designs Used

Types of research methods used. Table 13 presents the proportions of methodologies represented in the sample. As in Randolph's study, the most frequently used methodology is experimental/quasi-experimental, followed by explanatory descriptive, causal comparative, correlational, and exploratory descriptive. Approximately the same proportion (67.0%) of articles was experimental/quasi-experimental compared to Randolph's sample (64.6%); however, a noticeably greater proportion of articles employed explanatory descriptive methodologies (39.6% compared to 26.4%), with confidence intervals barely overlapping.

Table 14 presents methodology types classified as quantitative, qualitative, and mixed, operationalized as follows: studies exhibiting only explanatory descriptive methodologies are qualitative; studies not exhibiting explanatory descriptive methodologies are quantitative; studies exhibiting explanatory descriptive

Table 13

Proportions of Methodology Types Used

Methodology Type	*n* (of 91)	%	Lower CI 95%	Upper CI 95%
Experimental/quasi-experimental	61	67.0	57.1	76.9
Explanatory descriptive	36	39.6	29.7	49.5
Causal comparative	11	12.1	5.5	18.7
Correlational	9	9.9	4.4	16.5
Exploratory descriptive	5	5.5	1.1	11.0

Note. Column marginals do not sum to 91 (or 100%) because more than one type per article was possible.

Table 14

Proportions of Types of Methods

Type of method	*n*	%	Lower CI 95%	Upper CI 95%
Quantitative	53	58.2	48.4	68.1
Qualitative	26	28.6	19.8	38.5
Mixed	12	13.2	6.6	20.9
Total	91	100.0		

Table 15

Proportions of Types of Experimental/Quasi-Experimental Designs Used

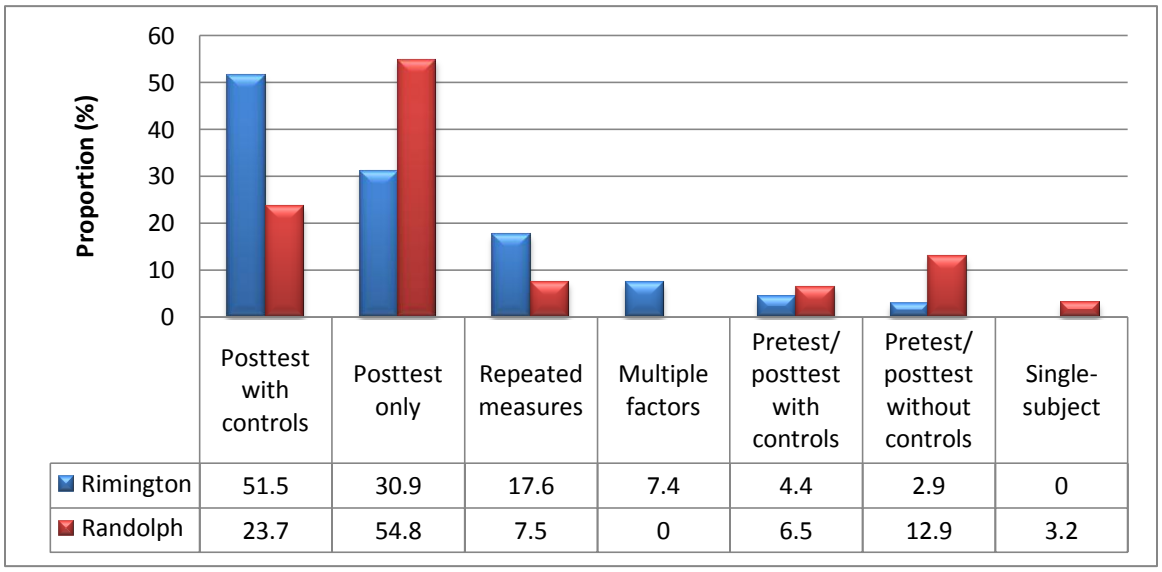
Type of experimental design	*n*	%	Lower CI 95%	Upper CI 95%
Posttest with controls	35	51.5	39.7	63.2
Posttest only	21	30.9	20.6	42.6
Repeated measures	12	17.6	8.8	26.5
Multiple factors	5	7.4	1.5	14.7
Pretest/posttest with controls	3	4.4	0	10.3
Pretest/posttest without controls	2	2.9	0	7.4
Single-subject	0	0		

Note. Column marginals do not sum to 68 (or 100%) because more than one research design type per article was possible.

methodologies and any of the other quantitative methodologies are mixed. The proportion of purely quantitative articles (58.2%) is significantly less than the proportion reported by Randolph (74.3%), with non-overlapping confidence intervals.

Sampling. Of the 91 articles dealing with human participants, 84 (92.3%) used convenience sampling, 5 (5.5%) used purposive (nonrandom) sampling, and 2 (2.2%) used random sampling, compared to 86.1% convenience sampling reported by Randolph.

Research designs. As shown in Table 15, the most frequently used research design was the controlled, posttest-only design, followed by the one-group posttest-



	Posttest with controls	Posttest only	Repeated measures	Multiple factors	Pretest/ posttest with controls	Pretest/ posttest without controls	Single-subject
Rimington	51.5	30.9	17.6	7.4	4.4	2.9	0
Randolph	23.7	54.8	7.5	0	6.5	12.9	3.2

Figure 4. Comparison of proportions of research designs between studies.

only design. This pattern, visualized in *Figure 4*, is the reverse of that reported by Randolph. Of the 21 studies that reported using the one-group posttest-only design, 14 used the design exclusively.

Of those dealing with human participants and using an experimental/quasi-experimental design, most used a quasi-experimental design, that is, used purposive, convenience, or self-selection for treatment. Of the 61 articles, 34 (55.7%) selected experimental and control groups using existing or convenience groups, or participants served as their own controls, 18 (29.5%) used randomized groups, and 9 (14.8%) used self-selected groups.

Independent, Dependent, and Moderating/Mediating Variables Investigated

Independent variables. As shown in Table 16, nearly all interventions and independent variables related to student instruction and the application of pair programming. Other kinds of interventions explored included distributed pair programming using a tool, the explicit application of pair programming to the design, test, or review phase of development, other kinds of collaborative development, and the application of the extreme programming (XP) methodology. The practice of XP is underrepresented (2.9%) in the experimental/quasi-experimental group, compared to the 8 (34.8%) studies utilizing XP in the non-experimental group. Other interventions described in anecdotal papers include variations on pair selection and trading, specialized projects and assignments, and collaborative programming games.

Table 16

Proportions of Types of Independent Variables Used

Type of independent variable used	*n* (of 68)	%	Lower CI 95%	Upper CI 95%
Student Instruction	66	97.1	92.6	100.0
Pair programming	63	92.6	85.3	98.5
Distributed pair programming using a tool[a]	5	7.4	1.5	14.7
Other kinds of collaborative programming[a]	5	7.4	1.5	14.7
Pair programming applied to design, testing, or reviews[a]	5	7.4	1.5	14.7
Extreme Programming[a]	2	2.9	0.0	7.4
Mentoring	1	1.5	0.0	4.4

Note. Column marginals do not sum to 68 (or 100%) because more than one independent variable type per article was possible.
[a]*This item not part of the original coding categories.*

Table 17

Proportions of Types of Dependent Variables Used

Type of dependent variable used	*n* (of 68)	%	Lower CI 95%	Upper CI 95%
Attitudes (student or teacher)	47	69.7	57.4	79.4
Achievement in computer science	25	36.8	25	48.5
Attendance	8	11.8	4.4	19.1
Socialization	3	4.4	0	10.3
Students' intention for future	2	2.9	0	7.4
Program cost	2	2.9	0	7.4
Computer use	2	2.9	0	7.4
Achievement in core (non-CS) courses	1	1.5	0	4.4
Task completion time[a]	9	13.2		
Defect rates or passed/failed test cases[a]	7	10.3		
Code metrics[a]	5	7.4		
Code quality (subjective measure)[a]	4	5.9		

Note. Column marginals do not sum to 68 (or 100%) because more than one dependent variable type per article was possible.

[a] *This item not part of the original coding categories.*

Dependent variables. Table 17 presents the proportions of types of dependent variables used in articles reporting quantitative statistics. As with Randolph's study, attitudes and achievement in computer science were the most frequently measured variables, though this study shows a noticeably greater proportion of studies measuring attitude and a decreased proportion of studies measuring achievement. Four additional variables were identified, including task completion time, defect rates or passed/failed test cases, code metrics, and subjective measures of code quality. Table 17 presents proportions of these variables without confidence intervals. Results for studies measuring teacher instruction or treatment fidelity are not included because the variables were not measured by any of the studies sampled.

Table 18

Proportions of Types of Mediating or Moderating Variables Investigated

Mediating or moderating variable investigated	*n* (of 20)	%	Lower CI 95%	Upper CI 95%
Gender	10	50.0	30.0	70.0
Student achievement	7	35.0	15.0	55.0
Race/ethic origin	2	10.0	0.0	25.0
SAT-M[a]	5	25.0		
Self-confidence or self-perception[a]	5	25.0		
Myers-Briggs personality type indicator[a]	3	15.0		
Felder-Silverman learning styles[a]	1	5.0		
Instructor[a]	1	5.0		

Note. Column marginals do not sum to 20 (or 100%) because more than one independent variable type per article was possible.

[a] *This item not part of the original coding categories.*

Mediating or moderating variables examined. Of the 68 studies presenting quantitative evidence, 20 (29.4%) investigated at least one mediating or moderating variable, as presented in Table 18. Additional factors reported include student SAT math scores, reports of self confidence or self-perceived aptitude, instructor or setting, Myers-Briggs personality type indicators (MBTI) and Felder-Silverman learning styles, all of which are presented in Table 18 without confidence intervals. Factors identified on the coding sheet but omitted from the report because no studies reported investigating them include nationality, disability status, and socioeconomic status of participants.

Types of Measures and Statistical Practices

Types of measures used. Table 19 presents the proportions of types of measures reported in the sample. There exist additional measures corresponding to the additional dependent variables identified in Table 17. The number of focus groups is not reported because no study reported measuring focus groups. Measurement validity or reliability

Table 19

Proportions of Types of Measures Used

Type of measure used	*n* (of 68)	%	Lower CI 95%	Upper CI 95%
Questionnaires	48	70.6	58.8	80.9
Grades	23	33.8	23.5	45.6
Student work	17	25.0	14.7	35.3
Teacher- or researcher-made tests	12	17.6	8.8	26.5
Interviews	8	11.8	4.4	19.1
Direct observation	5	7.4	1.5	14.7
Standardized tests	5	7.4	1.5	14.7
Existing records	4	5.9	1.5	11.8
Learning diaries	3	4.4	0	10.3
Log files	2	2.9	0	7.4

Note. Column marginals do not sum to 20 (or 100%) because more than measure type per article was possible.

was provided by 2 (4.2%) of the 48 studies utilizing questionnaires, and by none (0%) of the studies utilizing teacher- or researcher-made tests, direct observation, or standardized tests. Questionnaires represent a substantially greater proportion of this sample (70.6%) than the sample (52.8%) reported by Randolph (2007); all other measurements have confidence intervals that generally overlap, when comparing samples.

Types of inferential analyses used. Of the 65 articles that reported quantitative statistics, 43 (66.2%) also reported some kind of inferential statistic. Table 20 presents the kinds and proportions of inferential statistics, and the proportions of inferential statistics that present statistically adequate information.

Type of effect size reported. As shown in Table 21, of the 68 articles presenting quantitative evidence, 41 (60.3%) reported some type of effect size. Reports that did not report some type of effect size generally report only the results of a statistical

Table 20

Proportions of Types of Inferential Analyses Used

Type of inferential analysis	*N*	%	Lower CI 95%	Upper CI 95%
Parametric analysis (of 43)	31	66.2	55.4	76.9
Measure of centrality and dispersion reported (of 31)	7	22.6	9.7	38.7
Correlational analysis (of 43)	13	30.2	13.6	44.2
Sample size reported (of 13)	13	100.0		
Correlaction or covariance matrix reported (of 13)	2	15.4	0	38.5
Nonparametric analysis (of 43)	13	30.2	16.3	44.2
Raw data summarized (of 13)	9	69.2	46.2	92.3
Small sample analysis (of 43)	1	2.3	0.0	7.0
Entire data set reported (of 1)	1	100.0		
Multivariate analysis (of 43)	0	0.0		

Note. Column marginals do not sum to 43 (or 100%) because more than one statistical practice per article was possible.

Table 21

Proportions of Types of Effect Sizes Reported

Type of measure used	*n* (of 41)	%	Lower CI 95%	Upper CI 95%
Raw difference	41	100.0		
Standardized mean difference	3	7.3	0.0	17.1
Odds	1	2.4	0	7.3

Note. Column marginals do not sum to 41 (or 100%) because more than measure type per article was possible.

hypothesis test, or significance test. All 41 articles that reported an effect size reported raw difference of means, 3 (7.3%) reported the standardized mean, Cohen's *d*, and 1 (2.4%) study reported odds. Of the 41 articles reporting means, 16 (39.0%) did not report a standard deviation or other measure of dispersion. Note that, as in Randolph's

study, an author needed only to report two means so that a reader could compute the difference to classify as reporting raw difference.

Analysis of Cross Tabulations

This section contains cross tabulations for 12 of the 15 different relationships explored by Randolph. Contrasts presented here include comparisons of publication forum types, year of publication, and region of first author's affiliation to the proportions of anecdotal-only papers, experimental studies, attitude-only papers, and one-group posttest-only research designs. This section does not contain the final three of the relationships reported by Randolph, namely those dealing with empirical research using the explanatory descriptive research design, because too few articles met these criteria to enable credible analysis.

To compensate for the increased possibility of a Type I error caused by performing 12 tests for association, application of the Bonferroni correction seemed appropriate. This reduced the significance threshold to $p = .004$.

Because each cross tabulation involves a binary variable, I present adjusted residuals only for the yes-valued cells. Randolph, citing Agresti, indicates that adjusted residuals exceeding "about 2 or 3 in absolute value" is a good indicator of significance (2007, p. 88).

Differences between Journal and Conference Proceedings Articles

This section presents the results of comparing the publication forum type to the following classifications: (1) whether the paper presented only anecdotal evidence; (2) whether the paper used an experimental or quasi-experimental methodology; (3) whether the paper reported measures only for participant or researcher attitudes and reports of self learning; and, (4) whether the paper used only the one-group posttest-only research design. There is no statistically significant evidence in these findings to suggest that the proportion of articles from conferences and journals differs.

Anecdotal-only articles. Table 22 presents the proportions of articles dealing with human participants and reporting only anecdotal results. Journals published 16% fewer anecdotal-only articles than did conferences; however, though noteworthy, the finding was not statistically significant, $X^2(1, N = 89) = 2.72$, $p = 0.099$, having medium residuals.

Experimental/quasi-experimental articles. Table 23 presents the proportions of articles reporting empirical data that also reported an experimental or quasi-experimental research methodology. Conferences published experimental or quasi-experimental in 9.1% more cases; this finding is not statistically significant, $X^2(1, N = 66) = 0.72$, $p = 0.395$.

Attitudes-only articles. Table 24 presents the proportions of articles dealing with human participants and measuring only participant or researcher attitudes or self-reports of learning. Conferences published 2.4% fewer articles meeting this criterion, a finding that is not statistically significant $X^2(1, N = 89) = 0.05$, $p = 0.820$.

One-group posttest-only articles. Table 25 presents the proportions of articles using an experimental or quasi-experimental methodology, but employing only the one-group posttest-only design. Conferences published 6.6% fewer articles in this category than journals. The difference is not statistically significant, $X^2(1, N = 62) = 0.38$, $p = 0.535$.

Table 22

Cross Tabulation of Anecdotal-Only Papers by Forum Type

	Anecdotal-only			Percentage	Adjusted
Forum	Yes	No	**Total**	**Yes**	**residual**
Conference	18	39	57	31.6	1.6
Journal	5	27	32	15.6	-1.6
Total	23	66	89	25.8	

Table 23

Cross Tabulation of Experimental Papers by Forum Type

	Experimental			Percentage	Adjusted
Forum	Yes	No	**Total**	**Yes**	**residual**
Conference	31	8	39	79.5	0.8
Journal	19	8	27	70.4	-0.8
Total	50	16	66	25.8	

Table 24

Cross Tabulation of Attitudes-Only Papers by Forum Type

	Attitudes-only			Percentage	Adjusted
Forum	Yes	No	**Total**	**Yes**	**residual**
Conference	20	37	57	35.1	-0.2
Journal	12	20	32	37.5	0.2
Total	32	57	89	36.0	

Table 25

Cross Tabulation of One-Group Posttest-Only Papers by Forum Type

Forum	Posttest-only exclusively		Total	Percentage Yes	Adjusted residual
	Yes	No			
Conference	7	31	38	18.4	-0.6
Journal	6	18	24	25.0	0.6
Total	13	49	62	21.0	

Yearly Trends

Examination of the trends indicating proportions of types of articles published annually yielded no statistically significant results; however, there exist weak trends related to anecdotal-only papers and posttest-only research designs.

Anecdotal-only articles. Table 26 presents the trends of anecdotal-only publications by year. The findings are notable, but not statistically significant, $M^2(1, N = 89) = 3.50$, $p = 0.062$. The direction of the residuals is generally ascending, indicating that there may be an increasing trend in the proportions of anecdotal-only publications.

One-group posttest-only articles. Table 27 presents the trends of one-group posttest-only publications by year. The findings are not statistically significant, $M^2(1, N = 64) = 2.46$, $p = 0.117$; however, there does appear to be a weak descending trend, indicating that the rate of empirical articles utilizing this design may be declining.

Other types of articles.

Table 28 presents the proportions of experimental papers published by year, with no statistically significant evidence of a trend, $M^2(1, N = 68) = 0.65$, $p = 0.419$.

Table 29 presents the proportions of attitudes-only papers published by year, also with no statistically significant trend, $M^2(1, N = 91) = 0.02$, $p = 0.876$.

Table 26

Cross Tabulation of Anecdotal-Only Papers by Year

	Anecdotal-only			Percentage	Adjusted
Year	Yes	No	**Total**	**Yes**	**residual**
1999-2000	0	2	2	0.0	-0.8
2001-2002	0	4	4	0.0	-1.2
2003-2004	5	18	23	21.7	-0.5
2005-2006	10	29	39	25.6	0.0
2007-2008	8	13	21	38.1	1.5
Total	23	66	89	25.8	

Table 27

Cross Tabulation of One-Group Posttest-Only Papers by Year

	Posttest-only exclusively			Percentage	Adjusted
Year	Yes	No	**Total**	**Yes**	**residual**
1999-2000	2	1	3	66.7	2.0
2001-2002	1	3	4	25.0	0.2
2003-2004	3	12	15	20.0	0.0
2005-2006	5	24	29	17.2	-0.6
2007-2008	2	11	13	15.4	-0.5
Total	13	51	64	20.3	

Table 28

Cross Tabulation of Experimental Papers by Year

	Experimental			Percentage	Adjusted
Year	Yes	No	**Total**	**Yes**	**residual**
1999-2000	3	0	3	100.0	1.0
2001-2002	3	1	4	75.0	-0.1
2003-2004	11	7	18	61.1	-1.8
2005-2006	23	7	30	76.7	0.0
2007-2008	12	1	13	92.3	1.5
Total	52	16	68	76.5	

Table 29

Cross Tabulation of Attitudes-Only Papers by Year

Year	Attitudes-only Yes	Attitudes-only No	Total	Percentage Yes	Adjusted residual
1999-2000	2	1	3	66.7	1.2
2001-2002	1	3	4	25.0	-0.4
2003-2004	7	16	23	30.4	-0.5
2005-2006	13	27	40	32.5	-0.5
2007-2008	9	12	21	42.9	0.8
Total	32	59	91	35.2	

Region of First Author's Affiliation

Comparing types of paper to region of the first author's affiliation required collapsing some groups together. Doing so produced cell sizes more likely to produce meaningful comparisons, but at the sacrifice of some geographic precision. Groups, as presented here, are as follows: United States, Europe, and other, where other includes articles from Canada, Mexico, Israel, Thailand, and Australia.

Each comparison of types of paper to the region of the first author's affiliation yielded no statistically significant results; however, each category except the anecdotal-only category yielded results approaching statistical significance.

Attitudes-only papers. The results shows proportions of papers inspecting only student attitudes and reports of self-learning, grouped by region. Although the results are not statistically significant using the Bonferroni-adjusted significance threshold of

0.004, there would be evidence of a significant trend had the threshold not been adjusted, $X^2(2, N = 91) = 9.21$, $p = 0.010$. The United States published 39.1% more attitudes-only papers than did European nations, and 16.4% more attitudes-only papers than did the other nations represented in this sample. The residuals for Europe and the United States, which have absolute values greater than 2.7, strengthen the evidence of association.

Experimental/quasi-experimental articles. Table 31 presents the proportions of experimental or quasi-experimental papers, grouped by region. Although the association is not strongly significant, $X^2(2, N = 68) = 5.51$, $p = 0.064$, the residuals are moderately strong, providing evidence on an association. Note the absence of non-experimental methodologies employed by authors affiliated with European institutions, and the prevalence of non-experimental methodologies employed by authors in the United States.

One-group posttest-only articles. Table 32 presents the proportions of experimental articles using the one-group posttest-only design. There is no statistically significant evidence of an association, $X^2(2, N = 64) = 4.39$, $p = 0.111$, but the size of the residuals warrants merit. Note that no authors in this sample associated with European universities used the one-group posttest-only design exclusively; and 26.8% of authors associated with universities in the United States did use the one-group posttest-only design exclusively.

Anecdotal-only articles. There is no statistically significant evidence in this sample for an association between region of first author's association and the published article providing only anecdotal evidence, $X^2(2, N = 89) = 0.10$, $p = 0.950$.

Table 30

Cross Tabulation of Attitudes-Only Papers by Region of Affiliation

	Attitudes-only			Percentage	Adjusted
Region	Yes	No	**Total**	**Yes**	**residual**
Europe	1	16	17	5.9	-2.8
United States	27	33	60	45.0	2.7
Other	4	10	14	28.6	-0.6
Total	32	59	91	35.2	

Table 31

Cross Tabulation of Experimental Papers by Region of Affiliation

	Experimental			Percentage	Adjusted
Region	Yes	No	**Total**	**Yes**	**residual**
Europe	13	0	13	100.0	2.2
United States	31	14	45	68.9	-2.1
Other	8	2	10	80.0	0.3
Total	52	16	68	75.6	

Table 32

Cross Tabulation of One-Group Posttest-Only Papers by Region of Affiliation

	Posttest-only exclusively			Percentage	Adjusted
Region	Yes	No	**Total**	**Yes**	**residual**
Europe	0	13	13	0.0	-2.0
United States	11	30	41	26.8	1.7
Other	2	8	10	20.0	0.0
Total	13	51	64	20.3	

Table 33

Cross Tabulation of Anecdotal-Only Papers by Region of Affiliation

	Anecdotal-only			Percentage	Adjusted
Region	Yes	No	**Total**	**Yes**	**residual**
Europe	4	13	17	23.5	-0.2
United States	15	43	58	25.9	0.0
Other	4	10	14	28.6	0.3
Total	23	66	89	25.8	

DISCUSSION

Threats to Validity

Every effort was made to provide an honest and ethical evaluation of the literature; however, some threats to internal validity are manifest in this study. Perhaps the greatest limitation is the lack of inter-rater reliability measures. Without reliability measures, it is difficult to assert strong conclusions and well-qualified recommendations for change in policy. In an effort to reduce the risk of single-rater bias in the results, I read and classified all articles in the order they were drawn from the sample.

This study inherits, with its design, some of the limitations of Randolph's (2007) study; for example, this study "did not deeply analyze articles that exclusively used explanatory descriptive modes of inquiry" (2007, p. 127). Furthermore, Randolph's instrument did not clearly explain the difference between qualitative and pure-anecdotal research (Lister, The Randolph thesis: CSEd research at the crossroads, 2007, p. 17). Qualitative methodologies appear to be difficult to classify (Sheard et al., 2009, p. 98), which may be an indicator that qualitative report descriptions require improvement. An attempt to design and validate a new instrument for evaluating qualitative methodologies is out of the scope of this study.

A limitation related to the 12 cross tabulations is that, as a coder, I was not blind to the categorization (i.e., forum type, year, and region) of the article. To compensate for this risk, I classified these categories separately from the remaining data, that is, on

another pass. Doing so mitigates, but does not obviate, the limitation of employing a non-blind coder.

Interpretation of Descriptive Findings

Research on Human Participants

Of the 108 articles sampled, 85.5% dealt with human participants. This substantially exceeds the proportion reported by Randolph (66.3%). Because the confidence interval of the current study and that reported by Randolph do not overlap, I conclude that researchers of educational pair programming explore a greater proportion of studies with human participants than do researchers of general computer science education. This measure is easy to accept because pair programming is a human-centric practice, relatively simple and inexpensive to implement, and applicable to a broad class of assignment and task types.

Research Not Using Human Participants

Of the articles that did not report research using human participants, nearly half (46.7%) were philosophical or theoretical papers. About a quarter (26.7%) of the articles were program descriptions without analysis on the effects of the program on students. This contrasts sharply with the proportion of program descriptions (60%) reported by Randolph.

To understand why program descriptions are underrepresented in pair programming research, it is helpful to consider the following conclusion from Randolph (2007) regarding computer science education proper:

> …While many computer science educators may be experts at creating the software and hardware to create automated interventions to increase the learning of computer science, an increased emphasis should be put on the instructional design of the intervention rather than only or primarily on the software and hardware mechanisms for delivering the instructional intervention.... (p. 132)

This analysis does not appear to apply well to pair programming, which is neither hardware nor software, nor is it an automated intervention. It may be that, because pairs cannot be constructed, automated, or programmed, but can be organized, guided, and influenced, program descriptions less frequently apply to educational pair programming.

Proportions of Anecdotal-Only Articles

Randolph (2007) identified two hazards caused by excessive use of anecdotal evidence in the literature: first, anecdotal evidence is not appropriate for hypothesis confirmation (p. 136); second, use of anecdotes appears to encourage "a mismatch between what was claimed and what, in the spirit of scientific honesty, should have been claimed" (p. 137). In contrast to these hazards, anecdotal evidence plays the critical seed-planting role of hypothesis generation (p. 136).

Randolph cited Holloway (1995), who issued the harsh denunciation of software engineering research, "Rarely, if ever, are [empirical claims about software engineering] augmented with anything remotely resembling either logical or experimental evidence" (p. 136). Surprisingly, the proportion of anecdotal papers (25.3%) in the current study is noticeably less than the proportion (38.2%) reported by Randolph. Due to slightly-overlapping confidence intervals, conclusions about this difference must be made with

caution; however, it is worth noting that the current body of educational pair program research does not even closely reflect Holloway's conclusions.

It is difficult to argue whether this proportion is an indicator of health or of sickness, because there does not seem to be any authoritative direction indicating what a healthy ratio of anecdotal to empirical research would be. We can reason that, insofar as anecdotal evidence functions as a means of hypothesis generation, that a healthy research literature must include some representation from anecdotal evidence. Another consideration, suggested by Valentine (2004), is that researchers add some empirical element to what would otherwise be pure anecdotal research.

Types of Research Methods

As shown in Tables 13 and 14, about two-thirds (67.0%) of the articles in the current study used experimental or quasi-experimental methodologies. Slightly more than half (58.2%) of the articles sampled used purely quantitative methodologies, with the remaining articles using qualitative or mixed methodologies. This differs significantly from Randolph's sample, wherein nearly three-quarters (74.3%) of the articles sampled used purely quantitative methodologies.

As with the proportion of anecdotal evidence, there appears to be no authoritative direction for what the optimum proportion of quantitative, qualitative, and mixed methods research should be in the literature. Anecdotally, I observed that articles presenting purely qualitative methods generally did not present their methods with adequate detail, a sentiment that mirrors that of Sheard and colleagues (2009, p. 98). Pragmatically, however, I agree with Lister (2005) who, while discussing

quantitative and qualitative methods, concluded, “There are not bad methods, just bad research – the inappropriate use of a method” (p. 19).

Johnson and Onwuegbuzie (2004) advocated combining quantitative and qualitative research. They argue, “What is most fundamental is the research question—research methods should *follow* research questions in a way that offers the best chance to obtain useful answers. Many research questions and combinations of questions are best and most fully answered through mixed research solutions” (pp. 17-18). If Johnson and Onwuegbuzie are correct, then educational pair programming research must evolve to increase the current proportion of mixed-method research articles (13.2%).

Types of Measures Used

As with Randolph’s sample, the most frequently used kinds of measures were questionnaires, grades, student work, and teacher- or researcher-made tests, though the current sample has fewer teacher- or researcher-made tests than student work. The current sample exhibited more interviews (11.8%) and fewer log files (2.9%); however, due to overlapping confidence intervals, there is no strong evidence of difference between any measurement type when compared to Randolph’s sample.

Also like Randolph’s sample, nearly all surveys, tests, and observations neglected to collect or report reliability or validity information. Anecdotally, it appeared that studies reporting reliability information were more likely to see reuse of the instrument by other researchers. It seems as though researchers interested in promoting replication

of and validation of their research should consider investing time into evaluating reliability or validity of the instrument.

Dependent, Independent, and Mediating/Moderating Variables Examined

Randolph's findings conclude that student instruction, attitudes, and gender represented the greatest proportions of independent, dependent, and mediating/moderating variables, respectively. The current study supports these findings.

Randolph has argued that student attitudes "are unreliable indicators of learning or teaching quality," (2007, p. 140), and advised the exploration of other, more reliable measures; however, student attitudes play an important role in computer science education. Lister (2007) provided the following explanation for the prevalence of opinion-oriented surveys:

> I suspect that the focus in [computer science education] on student opinions may not always be as a proxy for student learning. Since the downturn in student numbers, educators have been looking for approaches to teaching that students enjoy, in the hope of attracting students back to computing. (p. 17)

Allowing for surveys and questionnaires to provide value other than confirming quality of learning and teaching, it seems some need for reform remains; questionnaires represented 70.6% of the articles sampled, almost entirely without reliability or validity information.

Experimental Research Design

Randolph reported that most articles in his sample used the posttest-only and posttest with controls research designs and that posttest-only designs were used nearly

twice as often as posttest with controls designs. The current study partially contradicts these results; while posttest-only and posttest with controls research designs are used more frequently than other designs, posttest with controls designs are used much more often (66.7%) than posttest-only designs. Because one-group posttest-only designs have nearly insurmountable flaws (Randolph, 2007, pp. 140-141), the results of the current study are encouraging.

It should be noted that one-group posttest-only designs, like anecdotal data, can provide some limited value to the literature. Gilner and Morgan (2000) asserted that, though the design "does not satisfy even the minimum condition for a research problem, which is investigation of a relationship or comparison," that, "If nothing else, it provides pilot data (a common term to indicate exploratory data) for a future study" (p. 95). Because 30.9% of the current sample utilizes the posttest-only design, I suggest that it is not reasonable to assume that all of these studies are designed or intended for pilot data.

Confirming the results of Randolph, most experimental or quasi-experimental studies reported in the current sample used convenience sampling and convenience assignment. Convenience samples might be considered the educational researcher's greatest renewable resource: available, accessible, and affordable. The ease of using a convenience sample can come with a price, however, by impairing the general applicability of a study.

Randolph discussed advantages and hazards of this kind of sampling, describing strategies that researchers can use to preserve research validity under such designs

(2007, pp. 142-144). One strategy is to vary the levels of treatment within the sample, for example, by varying the degrees of required adherence to the pair programming protocol. By comparing results at differing treatment levels, the researcher isolates the treatment from other confounding variables.

Report Structure

Investigating the proportions of articles adequately providing various report elements serves the purpose of evaluating the quality of communication contained in the report. It seems reasonable to insist that important report elements be adequately described, considering that the time and effort required to conduct a high quality study on human participants must be greater than the time and effort required to describe the process.

Randolph refrained from making assertions about report structure due to low levels of inter-rater reliability. With this admission, and with the current study lacking inter-rater reliability measures, it is perhaps inappropriate to draw conclusions from comparisons. Instead, I will discuss only themes observed in the current study.

Four report elements coded were present in fewer than two-thirds of the sample: research questions or hypotheses (46.2%), adequate description of instrument (47.3%), adequate description of procedure (54.9%), and separate treatment of results and discussion (61.5%). Articles that omit specific research questions, goals, or hypotheses limit the clarity with which readers can identify and understand their contribution to the research. Inadequate description of instrument and procedure limit the replicability of a study by other researchers. Researchers and publishers should

carefully consider each report element to ensure the highest quality of communication in published research. Note that, with regards to the separation of results and discussion, the American Psychological Association allows for situations wherein integrating discussion with results is appropriate (American Psychological Association, 2001, p. 26); therefore, I make no recommendations dealing with this report element.

Statistical Practices

Ensuring high quality and adequate detail in statistical reporting provides at least two benefits. Firstly, quality reporting validates and strengthens claims and conclusions made by the researcher. Secondly, quality reporting enables and facilitates meta-analysis, that is, efforts to search for and combine results from disparate, but related, studies (Cohen, 2001, pp. 237-239).

Much like Randolph's sample, the current sample contains a high proportion of articles using inferential statistics without adequate statistical detail, such as dispersion measures (standard deviation, range, confidence intervals, etc.).

More than one-third (39.7%) of the studies did not report effect sizes. Those studies that did reported only a comparison or difference of group means. I cannot conclude whether the proliferation of reports using only raw mean difference is an indicator of health or weakness in the literature. The APA Task Force on Statistical Inference identified conditions for which raw difference of means is the preferred effect size to report:

> Always present effect sizes for primary outcomes.... If the units of measurement are meaningful on a practical level (e.g., number of cigarettes smoked per day), then we usually prefer an unstandardized measure (regression coefficient or

> mean difference) to a standardized measure (r or d) (Wilkinson, L; APA Task Force on Statistical Inference, 1999, p. 599).

Perhaps of more concern than the lack of diversity in effect size types is the sample proportion reporting no effect size at all. Cohen (2001) emphasized the inadequacy if hypothesis testing without effect sizes, specifically about parametric *t*tests:

> What does a very large *t* value indicate? When a very large *t* is obtained, we can feel very sure that the effect size is not zero. However, no matter how certain we are that the effect size is not zero, this does not imply that the effect size must be fairly large. …Even a very tiny effect size can lead to a large expected *t* if very large samples are used. *It is important to remember that statistical significance does not imply that the effect size is large enough to be interesting or of any practical importance.* (emphasis added; p. 220)

It seems evident that ample need for improvement exists when reporting inferential statistics in educational pair programming research.

Islands of Practice

This section presents the results of the 12 cross tabulations. It is necessary to qualify my interpretation of these analyses with the acknowledgment that none of the 12 analyses qualified as statistically significant using the Bonferroni-adjusted threshold of $p < 0.004$. I believe, however, that some of the analyses were of practical significance, even though not of statistical significance.

Journal and Conference Papers

There seemed to be little evidence that journals accepting educational pair programming research differed from conferences in terms of number of experimental

articles, attitude-only papers, and one-group posttest-only designs. There was weak evidence of an association between type of publication forum and the article providing only anecdotal evidence. The residuals provide evidence of a moderate effect. If we accept this association, then we agree that journals favor a marginally greater proportion of empirical research articles than do conferences. This finding is consistent with the findings of Randolph (2007, p. 147), who found no compelling associations when analyzing conferences and journals with χ^2 analysis.

Yearly Trends

There was weak evidence of an increasing trend in anecdotal-only publications, and of a decreasing trend in one-group posttest-only articles, both with modest residuals. This finding partially contradicts Randolph's finding that anecdotal-only articles were decreasing. Though the anecdotal-only trend in the current study warrants some concern, the trend of decreasing one-group posttest-only research designs is encouraging.

Region of Origin

Analyzing research articles by region of the first author's affiliation yielded moderate statistical significance in all areas except the publication of anecdotal-only articles. In summary, the findings are:

1. Researchers affiliated with institutions in the United States are much more likely to produce a paper evaluating only student attitudes and self-reports of learning than researchers of European institutions. This behavior deviates

from Randolph's finding that researchers from Asian-Pacific or Eurasian institutions tended to measure attitudes only.

2. Researchers affiliated with institutions in Europe were much more likely to implement an experimental or quasi-experimental methodology when compared to researchers in the United States. This is the opposite of an effect reported by Randolph.
3. Researchers affiliated with institutions in the United States were much more likely to implement a posttest-only research design than their counterparts in Europe and other regions. Randolph did not find evidence of an effect for this comparison.

Combining these findings exposes a theme in educational pair programming research: researchers affiliated with institutions in the United States are more likely to use attitude-only, posttest-only designs, and less likely to employ experimental methodologies than researchers in other areas of the world, especially when contrasted with Europe. The consistency of this theme increases the practical significance of the claim that there exist islands of practice when examining educational pair programming by region.

Profile of the Average Educational Pair Programming Paper

Randolph's (2007) evaluation of pair programming included a sobering profile, comprised of combinations of median measurements from his sample, "because of the narrative efficiency in which it can characterize what computer science education

research papers, in general, are like" (p. 161). It is interesting to compare and contrast his profile with the current study's profile of educational pair programming research. Table 34 presents Randolph's CSE research profile side-by-side with the educational pair programming research profile.

Recommendations

The primary intent and value of this thesis is to provide inspiration and direction to educational pair programming researchers, to provide informed guidance to editors, publishers, and policy makers, and, as a result, increase the quality and credibility of the research. In this section, I provide again the recommendations of Randolph (2007), and assert additional recommendations informed by the results of this study.

The Randolph Recommendations

The interested reader is advised to read the evidence-based recommendations and accompanying explanations provided by Randolph (2007). Each recommendation is fully supported by the evidence from the current study. In summary, they are to:

- Be wary of investigations that only measure students' self-reports of learning,
- Accept anecdotal experience as a means of hypothesis generation, but not as a sole means of hypothesis confirmation,
- Insist that authors provide some kind of information about the reliability and validity of measures that they use,
- Realize that the one-group posttest-only research design is susceptible to almost all threats to internal validity,
- Report informationally adequate statistics, and
- Insist that authors provide sufficient detail about participants and procedures. (2007, pp. 162-166)

Table 34

Profile Comparison of Educational Pair Programming Research

Computer Science Education Research (Randolph, 2007, p. 162) ***Emphasis added.***	**Educational Pair Programming Research (Current Study)**
The typical computer science education research paper is a *5-page* conference paper written by two authors.	The typical educational pair programming research paper is a *7-page* conference paper written by two or three authors.
The first author is most likely affiliated with a university in North America.	Same.
If the article does not deal with human participants, then it is likely to be a *description of some kind of an intervention, such as a new tool or a new way to teach a course*.	If the article does not deal with human participants, then it is likely to be a *philosophical, opinion paper, or one asserting the expected value of some methodology*.
If the article does deal with human participants, then there is a *40%* chance that it is basically a description of an intervention in which only anecdotal evidence is provided.	If the article does deal with human participants, then there is a *25%* chance that it is basically a description of an intervention in which only anecdotal evidence is provided.
If more than anecdotal evidence is provided the authors probably used a *one-group posttest-only design* in which they gave out an attitude questionnaire, after the intervention was implemented, to a convenience sample of first-year undergraduate computer science students.	If more than anecdotal evidence is provided the authors probably used a *posttest-only with controls design* in which they gave out an attitude questionnaire, after the intervention was implemented, to a convenience sample of first-year undergraduate computer science students.
The students were expected to report on how well they liked the intervention or how well they thought that the intervention helped them learn.	Same.
Most likely, the authors presented raw statistics on the proportion of students who held particular attitudes.	Same.

I am confident that the application of these six recommendations will improve the applicability, replicability, and credibility of the educational pair programming literature.

Curriculum Recommendations

This section provides four additional evidence-based recommendations for consideration by the computer science educator community for the improvement of future research.

Form an interdisciplinary research partnership whenever possible if conducting research on human participants. The practice of forming an interdisciplinary research partnership occurs infrequently in the community. Most authors of educational pair programming research articles have technical backgrounds rather than educational, behavioral, or cognitive psychology experience and training.

An example of an interdisciplinary research partnership in practice is the work of McDowell and colleagues (2006), who regularly include as authors representatives of their institution's psychology department. In the sample, McDowell and colleagues' research typically included sufficient treatment of each report element, and stronger research designs than the infamous one-group posttest-only design. In their parametric inferential analyses, they provided appropriate measures of dispersion, sufficient to qualify their research as a candidate for future meta-analysis. Because of the design quality evident in their interdisciplinary work, a researcher can place increased trust in conclusions related to increased retention, confidence, and program quality, and in the narrowing of the observed student gender gap. Theirs is a pattern worth emulation.

Insist upon and provide training to student and faculty researchers in the practices of gathering and reporting reliable statistical information. It seems reasonable to expect that improvements in researcher training will result in improvements in the quality of research measures and reports. Consider encouraging courses supporting interdisciplinary statistical practices, such as psychological, educational, or behavioral statistics. Courses such as these should instruct students on the best practices for reporting statistics, in addition to the proper application of a given statistic to appropriate situations. Exposure to and understanding of the appropriate application of research statistics could promote both quality and diversity in statistical measures.

Encourage interregional dialogue and research partnerships. The analysis of regional islands of practice indicated that different regions in the world practice educational pair programming research somewhat differently. Researchers should aggressively familiarize themselves with the practices, habits, and styles of researchers throughout the world community for the intent of assimilating characteristics that improve the credibility and general applicability of research results. For example, some researchers in the United States could benefit from exposure to the quantitative research published by European authors, while authors in Europe could benefit from exposure to the variety of interview protocols used in qualitative research published by institutions in the United States.

Encourage diversity in research methodologies, designs, and measures. Advocate studies that promote diversity in the practice of research. Mixed qualitative and quantitative studies may require additional space in journals and conference

proceedings to adequately describe procedures. Careful literature review prior to conducting new research can expose areas of research unexplored by the community, and thus provide opportunities to increase the depth and breadth of the literature. Consider each dependent, independent, and mediating or moderating variable reported in this study with low proportions to be an area requiring future research.

Recommended Future Research

This section presents several areas of research that are underrepresented or unrepresented in this sample that can, or should, be of interest to the educational pair programming community. I present each area as a question with some discussion.

What are the effects of pair programming on students K-12? Of the 108 articles sampled, only one dealt with pre-collegiate students. It is surprising that the sample contained so few studies on younger students, considering that some effects of pair programming reported on undergraduate students could be very valuable to younger students, including increased recruitment and retention to the field of computing, and increased performance and competence. Can pair programming improve the probability a young student attends higher education, selects a computer science-related field of study, and succeeds in the field? Can pair programming have a positive effect on success in other core K-12 classes? What instructional methodologies are most effective when implementing pair programming in K-12 computer science pedagogy? These questions demonstrate the need to expand the exploration of pair programming to younger students.

What are the effects of pair programming on students from low-income families, or on students with disabilities? Socioeconomic status and disability status were factors that were unexplored by the current body of research. Because computer science education provides opportunities for well-paid, well-trained professions, educators should consider whether pair programming offers students increased opportunities for socioeconomic development. Research in this area using participants of any age group can promote diversity and significance to the field.

How does fidelity to a pair programming intervention influence effects? Although articles in the sample measured a broad range of effects on pair programming groups, measuring the degree to which students adhered to the pair programming protocol was scarce. Often, if treatment fidelity was measured at all, measurements consisted of peer evaluations that were incorporated into student grades. Like all other attitude surveys, these measures may not fully reflect the effect. What proportion of time should be spent pairing on a task to achieve the greatest effects? Is there a correlation between treatment fidelity and some effect? Answers to these questions could provide guidance for maximizing the benefits and minimizing the costs of educational pair programming.

What are the effects of pair programming if integrated as a core component of the computer science curriculum? Unaddressed in the 108 articles sampled are best practices for implementing pair programming as a central practice of computer science pedagogy throughout the curriculum. Usually, the reported practice of pair programming is limited to a single course or a small set of courses involving first- and second-year undergraduates. Some researchers report reverting to solo programming

after the first year to ensure student independence, but the sample contains no published evidence that terminating the practice of pair programming has a negative or positive effect on students. Such long-term studies are difficult to design and implement; however, long term studies can resolve doubts some may have that pair programming is more effective because it is “new,” rather than more effective. Certainly, the record of positive effects reported over nine years of research warrant consideration for experimental, curriculum-wide implementation.

CONCLUSION

Summary

Pair programming in computer science education is a growing area of research. In an effort to improve the quality of the research, I conducted a thorough methodological review, modeled after the review conducted by Randolph (2007), of educational pair programming research published between 2000 and 2008. A 112-variable scale for characteristics of the research reports, designs, and methodologies was used to classify the sample of 108 research articles. The major findings of the review include:

1. About one-sixth of the articles did not report research on human participants, which is about half the proportion that is typical in computer science education research.
2. About half of the articles that did not involve human participants were philosophical or theoretical in nature.
3. About one-quarter of articles that dealt with human participants only provided anecdotal evidence for their claims, which is a smaller proportion than is typical in computer science education research.
4. Of the articles that provided empirical evidence, most articles used experimental or quasi experimental methods, which is similar to general computer science education research.

5. Of the articles that used an experimental research design, the majority used a controlled posttest-only design, which is markedly different than typical computer science education research that usually implements a one-group posttest-only design.
6. Like typical computer science education research, student instruction, attitudes, and gender were the most frequent independent, dependent, and mediating/moderating variables, respectively.
7. Like typical computer science education research, questionnaires were the most frequently used type of measurement instrument, and usually lacked measures of psychometric validity.
8. Like typical computer science education research, inferential statistics often lacked adequate statistical information.
9. There was weak evidence that journals publish a smaller proportion of articles that provide only anecdotal evidence than do conferences.
10. There was weak evidence of an increasing yearly trend in anecdotal-only articles and a decreasing yearly trend in the use of the one-group posttest-only research design.
11. There was moderate evidence that first authors affiliated with institutions in the United States published a greater proportion of attitude-only papers and one-group posttest-only research designs, and a smaller proportion of experimental studies than their counterparts affiliated with other regions,

especially when compared to first authors affiliated with European institutions.

Based on the results of this content analysis, I reassert Randolph's (2007, pp. 162-166) recommendations with the following additions:

1. Form an interdisciplinary research partnership whenever possible if conducting research on human participants;
2. Insist upon and provide training to student and faculty researchers in the practices of gathering and reporting reliable statistical information;
3. Encourage interregional dialogue and research partnerships; and
4. Encourage diversity in research methodologies, designs, and measures.

Finally, I propose several areas of research that were unrepresented or underrepresented by the sample, which I summarize with the following high-level research questions:

1. What are the effects of pair programming on students K-12?
2. What are the effects of pair programming on students from low-income families, or on students with disabilities?
3. How does fidelity to a pair programming intervention influence effects?
4. What are the effects of pair programming if integrated as a core component of the computer science curriculum?

Expanding the Horizons of Educational Pair Programming

I once remarked to a respected instructor that research in the topic of pair programming was exhausted, and that I planned to explore research somewhere else. He responded, for which I am deeply grateful, that he did not think this was the case, and that perhaps, appearing exhausted, the field was at last ready for a review. Concluding that review, I feel much like a marathon athlete, cresting the top of a great hill to witness both the broad expanse of tamed fields and orchards, and the beckoning thrill of unexplored peaks and shores. The pair programming literature also contains broad, well-explored areas, and unexplored wilderness.

There exists both a capacity and a need for this area of research to grow. If researchers and publishers will commit to permitting only the highest quality of research methods, and to using studies designed and dedicated to confirming the growing body of knowledge, we will see, at last, resolution to the question: *Are the effects of pair programming compelling enough to affect policy in how we provide computer science education?*

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APPENDICES

Appendix A:

A List of the Articles Included in the Sample

Ahern, T. C. (2005). Work in progress - Effect of instructional design and pair programming on student performance in an introductory programming course. *FIE 2005: Proceedings of the 35th Annual Conference of Frontiers in Education,* October 19-20, F3E - 11-12.

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Appendix B:

Methodological Review Coding Form

Demographic Characteristics		DE0: _____	DE0a: _____
DE1.	Reviewer	1 = Keith, 2 = Other _____	
DE2.	Forum	Write in:	
DE2a.	Forum Type	1 = Conference, 2 = Journal, 3 = Other	
DE3.	Year	0 = 2000, 1 = 2001, 2 = 2002, 3 = 2003, 4 = 2004, 5 = 2005, 6 = 2006, 7 = 2007, 8 = 2008	
DE4.	Page	_ _ _ _ (up to four digits)	
DE5.	Pages	_ _ _ _ (up to four digits)	
DE6.	Region	1 = Africa, 2 = Asian-Pacific or Eurasia, 3 = Europe, 4 = Middle East, 5 = North America, 6 = South or Central America, 7 = IMPDET	
DE7.	University	Write in:	
DE8.	Authors		
DE9.	1st Author	_____, __. __.	
DE10.	Subject	1 = New way to organize a course, 2 = Tool, 3 = curriculum, 4 = classroom development methodology, 5 = general development methodology, 6 = Other _____	
DE11.	Taxonomy	1 = Experimental, 2 = Marco Polo, 3 = Tools, 4 = John Henry, 5 = Philosophy, 6 = Nifty	
DE12.	Human Part.	1 = yes, 2 = no. (If *no*, go to A1.)	
DE12a.	Anecdotal	1 = yes, 2 = no. (If *yes*, end, otherwise go to A2)	
Type of papers that did not report research on human participants			
A1.	Type of other	1 = Literature review, 2 = Program description, 3 = Theory, Methodology, Philosophy paper, 4 = Technical, 5 = Other (if 1-4, end; if 5 go to A1a)	
A1a.	Other other	If A1 = 5, Write in a short description (end).	
Report Structure			
A2.	Abstract	1 = narrative, 2 = structured, 3 = no abstract	
A3.	Introduce Problem	1 = yes, 2 = no	
A4.	Literature Review	1 = yes, 2 = no	
A5.	Purpose/Rationale	1 = yes, 2 = no	
A6.	Questions/Hypotheses	1 = yes, 2 = no	
A7.	Participants	1 = yes, 2 = no	
A7a.	Grade Level (Answer if A7 is *yes*)	1 = preschool 2 = K-3 3 = 4-6 4 = 7-9 5 = 10-12 6 = undergraduate 7 = graduate 8 = post-graduate 9 = other 10 = cannot determine	
A7b	Undergraduate curriculum year (Answer only if A7a is 6)	1 = first year 2 = second year 3 = third year 4 = fourth year	
A8.	Settings	1 = yes, 2 = no	

A9.	Instruments	1 = yes, 2 = not described, 3 = none
A10.	Procedure	1 = yes, 2 = no
A11.	Results and Discussion	1 = yes, 2 = no

Methodology type		
T1.	Experimental/quasi-experimental	1 = yes, 2 = no
T1a.	Assignment (If not M1, skip)	1 = self-selection, 2 = random, 3 = researcher-assigned
T2.	Explanatory descriptive	1 = yes, 2 = no
T3.	Exploratory description	1 = yes, 2 = no
T4.	Correlational	1 = yes, 2 = no
T5.	Causal-comparative	1 = yes, 2 = no
T6.	IMPDET or anecdotal	1 = yes, 2 = no (if yes, then end)
T7.	Selection	1 = random, 2 = purposive, 3 = convenience/preexisting

Experimental research designs		
RD1.	Experimental Design(s)	1 = yes, 2 = no (if *no*, then go to I1)
RD2.	Posttest, no controls	1 = yes, 2 = no
RD3.	Posttest, with controls	1 = yes, 2 = no
RD4.	Pretest/posttest without controls	1 = yes, 2 = no
RD5.	Pretest/posttest with controls	1 = yes, 2 = no
RD6.	Group reported measures	1 = yes, 2 = no
RD6a.	If RD6, was there an experimental between-group factor?	1 = yes, 2 = no
RD7.	Multiple factor	1 = yes, 2 = no
RD8.	Single-subject	1 = yes, 2 = no
RD9.	Other	1 = yes, 2 = no
RD10.	If RD9, explain:	
RD11.	Posttest only highest	1 = yes, 2 = no

Independent Variables (interventions)		
I1.	Was an independent (manipulatable) variable used in this study?	1 = yes, 2 = no
[if yes, go to I2, otherwise go to D1]		
I2.	Student instruction	1 = yes, 2 = no
I3.	Teacher instruction	1 = yes, 2 = no
I4.	CS fair/contest	1 = yes, 2 = no
I5.	Mentoring	1 = yes, 2 = no
I6.	Speakers at school	1 = yes, 2 = no
I7.	CS field trips	1 = yes, 2 = no
I8.	Pair Design/Testing/Programming	1 = yes, 2 = no
I9	Other	Write in:
[go to D1]		

Dependent Variables		
D1.	Attitudes	1 = yes, 2 = no
D2.	Attendance	1 = yes, 2 = no
D3.	Core achievement	1 = yes, 2 = no

D4.	CS achievement	1 = yes, 2 = no
D5.	Teaching practices	1 = yes, 2 = no
D6.	Intentions for future	1 = yes, 2 = no
D7.	Program implementation	1 = yes, 2 = no
D8.	Costs and benefits $	1 = yes, 2 = no
D9.	Socialization	1 = yes, 2 = no
D10.	Computer use	1 = yes, 2 = no
D11.	Other	1 = yes, 2 = no
D11a.	If D11, explain:	
[go to M1]		

Measures		
M1.	Grades	1 = yes, 2 = no
M2.	Diary	1 = yes, 2 = no
M3.	Questionnaire	1 = yes, 2 = no
M3a.	Questionnaire w/ psych	1 = yes, 2 = no
M4.	Log files	1 = yes, 2 = no
M5.	Test	1 = yes, 2 = no
M5a.	Test w/ psych	1 = yes, 2 = no
M6.	Interviews	1 = yes, 2 = no
M7.	Direct	1 = yes, 2 = no
M7a.	Direct w/ psych	1 = yes, 2 = no
M8.	Standardized Test	1 = yes, 2 = no
M8a.	Standardized Test w/ psych	1 = yes, 2 = no
M9.	Student work	1 = yes, 2 = no
M10.	Focus groups	1 = yes, 2 = no
M11.	Existing data	1 = yes, 2 = no
M12.	Other	1 = yes, 2 = no
M12a	If M12, explain:	
[go to F1]		

Factors (non-manipulatable variables)		
F1.	Were any non-manipulatable factors examined as covariates?	1 = yes, 2 = no
[if F1, go to F2, else go to S1]		
F2.	Gender	1 = yes, 2 = no
F3.	Aptitude	1 = yes, 2 = no
F4.	Race/Ethnic Origin	1 = yes, 2 = no
F5.	Nationality	1 = yes, 2 = no
F6.	Disability	1 = yes, 2 = no
F7.	SES	1 = yes, 2 = no
F8.	Other	1 = yes, 2 = no
F8a.	If F8, explain:	
[go to S1]		

Statistical Practices		
S1.	Were quantitative results reported?	1 = yes, 2 = no
[if S1, go to S2, else end]		
S2.	Were inferential statistics used?	1 = yes, 2 = no
[if S2, go to S3, else go to S8]		
S3.	Parametric test of location used?	1 = yes, 2 = no
[if S3, go to S3a, else go to S4]		
S3a.	Were cell means and cell variances or cell means, mean square error and degrees of freedom reported?	1 = yes, 2 = no
S4.	Were randomized block, repeated measures, or MANOVA used?	1 = yes, 2 = no
[if S4, go to S4a, else go to S5]		
S4a.	Were cell means reported?	1 = yes, 2 = no
S4b.	Were cell sample sizes reported?	1 = yes, 2 = no
S4c.	Was pooled within variance or covariance matrix reported?	1 = yes, 2 = no
S5.	Were correlational analyses done?	1 = yes, 2 = no
[if S5, go to S5a, else go to S6]		
S5a.	Was sample size reported?	1 = yes, 2 = no
S5b.	Was variance – covariance, or correlation matrix reported?	1 = yes, 2 = no
S6.	Were cell means reported?	1 = yes, 2 = no
[if S6, go to S6a, else go to S7]		
S6a.	Were raw data summarized?	1 = yes, 2 = no
S7.	Were analyses for very small samples done?	1 = yes, 2 = no
[if S7, go to S7a, else go to S8]		
S7a.	Was entire data set reported?	
S8.	Was an effect size reported?	1 = yes, 2 = no
[if S8, go to S8a, else end]		
S8a.	Difference in means, proportions?	1 = yes, 2 = no
S8aa.	If S8a, was a measure of dispersion reported?	1 = yes, 2 = no
S8b.	Standardized mean difference effect size?	1 = yes, 2 = no
S8c.	Correlational effect size?	1 = yes, 2 = no
S8d.	Odds ratios?	1 = yes, 2 = no
S8e.	Odds?	1 = yes, 2 = no
S8f.	Relative risk?	1 = yes, 2 = no
S8g.	Risk difference?	1 = yes, 2 = no
S8h.	Other?	1 = yes, 2 = no
S8i.	If S8h, explain:	
[end]		

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Appendix C:

Methodological Review Coding Book

DEMOGRAPHIC CHARACTERISTICS

The variables in this section encode the demographic characteristics of each study.

DE0. This is the case number, assigned by the primary coder.

DE0a. If filled by the primary coder, this article was part of the inter-rater reliability sample.

DE1. Circle the number that corresponds with your name. If your name is not on the list, choose *other* and write in your name. (Choose one.)

DE2. Write in the name of the publication forum.

DE2a. Circle the number that corresponds to the type of publication. Choose 1 *Conference* if the article is published in conference proceedings. Choose 2 *Journal* if the article is published in a journal. Chose 3 *Other* if the article is published in a book, magazine, or other forum.

DE3. Encircle the year of publication.

DE4. Write in the page on which the article begins. Use four digits (e.g. if article begins on page 347 = 0347). If there is not a page number, write in 0000.

DE5. Write in the length of the article in pages. If the article had no page numbers (e.g. the article is a web page), write in -9.

DE6. Choose the region of origin of the first author's affiliation. Choose only one. If the regions of the first author's affiliation cannot be determined, use 7 (IMPDET = impossible to determine).

DE7. Write in the name of the university or affiliation of the first author.

DE8. Write in the number of authors.

DE9. Write in the name of the first author. Last name first, and then initials, which are followed by a period (e.g. Justus Joseph Randolph = Randolph, J. J.). Use a hyphen if a name is hyphenated (Randolph-Ratilainen), but do not use special characters.

DE10. Only choose one. If an article could belong in more than one category, choose the category that the article discusses the most. 'Tool' articles supersede 'new ways to teach a course,' when the new way to teach a course involves using a new tool.

- Choose 1 if the subject of the study involved new ways to organize a course. For example, some courses might include "single new assignments" or "more drastic changes in the course." An example is (Nagappan, et al., 2003).
- Choose 2 if the article discusses "a new tool or experiences using a new tool." An example is (Hickey, 2005).
- Choose 3 if the article discusses the CSE curriculum. These types of articles "mainly present a new curriculum in their institution and elaborate on teachers and students' experiences."

- Choose 4 if the article discusses software development methodology in a computer science education context.
- Choose 5 if the article discusses pair programming or software development methodology without discussing computer science education.
- Choose 6 if none of the categories above apply.

DE11. This variable is from Valentine's (2004) methodological review. (The quotes are all from Valentine.) Choose only one category, from the categories listed below.

1. Experimental:

> If the author made any attempt at assessing the "treatment" with some scientific analysis, I counted it as an "Experimental" presentation…. Please note that this was a preemptive category, so if the presentation fit here and somewhere else (e.g. a quantified assessment of some new Tool), it was placed here. (p. 256)

Note if *experimental* was selected on DE11, then DE12 should be *yes* and DE12a should be *no*. If DE12a was *yes*, then DE11 should be something other than *experimental* – the assumption being that informatl anecdotal accounts are not appropriate empirical analyses.

2. Marco Polo

> [This] category is what has been called by others "Marco Polo" presentations: "I went there and I saw this." SIGCSE veterans recognize this as a staple at the Symposium. Colleagues describe how their institution has tried a new curriculum, adopted a new language, or put up a new course. The reasoning is defined, the component parts are explained, and then (and this is the giveaway for this category) a conclusion is drawn like "Overall, I believe the [topic] has been a big success," or "Students seemed to really enjoy the new [topic]". (p. 256)

3. Tools

> Next there was a large collection of presentations that I classified "Tools". Among many other things, colleagues have developed software to animate algorithms, to help grade student programs, to teach recursion, and to provide introductory development platforms. (p. 257)

4. John Henry

> [Another], and (happily) the smallest category of presentations would be "John Henry" papers. Every now and then a colleague will describe a course that seems so outrageously difficult (in my opinion), that one suspects it is telling us more about the author than it is about the pedagogy of the class. To give a silly example, I suppose you could teach CS1 as a predicate logic course in IBM 360 assembler – but why would you want to do that? (p. 257)

5. Philosophy

> [Another] classification would be "Philosophy" where the author has made an attempt to generate debate of an issue, on philosophical grounds, among the broader community. (p. 257)

6. Nifty

> The most whimsical category would be called "Nifty", taken from the panels that are now a fixed feature of the TSP. Nifty assignments, projects, puzzles, games, and paradigms are the bubbles in the champagne of SIGCSE. Most of us seem to appreciate innovative, interesting ways to teach

> students our abstract concepts. Sometimes the difference between Nifty and Tools was fuzzy, but generally a Tool would be used over the course of a semester, and a Nifty assignment was more limited in duration. (p. 257)

DE12. Choose *yes* if the article reports direct research on human participants – even if the reporting is anecdotal. Choose *no* if the authors did not report doing research on human participants. For example, if the author wrote, "the participants reported that they liked using the Jeliot program," then *yes* should be chosen. If the author instead wrote, "in other articles, people reported that they enjoyed using the Jeliot program," choose *no* since the research was not done directly by the author. (If *yes* go directly to DE12a; otherwise, go to A1.)

DE12a. Choose this if the article reported on investigations on human participants, but *only* provided anecdotal information. If *yes* on DE12 and DE12a, end. If *no*, on DE12a, then go to A2 and mark A1 and A1a as -9. This might include studies that the author purported to be a 'qualitative study,' but is without evidence that the researchers used a qualitative methodology.

A1. If the article did not report research on human participants, classify what type of article it is. Choose 1 – *literature review* if the article is primarily a literature review, meta-analysis, methodological review, review of websites, review of programs, etc. Choose 2 – *program description* if the article primarily describes a program/software/intervention and does not have even an anecdotal evaluation section. Choose 3 – *theory, methodology, or philosophy paper* if the paper is primarily a theoretical paper, discussing methodology or philosophical issues, policies, etc. For example, an article that discusses how constructivism is important for computer science education would go into this category. Choose 4 - *technical* if the article is primarily a technical computer science paper. For example, an article would go into this category if it compared the speed of two algorithms. Finally, choose the (5) *other* category if the article did not fit into any of the categories above. Use category (5) as a last resort. (If categories 1, 2, 3, or 4 are chosen, go to A2, otherwise, go to A1a.) (Choose only one.)

A1a. If you chose category 5 on variable A1, please write a description of the paper and describe what type of paper you think that it is.

REPORT STRUCTURE

In this section, which is based on the structure suggested for empirical papers by the APA publication manual (2001, pp. 10-30), you will examine the structure of the report. Filling out the report structure is not necessary if it was an explanatory descriptive study, since this report structure does not necessarily apply to qualitative (explanatory descriptive) reports.

A2. Choose 1 – *narrative* if the abstract was a short (150-250) narrative description of the article. Choose 2 – *structured* if the abstract is long (450 words) and was clearly broken up into sections. Some of the abstract section headings you might see are 'background', 'purpose', 'research questions', 'participants', 'design', 'procedure', etc. A structured abstract doesn't necessarily have to have these headings, but it does have to be broken up into sections. Choose 3 – *no abstract* if there is not an abstract for the paper.

A3. Choose 1 – *yes* if the paper had even a brief section that describes the background/need/context/problem of the article. Choose 2 – *no* if there was not a section that puts the article in context, describes the background, or importance of the subject. For example, you should choose *yes* if an article on gender differences in computing began with a discussion of the gender imbalance in computer science and engineering.

A4. Choose 1 – *yes* if the author at least mentioned one piece of previous research on the same topic or a closely related topic *and* related the previous research to the current research. Choose 2 – *no* if the

author did not discuss previous research on the same or a closely related topic *or* related the previous research to the current research.

A5. Choose 1 – *yes* if the author explicitly mentioned why the research had been done or how the problem will be solved by the research. Choose 2 – *no* if the author did not give a rationale for carrying out the study.

A6. Choose 1 – *yes* if the author *explicitly* stated the research question(s) or hypotheses of the paper. Choose 2 – *no* if the author did not explicitly state the research question(s) or hypotheses of the paper.

A7. Choose 1 – *yes* if the author made any attempt at describing the demographic characteristics of the participants in the study. Choose 2 – *no* if the author did not describe any of the characteristics of the participants in the study. (Choose 2 if the author only described how many participants were in the study.)

A7a. If A7 is not *yes* then you do not need to answer this question. Categorize articles based on the grades of the participants in the study. If ages are given and grades are not, use the age references. (Grades take precedent over age when there is a conflict.)

- Choose 1 if the students are in pre-school (less than 6 years old).
- Choose 2 if the participants are in grades Kindergarten to 3rd-grade (ages 6-9).
- Choose 3 if the participants are in grades 4 through 6 (ages 10-12).
- Choose 4 if the participants are in grades 7-9 (ages 13-15).
- Choose 5 if the participants are in grades 10-12 (ages 16-18).
- Choose 6 if the participants are undergraduate students (ages 18-22).
- Choose 7 if the participants are graduate students (ages 23-30).
- Choose 8 if the participants are post-graduate students (ages 31+).
- Choose 9 if the participants come from multiple categories or if they come from some other category than listed above.
- Choose 10 if it is impossible to determine the grade level of the participants

A7b. If A7a is not 6 – *undergraduate* then do not answer this question. Choose the year (1-4) of the corresponding undergraduate computing curriculum dealt with by the article.

A8. Choose 1 – *yes* if the author made any attempt at describing the setting where the investigation occurred. *Setting* includes characteristics such as type of course, environment, type of institution, etc. Choose 2 – *no* if the author did not describe the setting of the study. This might include a description of participants who usually attended a course or a description of the organization of the author's affiliation.

A9. Choose 1 – *yes* if special instruments were used to conduct the study and they were described. (For example, if a piece of software was used to measure student responses, then choose 1 if the software was described.) Choose 2 – *not described* if special instruments were used, but they weren't described. Choose 3 – *none* if no special instruments were used in the study.

A10. Choose 1 – *yes* if the author described the procedures in enough detail that the procedure could be replicated. (If an experiment was conducted, choose yes only if both control and treatment procedures were described.) Choose 2 – *no* if the author did not describe the procedures in enough detail that the procedure could be replicated. For example, if the author only wrote, "we had students use our program and found that they were pleased with its usability," then the procedure was clearly not described in enough detail to be replicated and 2 (*no*) should be chosen.

A11. Choose 1 – *yes* if there is a section/paragraph of the article that deals solely with results. Choose 2 – *no* if there is not a section/paragraph just for reporting results. For example, choose 2 (no) if the results are dispersed throughout the procedure, discussion, and conclusion sections.

METHODOLOGY TYPE

In this section, you will encode the type of methodology used by the study. Since articles can report multiple methods, choose all that apply.

T1. If the researcher manipulated a variable and compared a factual and counterfactual condition, the case is *experimental or quasi-experimental*. For example, if a researcher developed an intervention then measured achievement before and after the delivery of the intervention, then an experimental or quasi-experimental methodology was used. Choose 1 – *yes* if the study used an experimental or quasi-experimental methodology. Choose 2 – *no* if the study did not use an experimental or quasi-experimental methodology. Note that the study is experimental/quasi-experimental if the researcher administered a one-group posttest-only or a retrospective posttest on an intervention that the researcher implemented. The posttest in this case might actually be a survey.

T1a. Use 1 – *self-selection* when participants knowingly self-selected into treatment and control groups or when the participants decided the order of treatment and controls themselves. Use 2 - *random* when participants or treatment and control conditions were assigned randomly (Also use 2 for an alternative treatment design.) Use 3 – *researcher-assigned* when the researcher purposively assigned participants to treatment and control conditions or the order of treatment and control conditions or in designs where participants serve as their own controls. Also, use 3 when assignment is done by convenience or in existing groups.

T2. Studies that provided deductive answers to "how" questions by explaining the causal relationships involved in a phenomenon is *explanatory descriptive*. Studies using qualitative methods often fall into this category. For example, if a researcher did in-depth interviews to determine the process that expert programmers go through when debugging a piece of software, this study uses an explanatory descriptive methodology. Choose 1 – *yes* if the study used an explanatory descriptive methodology and choose 2 – *no* otherwise. This does not include content analysis, where the researcher simply quantifies qualitative data (e.g., the researcher classifies qualitative data into categories, and then presents the distribution of units into categories.)

T3. Studies that answered "what" or "how much" questions but did not make any causal claims used an *exploratory descriptive* methodology. Pure survey research is perhaps the most typical example of the exploratory descriptive category, but certain kinds of case studies might qualify as exploratory descriptive research as well. Choose 1 – *yes* if the study used an exploratory descriptive methodology and choose 2 – *no* if it did not. Note: if a researcher gave a survey to the participants and the investigation did not examine the implementation of an intervention, then the study was exploratory descriptive.

T4. A study is *correlational* if it analyzed how continuous levels of one variable systematically covaried with continuous levels of another variable. Studies that conducted correlational analyses, structural equation modeling studies, factor analyses, cluster analyses, and multiple regression analyses are examples of correlational methodologies. Choose 1 – *yes* if the study used a correlational methodology and choose 2 – *no* otherwise.

T5. If researchers compared two or more groups on an inherent variable, an article is *causal-comparative*. For example, if a researcher compares computer science achievement between boys and girls, that case is causal-comparative, because gender is a variable that is inherent in the group and cannot be naturally manipulated by the researcher. Choose 1 – *yes* if the study used a correlational methodology and choose 2 – *no* otherwise.

T6. If not enough information was given to determine what type of methodology or methodologies were used. If T6, then end.

Examples: A researcher used a group repeated measures design with one between factor (gender) and two within factors (measures, treatment condition). That investigation is an experiment because the researcher manipulated a variable and compared factual and counterfactual conditions (the treatment-condition within factor). The investigation should also be classified as causal-comparative because of the between factor in which two levels of a non-manipulatable variable were compared. Had the researcher not examined the gender variable, this investigation would not be causal-comparative.

A researcher did a regression analysis to regress the number of hours using Jeliot (computer education software) on a test of computer science achievement. In addition, the researcher also examined a dummy variable where Jeliot was used with and without audio feedback. Because of the multiple regression, the investigation was correlational. Because of the manipulatable dummy variable, the investigation also has an experimental or quasi-experimental design.

A researcher gave only a posttest survey to a class after they used the intervention that the researcher assigned. The researcher claimed that 60% of the class, after using the intervention, exhibited mastery on the posttest. Since the researcher claimed that 60% of the class exhibited mastery on the posttest because of the intervention, then the investigation was experimental/quasi-experimental (in M1), using a one-group posttest-only research design (RD2). (Had the researcher done a survey, but not measure the effects of an intervention, then it would have just been exploratory descriptive and not a one-group posttest-only experiment.)

T7. Choose 1 – *random* if the sampling units were randomly selected. Choose 2 – *purposive* if the participants were purposively selected. (For example, if the researcher chose to examine only extreme cases this would be purposive selection.) Choose 3 if the researcher chose a convenience sample or existing group. Choose 3 unless there is evidence for random or purposive sampling.

EXPERIMENTAL RESEARCH DESIGNS

If the researcher used an experimental/quasi-experimental methodology, classify the methodology into research design types. Choose 1 for *yes* and 2 for *no*.

RD1. Choose 1 if M1 was marked as *yes*. If *yes*, one of the following RD# variables must also be a *yes*, otherwise, go to I1.

RD2. Use this for the one-group posttest-only without controls design. In the one-group posttest only design, the researcher only gives a posttest to a single group and tries to make causal claims. (In this design, the observed mean might be compared to an expected mean.) This includes retrospective posttests, in which participants estimate impact between counterfactual and factual conditions.

RD3. Use this for the posttest with controls design. In the posttest with controls design, the researcher only gives a posttest to both a control and treatment group. Put the regression-discontinuity design into this category too and regressions with a dummy treatment variable into this design. (The independent T-test, regression with a dummy variable, or univariate ANOVA analyses might be used with this research design.)

RD4. Use this for the pretest/posttest without controls design. In pretest/posttest without controls design, the researcher gives a pretest and posttest to only a treatment group. (Dependent T-tests might be used in this design.)

RD5. Use this for the pretest/posttest with controls design. In the pretest/posttest with controls design, the researcher gives a pretest and posttest to both a treatment group and one or more control groups. (Independent T-tests of gain scores or ANCOVA might be used on these designs.)

RD6. Use this for repeated measures designs. In the group repeated measures design, the researchers use participants as their own controls, measured over multiple points of time or levels of treatment. (Repeated measures analysis might be used in this design.)

RD6a. Use 1 – *yes* if there is an experimental between-group factor, that is, if there exists a variable that is varied between groups. Select 2 – *no* otherwise.

RD7. Use this for designs with multiple factors that examine interactions. If only main effects are examined, code the research design as a control group design (like the case in a one-way ANOVA).

RD8. Use this for single-subject designs. In this design, a researcher uses the logic of the repeated measures design, but only examines a few cases. (Interrupted time series designs apply to this category.)

RD9. Use this if the author did not give enough information to determine the type of experimental research design.

RD10. Use this category if the research design is well explained but not RD2-RD8.

RD11. Choose 1 – *yes* if the only research design used was the one-group posttest-only design (i.e., if RD2 was marked *yes*, and RD3 through RD9 were marked *no*), otherwise mark *no*. The construct behind this variable is whether a researcher compared a factual with a counterfactual occurrence. It assumes here that the one-group posttest-only design does not compare a factual with a counterfactual condition.

INTERVENTION (INDEPENDENT VARIABLE)

For this group of variables, choose 1 – *yes* if the listed intervention was used in the article and choose 2 - *no* if a intervention was not used. Choose all that apply.

I1. Choose 1 - *yes* if an intervention was used in this investigation. Choose 2 - *no* if an intervention was not used. There might be an intervention in an experimental/quasi-experimental study or in an explanatory descriptive study; however, there would not be an intervention in a causal-comparative study, since it examines variables not manipulated by the researcher. Also, there would not be an intervention in an exploratory descriptive study (e.g., survey study) since exploratory descriptive research is described here as research on a variable that is not manipulated by the researcher.

If I1 = 1, go to I2, otherwise go to D1.

I2. Choose *yes* if participants received instruction in computer science by a human or by a computerized tool. Otherwise, choose *no*.

I3. Choose *yes* if teachers received instruction on the pedagogy of computer science. Otherwise, choose *no*.

I4. Choose *yes* if participants participated in a computer science fair or programming contest. Otherwise, choose *no*.

I5. Choose *yes* if participants were assigned to a computer science mentor. Otherwise, choose *no*.

I6. Choose *yes* if participants listened to speakers who are computer scientists. Otherwise, choose *no*.

I7. Choose *yes* if participants took a field trip to a computer-science-related site. Otherwise, choose *no*.

I8. Choose *yes* if participants used pair design, pair testing, or pair programming. Otherwise, choose *no*.

I9. Write in any other interventions employed by the study.

DEPENDENT VARIABLES

In this section, you encode the dependent variables' outcomes that were examined. Choose 1 for *yes* and 2 for *no*. Choose all that apply.

D1. Choose *yes* if the study measured participant attitudes, including satisfaction, self-reports of learning, motivation, confidence, etc. Otherwise, choose *no*.

D2. Choose *yes* if the study measured participant attendance or enrollment in a program, including attrition. Otherwise, choose *no*.

D3. Choose *yes* if the study measured achievement in core courses that are not computer science. Otherwise, choose *no*.

D4. Choose *yes* if the study measured achievement in computer science. This includes CS test scores, quizzes, assignments, and number of assignments completed. Otherwise, choose *no*.

D5. Choose *yes* if the study measured how teachers instruct students. Otherwise, choose *no*.

D6. Choose *yes* if the study measured what courses, fields of study, careers, etc, that students planned to take in the future. Otherwise, choose *no*.

D7. Choose *yes* if the study measured how well a program or intervention was implemented; that is, treatment fidelity. Otherwise, choose *no*.

D8. Choose *yes* if the study measured how much a certain intervention/policy/program costs. Otherwise, choose *no*.

D9. Choose *yes* if the study measured how much students socialize with each other or with the instructor. Otherwise, choose *no*.

D10. Choose *yes* if the study measured how much or in what way students use computers. Otherwise, choose *no*.

D11. Use this category for dependent variables that are not included above. Otherwise, choose *no*.

D11a. If D11, describe the dependent variable(s). Otherwise, choose *no*.

MEASURES

In this section, you will encode the kinds of measures used to measure the dependent variables. For some measures, you will note if psychometric information, operationalized as the author making any attempt at report information about the reliability or validity of a measure. Choose 1 for *yes* and 2 for *no*.

M1. Choose *yes* if the study measured grades in a computer science course – or overall grades (e.g. GPA). Otherwise, choose *no*.

M2. Choose *yes* if a learning diary was a measure. Otherwise, choose *no*.

M3. Choose *yes* if a questionnaire or survey was a measure. Otherwise, choose *no*.

M3a. Choose *yes* if psychometric information was given about the survey or questionnaire. Otherwise, choose *no*.

M4. Choose *yes* if computerized log files of participants' behaviors when using computers was a measure. Otherwise, choose *no*.

M5. Choose *yes* if the study utilized teacher-made or researcher-made tests or quizzes. Otherwise, choose *no*.

M5a. Choose *yes* if psychometric information is given about the test or quiz. Otherwise, choose *no*.

M6. Choose *yes* if interviews with students or teachers was a measure. Otherwise, choose *no*.

M7. Choose *yes* if the researchers observed strictly operationalized behaviors. Otherwise, choose *no*.

M7a. Choose *yes* if the study provided reliability information (e.g., inter-rater agreement) about the direct observation. Otherwise, choose *no*.

M8. Choose *yes* if a standardized test in core subjects or computer science was a measure. Otherwise, choose *no*.

M8a. Choose *yes* if the study provided psychometric information for each standardized test. Otherwise, choose *no*.

M9. Choose *yes* if exercises/assignments in computer science were a measure – this might include portfolio work. This does not include work on tests, grades, or standardized tests. Otherwise, choose *no*.

M10. Choose *yes* if focus groups, SWOT analysis, or the Delphi technique were measures. Otherwise, choose *no*.

M11. Choose *yes* if records such as attendance data, school history, etc. were measures. This does not include log files. Otherwise, choose *no*.

M12. Choose *yes* if there were measures not included above. Otherwise, choose *no*.

M12a. If M12, describe.

FACTORS (NON-MANIPULATABLE VARIABLES)

In this section, you will examine the factors or non-manipulatable variables examined by the study. (If they were manipulatable, they should be mentioned as an intervention.) Chose 1 for yes and 2 for no.

F1. Choose *yes* if the study examined any non-manipulatable factors. Otherwise, choose *no*. [If yes, go to F2, otherwise go to S1]

F2. Choose *yes* if the gender of participants or teacher was used as a factor. Otherwise, choose *no*.

F3. Choose *yes* if the researcher make a distinction between high and low achieving participants. Otherwise, choose *no*.

F4. Choose *yes* if race/ethnic origin of participants was a factor. Otherwise, choose *no*.

F5. Choose *yes* if nationality, geographic region, or country of origin was a factor. Otherwise, choose *no*.

F6. Choose *yes* if disability status of participants was a factor. Otherwise, choose *no*.

F7. Choose *yes* if the socio-economic status of participants was a factor. Otherwise, choose *no*.

F8. Choose *yes* if the researchers examined factors not listed above. Otherwise, choose *no*.

F8a. If F8, describe.

STATISTICAL PRACTICES

In this section, you will code for the statistical practices used. Choose 1 for *yes* and 2 for *no*. Check all that apply. These categories come from the section *informational adequate statistics section* of the APA Publication Manual (2001, pp. 23-24).

S1. Choose *yes* if quantitative results were reported. Otherwise, choose *no*. [If *yes*, go to S2, otherwise end]

S2. Choose *yes* if inferential statistics were used. Otherwise, choose *no*. [If *yes*, go to S3, otherwise go to S8]

S3. Choose *yes* if parametric tests of location were used (e.g., single-group, multiple-group, or multiple-factor tests of means). Otherwise, choose *no*.

S3a. If S3, choose *yes* if either cell means and cell sizes were reported or if means cell variances or mean square error and degrees of freedom were reported. Otherwise, choose *no*.

S4. Choose *yes* if multivariate types of analysis were used. Otherwise, choose *no*.

S4a. If S4, choose *yes* if cell means were reported. Otherwise, choose *no*.

S4b. If S4, choose *yes* if sample sizes were reported. Otherwise, choose *no*.

S4c. If S4, choose *yes* if pooled within variance or a covariance matrix was reported. Otherwise, choose *no*.

S5. Choose *yes* if correlational analyses were done (e.g. multiple regression analyses, factor analysis, and structural equation modeling). Otherwise, choose *no*.

S5a. If S5, choose *yes* if sample size was reported. Otherwise, choose *no*.

S5b. If S5, choose *yes* if a variance-covariance or correlation matrix was reported. Otherwise, choose *no*.

S6. Choose *yes* if non-parametric analyses were used. Otherwise, choose *no*.

S6a. Choose *yes* if raw data were summarized. Otherwise, choose *no*.

S7. Choose *yes* if analyses for very small samples were done. Otherwise, choose *no*.

S7a. If S7, choose *yes* if the entire dataset was reported. Otherwise, choose *no*.

S8. Choose *yes* if an effect size reported. Otherwise, choose *no*. [If yes, go to S8a, otherwise end.]

S8a. Choose *yes* if there was a difference in means, proportions, medians reported. Otherwise, choose *no*. (Here, authors just needed to present two or more means or proportions. They did not actually have to subtract one from the other. This also includes what is called 'risk difference.')

S8aa. If S8a, choose *yes* if a mean was reported *and* if a standard deviation was reported. If a median was reported, choose *yes* if a range was also reported. Otherwise, choose *no*.

S8b. Choose *yes* if a standardized mean difference effect size was reported. Otherwise, choose *no*.

S8c. Choose *yes* if a correlational effect size was reported. Otherwise, choose *no*.

58d. Choose *yes* if odds ratios were reported. Otherwise, choose *no*.

58e. Choose *yes* if odds were reported. Otherwise, choose *no*.

58f. Choose *yes* if relative risk was reported. Otherwise, choose *no*.

58h. Choose *yes* if some type of effect size not listed above was reported. Otherwise, choose *no*.

58i. if 58h, explain.

End

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Appendix D:

C#.NET 3.5 SP1 Code for Confidence Intervals around a Proportion from a Random Sample

---

```
// Requires references to System, System.Core, System.Data and System.Data.Linq
namespace Noc.Data.Thesis
{
  using System;
  using System.Collections.Generic;
  using System.Linq;

  /// <summary>
  /// Data type representing the results of resample analysis.
  /// </summary>
  /// <typeparam name="TValue">The type of the variable.</typeparam>
  public class ResampleResult<TValue>
  {
    /// <summary>Gets or sets the cell value.</summary>
    /// <value>The cell value.</value>
    public TValue Value { get; set; }

    /// <summary>Gets or sets the cell size.</summary>
    /// <value>A value between 0 and the overall size of the
population.</value>
    public int N { get; set; }

    /// <summary>Gets or sets the relative cell weight.</summary>
    /// <value>A value between 0.0 and 100.0.</value>
    public double Percent { get; set; }

    /// <summary>Gets or sets the lower confidence interval of the
mean.</summary>
    /// <value>A value between 0.0 and 100.0.</value>
    public double LowerCI { get; set; }

    /// <summary>Gets or sets the upper confidence interval of the
mean.</summary>
    /// <value>A value between 0.0 and 100.0.</value>
    public double UpperCI { get; set; }

    /// <summary>Returns a string that represents the resampling
result.</summary>
    /// <returns>
    /// A <see cref="T:System.String"/> that represents the resampling result.
    /// </returns>
    public override string ToString()
    {
      return string.Format(
        @"""{0}"",{1},{2:00.0},{3:00.0},{4:00.0}",
        this.Value,
        this.N,
        this.Percent * 100.0,
        this.LowerCI * 100.0,
        this.UpperCI * 100.0);
    }
  }
```

```
  /// <summary>
  /// Class contains logic for resampling for confidence intervals around a
  /// proportion. Requires that the statistical variables be provided as
  /// enumerable collections of equatable values. Requires .NET Framework
  /// 3.5 SP1.
  /// </summary>
  public static class Resampler
  {
    /// <summary>
    /// Resamples the specified source, with replacement, up to a specified
    /// number of times and reports a collection of <c>ResampleResult</c>
    /// objects, each containing cell sizes, means, and confidence intervals.
    /// </summary>
    /// <typeparam name="TResult">The type of the value to
resample.</typeparam>
    /// <param name="source">The source collection of values.</param>
    /// <param name="resampleCount">The number of random resamples.</param>
    /// <param name="groupThreshold">Values with frequency less than this
threshold
    /// are reported as the value "Other".</param>
    /// <returns>
    ///   <c>ResampleResult</c> containing the results of the analysis.
    /// </returns>
    public static IEnumerable<ResampleResult<TResult>> Resample<TResult>(
      this IEnumerable<TResult> source,
      int resampleCount,
      int groupThreshold)
    {
      var values = source.ToArray();
      var samples = new Dictionary<object, int[]>();
      var valueCount = values.Length;
      var otherCount = values.Length;
      var otherKey = DBNull.Value;
      var idxlci = (int)Math.Round(resampleCount * 0.025);
      var idxuci = (int)Math.Round(resampleCount * 0.975);
      var distinctvals = values.GroupBy(v => v)
                               .Where(g => g.Count() >= groupThreshold)
                               .Select(g => g.Key)
                               .ToArray();
      distinctvals.Execute(v => samples[v] = new int[resampleCount]);
      samples[otherKey] = new int[resampleCount];

      // conduct *resamples* number of resamples.
      for (int i = 0; i < resampleCount; i++)
      {
        // draw *count* number of items with replacement.
        for (int j = 0; j < valueCount; j++)
        {
          var value = values.NextValue();
          var sample = samples.ContainsKey(value) ? samples[value] :
samples[otherKey];
          sample[i]++;
        }
      }

      // Sort the resamples for each value to find the 2.5 and 97.5 percentile.
      foreach (var value in distinctvals)
      {
        var sample = samples.ContainsKey(value) ? samples[value] :
samples[otherKey];
        Array.Sort(sample);
        var n = values.Count(v => v.Equals(value));
        otherCount -= n;
        var result = new ResampleResult<TResult>()
        {
          Value = value,
          N = n,
          Percent = n / (double)valueCount,
          LowerCI = sample[idxlci] / (double)valueCount,
          UpperCI = sample[idxuci] / (double)valueCount
        };
```

```
            yield return result;
          }

          // Return the "other" category, if it exists.
          if (otherCount > 0)
          {
            yield return new ResampleResult<TResult>()
            {
              Value = default(TResult),
              N = otherCount,
              Percent = otherCount / (double)valueCount,
              LowerCI = samples[otherKey][idxlci] / (double)valueCount,
              UpperCI = samples[otherKey][idxuci] / (double)valueCount
            };
          }
        }

        /// <summary>
        /// Resamples the specified source, with replacement, up to a specified
        /// number of times and reports a collection of <c>ResampleResult</c>
        /// objects, each containing cell sizes, means, and confidence intervals.
        /// </summary>
        /// <typeparam name="TResult">The type of the value to
    resample.</typeparam>
        /// <param name="source">The source collection of values.</param>
        /// <param name="resampleCount">The number of random resamples.</param>
        /// <param name="percentile025">The value of the 2.5th percentile.</param>
        /// <param name="percentile975">The value of the 97.5th percentile.</param>
        public static void ResampleMedian<TResult>(
          this IEnumerable<TResult> source,
          int resampleCount,
          out TResult percentile025,
          out TResult percentile975)
        {
          var values = source.ToArray();
          var samples = new Dictionary<object, int>();
          var valueCount = values.Length;
          var medCount = values.Length / 2;
          var idxlci = (int)Math.Round(resampleCount * 0.025);
          var idxuci = (int)Math.Round(resampleCount * 0.975);
          var medians = new TResult[resampleCount];
          var distinctvals = values.Distinct()
                                   .OrderBy(v => v)
                                   .ToArray();

          // conduct *resamples* number of resamples.
          for (int i = 0; i < resampleCount; i++)
          {
            distinctvals.Execute(v => samples[v] = 0);

            // draw *count* number of items with replacement.
            for (int j = 0; j < valueCount; j++)
            {
              var value = values.NextValue();
              samples[value]++;
            }

            var sum = 0;
            var median = distinctvals.First(v => medCount < (sum += samples[v]));
            medians[i] = median;
          }

          Array.Sort(medians);
          percentile025 = medians[idxlci];
          percentile975 = medians[idxuci];
        }
      }

      /// <summary>
      /// Utility methods supporting the resampler library.
      /// </summary>
      public static class Extensions
```

```
  {
    /// <summary>
    /// Pseudo-random number generator.
    /// </summary>
    private static Random rand = new Random();

    /// <summary>
    /// Executes an action on each element of the collection.
    /// </summary>
    /// <typeparam name="TResult">The type of the result.</typeparam>
    /// <param name="source">The source collection.</param>
    /// <param name="action">The action to perform.</param>
    public static void Execute<TResult>(
      this IEnumerable<TResult> source,
      Action<TResult> action)
    {
      foreach (var elem in source)
      {
        action(elem);
      }
    }

    /// <summary>
    /// Retrieves a random value, with replacement, from the collection.
    /// </summary>
    /// <typeparam name="TResult">The type of the result.</typeparam>
    /// <param name="source">The source collection.</param>
    /// <returns>A random value retrieved from the collection.</returns>
    public static TResult NextValue<TResult>(this TResult[] source)
    {
      return source[rand.Next(source.Length)];
    }
  }
}

namespace Noc.Data.Thesis.Test
{
  using System.Collections.Generic;
  using System.IO;
  using System.Linq;
  using Microsoft.VisualStudio.TestTools.UnitTesting;

  /// <summary>
  /// Sample test harness for resampling. Full test harness not included in
this work.
  ///</summary>
  [TestClass()]
  public class ResamplerTest
  {
    /// <summary>
    /// The data access context.
    /// </summary>
    private static ThesisData data;

    /// <summary>
    ///Gets or sets the test context which provides
    ///information about and functionality for the current test run.
    ///</summary>
    public TestContext TestContext { get; set; }

    /// <summary>
    /// Setups the specified test context.
    /// </summary>
    /// <param name="testContext">The test context.</param>
    [ClassInitialize]
    public static void Setup(TestContext testContext)
    {
      data = new ThesisData();
      if (File.Exists("resamples.csv"))
      {
        File.Delete("resamples.csv");
      }
```

```
    }

    /// <summary>
    /// Posttest cleanup.
    /// </summary>
    [ClassCleanup]
    public static void Cleanup()
    {
      data.Dispose();
      data = null;
    }

    /// <summary>
    /// Gathers aggregate statistics for the DE variables.
    /// </summary>
    [TestMethod]
    public void DETest()
    {
      short lcimedian, ucimedian;
      var count = 10000;
      var records = data.Records;
      var humanrecords = data.Records.Where(r => r.DE12 == true);

      var de02 = records.Select(r => r.DE2).Resample(count, 5);
      AppendResults(de02, "DE2");

      var de02a = records.Select(r => r.DE2a).Resample(count, 0);
      AppendResults(de02a, "DE2a");

      var de03 = records.Select(r => r.DE3).Resample(count, 0);
      AppendResults(de03, "DE3");

      var de05 = records.Select(r => r.DE5).Resample(count, 0);
      AppendResults(de05, "DE5");

      records.Select(r => r.DE5 ?? -1).ResampleMedian(count, out lcimedian, out
ucimedian);
      AppendMedianResults(lcimedian, ucimedian, "DE5");

      var de06 = records.Select(r => r.DE6).Resample(count, 0);
      AppendResults(de06, "DE6");

      var de07 = records.Select(r => r.DE7).Resample(count, 3);
      AppendResults(de07, "DE7");

      var de08 = records.Select(r => r.DE8).Resample(count, 0);
      AppendResults(de08, "DE8");

      records.Select(r => r.DE8 ?? -1).ResampleMedian(count, out lcimedian, out
ucimedian);
      AppendMedianResults(lcimedian, ucimedian, "DE8");

      var de09 = records.Select(r => r.DE9).Resample(count, 3);
      AppendResults(de09, "DE9");

      var de10 = records.Select(r => r.DE10).Resample(count, 0);
      AppendResults(de10, "DE10");

      var de11 = records.Select(r => r.DE11).Resample(count, 0);
      AppendResults(de11, "DE11");

      var de12 = records.Select(r => r.DE12).Resample(count, 0);
      AppendResults(de12, "DE12");

      var de12a = humanrecords.Select(r => r.DE12a).Resample(count, 0);
      AppendResults(de12a, "DE12a");
    }


    /// <summary>
    /// Appends the results to a CSV file for analysis.
    /// </summary>
```

```
    /// <typeparam name="TValue">The type of the value.</typeparam>
    /// <param name="results">The results to append.</param>
    /// <param name="heading">The heading text for the results section.</param>
    private static void AppendResults<TValue>(
      IEnumerable<ResampleResult<TValue>> results,
      string heading)
    {
      using (var writer = File.AppendText("resamples.csv"))
      {
        writer.WriteLine("{0},N (of {1}),%,Lower CI 95%,Upper CI 95%", heading,
results.Sum(r => r.N));
        foreach (var result in results.OrderByDescending(r => r.N))
        {
          writer.WriteLine(result.ToString());
        }

        writer.WriteLine();
      }
    }

    /// <summary>
    /// Appends the median results to a CSV file for analysis.
    /// </summary>
    /// <typeparam name="TValue">The type of the value.</typeparam>
    /// <param name="percentile025">The 2.5th percentile.</param>
    /// <param name="percentile975">The 97.5th percentile.</param>
    /// <param name="heading">The heading text for the results section.</param>
    private static void AppendMedianResults<TValue>(
      TValue percentile025,
      TValue percentile975,
      string heading)
    {
      using (var writer = File.AppendText("resamples.csv"))
      {
        writer.WriteLine("{0} Median,Value", heading);
        writer.WriteLine("2.5%,{0}", percentile025);
        writer.WriteLine("97.5%,{0}", percentile975);
        writer.WriteLine();
      }
    }
  }
}
```

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Appendix E:

C#.NET 3.5 SP1 Code for Computing the χ^2 and M^2 Statistics, and Associated Significance Tests

Note: Source code in this appendix depends on the open source Math.NET Iridium library for computing the cumulative probability of a χ^2 statistic. See http://mathnet.opensourcedotnet.info.

```
namespace Noc.Data.Thesis
{
  using System;
  using System.Collections.Generic;
  using System.IO;
  using System.Linq;
  using MathNet.Numerics.Distributions;

  /// <summary>
  /// Data type representing the results of chi-square analysis.
  /// </summary>
  /// <typeparam name="TValue">The type of the variable.</typeparam>
  public class ChiSquareResult
  {
    /// <summary>
    /// Initializes a new instance of the <see cref="ChiSquareResult"/> class.
    /// </summary>
    /// <param name="df">The degrees of freedom.</param>
    /// <param name="n">The sample size.</param>
    /// <param name="x">The the value to evaluate.</param>
    public ChiSquareResult(int df, int n, double x)
    {
      var dist = new ChiSquareDistribution(df);
      this.Df = df;
      this.N = n;
      this.X = x;
      this.P = 1.0 - dist.CumulativeDistribution(x);
    }

    /// <summary>Gets the degrees of freedom.</summary>
    /// <value>The degrees of freedom.</value>
    public int Df { get; private set; }

    /// <summary>Gets the sample size.</summary>
    /// <value>The sample size.</value>
    public int N { get; private set; }

    /// <summary>Gets the chi-square value.</summary>
    /// <value>The chi-square value.</value>
    public double X { get; private set; }

    /// <summary>Gets the P-value of the test for independence.</summary>
    /// <value>The P-value of the test for independence.</value>
    public double P { get; private set; }

    /// <summary>
    /// Returns a string that reports this χ^2 per APA publication guidelines.
    /// </summary>
```

```
    /// <returns>
    /// A <see cref="T:System.String"/> that represents the chi-square result.
    /// </returns>
    public override string ToString()
    {
      return string.Format(
        @"""χ^2({0}, N={1})={2:0.00}, p={3:0.000}""",
        this.Df,
        this.N,
        this.X,
        this.P);
    }
  }

  /// <summary>
  /// Data type representing the results of M-square analysis.
  /// </summary>
  public class MSquareResult
  {
    /// <summary>
    /// Initializes a new instance of the <see cref="MSquareResult"/> class.
    /// </summary>
    /// <param name="n">The sample size.</param>
    /// <param name="x">The value of the m-square statistic.</param>
    public MSquareResult(int n, double x)
    {
      var dist = new ChiSquareDistribution(1);
      this.N = n;
      this.X = x;
      this.P = 1.0 - dist.CumulativeDistribution(x);
    }

    /// <summary>Gets the sample size.</summary>
    /// <value>The sample size.</value>
    public int N { get; private set; }

    /// <summary>Gets the m-square value.</summary>
    /// <value>The m-square value.</value>
    public double X { get; private set; }

    /// <summary>Gets the P-value of the test for independence.</summary>
    /// <value>The P-value of the test for independence.</value>
    public double P { get; private set; }

    /// <summary>
    /// Returns a string that reports this M^2 per APA publication guidelines.
    /// </summary>
    /// <returns>
    /// A <see cref="T:System.String"/> that represents the chi-square result.
    /// </returns>
    public override string ToString()
    {
      return string.Format(
        @"""M^2(1, N={0})={1:0.00}, p={2:0.000}""",
        this.N,
        this.X,
        this.P);
    }
  }

  /// <summary>
  /// Data type representing two values for cross tabulation
  /// </summary>
  public class CrossTableKey
  {
    /// <summary>
    /// Initializes a new instance of the <see cref="CrossTableKey"/> class.
    /// </summary>
    public CrossTableKey()
    {
    }
```

```
    /// <summary>
    /// Initializes a new instance of the <see cref="CrossTableKey"/> class.
    /// </summary>
    /// <param name="first">The first value.</param>
    /// <param name="second">The second value.</param>
    public CrossTableKey(object first, object second)
    {
      this.First = first;
      this.Second = second;
    }

    /// <summary>
    /// Gets or sets the value of the first member of the pair.
    /// </summary>
    /// <value>The value of the first member of the pair.</value>
    public object First { get; set; }

    /// <summary>
    /// Gets or sets the value of the second member of the pair.
    /// </summary>
    /// <value>The value of the second member of the pair.</value>
    public object Second { get; set; }
  }

  /// <summary>
  /// Data type representing the results of resample analysis.
  /// </summary>
  public class CrossTable
  {
    /// <summary>
    /// Array contains a sorted set of distinct values for the rows of the
crosstable.
    /// </summary>
    private object[] firstKeys;

    /// <summary>
    /// Array contains a sorted set of distinct values for the columns of the
crosstable.
    /// </summary>
    private object[] secondKeys;

    /// <summary>
    /// Counts for individual cells in the crosstable.
    /// </summary>
    private int[,] cells;

    /// <summary>
    /// Container for the values of adjusted residuals and relative cell
weights.
    /// </summary>
    private double[,] residuals, proportions;

    /// <summary>
    /// The labels for the row and column axes.
    /// </summary>
    private string labela, labelb;

    /// <summary>
    /// Gets the chi square analysis result.
    /// </summary>
    /// <value>The chi square analysis result.</value>
    public ChiSquareResult ChiSquare
    {
      get
      {
        var lena = this.firstKeys.Length;
        var lenb = this.secondKeys.Length;
        double n = this.cells[lena, lenb], chisquare = 0.0;

        // Accumulate the chi-square statistic.
        for (int idxa = 0; idxa < lena; idxa++)
        {
```

```
          for (int idxb = 0; idxb < lenb; idxb++)
          {
            var expected = (double)this.cells[lena, idxb] * this.cells[idxa,
lenb] / n;
            var actual = (double)this.cells[idxa, idxb];
            chisquare += (actual - expected) * (actual - expected) / expected;
          }
        }

        return new ChiSquareResult((lena - 1) * (lenb - 1), (int)n, chisquare);
      }
    }

    /// <summary>
    /// Gets the M square analysis result.
    /// </summary>
    /// <value>The M square analysis result.</value>
    public MSquareResult MSquare
    {
      get
      {
        var lena = this.firstKeys.Length;
        var lenb = this.secondKeys.Length;
        double ubar = 0.0, vbar = 0.0;
        double sdevu = 0.0, sdevv = 0.0;
        double cov = 0.0, reg, msquare;
        double n = this.cells[lena, lenb];

        // Accumulate the rank score, u-bar, using the array index for u.
        for (int idxa = 0; idxa < lena; idxa++)
        {
          ubar += idxa * this.proportions[idxa, lenb];
        }

        // Accumulate the rank score, v-bar, using the array index for v.
        for (int idxb = 0; idxb < lenb; idxb++)
        {
          vbar += idxb * this.proportions[lena, idxb];
        }

        // Compute the covariance component of the result.
        for (int idxa = 0; idxa < lena; idxa++)
        {
          for (int idxb = 0; idxb < lenb; idxb++)
          {
            cov += (idxa - ubar) * (idxb - vbar) * this.proportions[idxa,
idxb];
          }
        }

        // Compute the squared standard deviation of the row values.
        for (int idxa = 0; idxa < lena; idxa++)
        {
          sdevu += (idxa - ubar) * (idxa - ubar) * this.proportions[idxa,
lenb];
        }

        // Compute the squared standard deviation of the column values.
        for (int idxb = 0; idxb < lenb; idxb++)
        {
          sdevv += (idxb - vbar) * (idxb - vbar) * this.proportions[lena,
idxb];
        }

        // Compute the regression value and, finally, the m-square statistic.
        reg = cov / Math.Sqrt(sdevu * sdevv);
        msquare = (n - 1) * reg * reg;

        return new MSquareResult((int)n, msquare);
      }
    }
```

```
        /// <summary>
        /// Creates a cross table using values from the specified source.
        /// </summary>
        /// <param name="source">The source values.</param>
        /// <param name="labela">The label for the row values.</param>
        /// <param name="labelb">The label for the column values.</param>
        /// <returns>A cross table with cell counts, proportions, and residuals
    populated.</returns>
        public static CrossTable Create(
          IEnumerable<CrossTableKey> source,
          string labela,
          string labelb)
        {
          var table = new CrossTable();
          var values = source.ToArray();
          table.firstKeys = values.Select(v => v.First)
                                  .Distinct()
                                  .OrderBy(v => v)
                                  .ToArray();
          table.secondKeys = values.Select(v => v.Second)
                                   .Distinct()
                                   .OrderBy(v => v)
                                   .ToArray();
          var lena = table.firstKeys.Length;
          var lenb = table.secondKeys.Length;
          table.cells = new int[lena + 1, lenb + 1];
          table.proportions = new double[lena + 1, lenb + 1];
          table.residuals = new double[lena + 1, lenb + 1];
          table.labela = labela;
          table.labelb = labelb;

          // Compute cell counts, including row and column cumulative counts.
          foreach (var value in values)
          {
            var idxa = Array.IndexOf(table.firstKeys, value.First);
            var idxb = Array.IndexOf(table.secondKeys, value.Second);
            table.cells[idxa, idxb]++;
            table.cells[idxa, lenb]++;
            table.cells[lena, idxb]++;
            table.cells[lena, lenb]++;
          }

          // Compute cell proportions and residuals.
          double total = table.cells[lena, lenb];
          for (int idxa = 0; idxa <= lena; idxa++)
          {
            for (int idxb = 0; idxb <= lenb; idxb++)
            {
              var na = table.cells[lena, idxb] / total;
              var nb = table.cells[idxa, lenb] / total;
              var expected = na * nb * total;
              var actual = (double)table.cells[idxa, idxb];
              table.proportions[idxa, idxb] = actual / total;
              table.residuals[idxa, idxb] =
                (actual - expected) / Math.Sqrt(expected * (1 - na) * (1 - nb));
            }
          }

          return table;
        }

        /// <summary>
        /// Returns a string formatted as a CSV block representing the
        /// resampling result and residuals.
        /// </summary>
        /// <returns>
        /// A <see cref="T:System.String"/> that represents the resampling result.
        /// </returns>
        public override string ToString()
        {
          using (var writer = new StringWriter())
          {
```

```
        writer.Write(@"""{0}/{1}""", this.labela, this.labelb);
        this.secondKeys.Execute(s => writer.Write(",{0}", s));
        writer.Write(",Total");
        this.secondKeys.Execute(s => writer.Write(",Pct.{0}", s));
        this.secondKeys.Execute(s => writer.Write(",resid.{0}", s));
        writer.WriteLine();

        for (int idxa = 0; idxa <= this.firstKeys.Length; idxa++)
        {
          writer.Write(idxa == this.firstKeys.Length ? (object)"Total" :
this.firstKeys[idxa]);

          for (int idxb = 0; idxb <= this.secondKeys.Length; idxb++)
          {
            writer.Write(",{0}", this.cells[idxa, idxb]);
          }

          for (int idxb = 0; idxb < this.secondKeys.Length; idxb++)
          {
            var total = (double)this.cells[idxa, this.secondKeys.Length];
            writer.Write(",{0:0.0}", 100.0 * this.cells[idxa, idxb] / total);
          }

          if (idxa < this.firstKeys.Length)
          {
            for (int idxb = 0; idxb < this.secondKeys.Length; idxb++)
            {
              writer.Write(",{0:0.0}", this.residuals[idxa, idxb]);
            }
          }

          writer.WriteLine();
        }

        return writer.ToString();
      }
    }
  }
}

namespace Noc.Data.Thesis.Test
{
  using System;
  using System.IO;
  using System.Linq;
  using Microsoft.VisualStudio.TestTools.UnitTesting;

  /// <summary>
  /// Sample CrossTable test harness. The full harness is not included here.
  /// </summary>
  [TestClass()]
  public class CrossTablerTest
  {
    /// <summary>
    /// The data access context.
    /// </summary>
    private static ThesisData data;

    /// <summary>
    ///Gets or sets the test context which provides
    ///information about and functionality for the current test run.
    ///</summary>
    public TestContext TestContext { get; set; }

    /// <summary>
    /// Setups the specified test context.
    /// </summary>
    /// <param name="testContext">The test context.</param>
    [ClassInitialize]
    public static void Setup(TestContext testContext)
    {
      data = new ThesisData();
```

```
      if (File.Exists("crosstables.csv"))
      {
        File.Delete("crosstables.csv");
      }
    }

    /// <summary>
    /// Posttest cleanup.
    /// </summary>
    [ClassCleanup]
    public static void Cleanup()
    {
      data.Dispose();
      data = null;
    }

    /// <summary>
    /// Performs crosstable analysis on forum types.
    /// </summary>
    [TestMethod]
    public void ForumTypeTest()
    {
      var records = data.Records;
      var humanrecords = data.Records.Where(r => r.DE12 == true);
      var forumrecords = humanrecords.Where(r => r.DE2a != 3);
      var empiricalrecords = data.Records.Where(r => r.DE12 == true && r.DE12a
== false);
      var empiricalforums = empiricalrecords.Where(r => r.DE2a != 3);
      var experimentalrecords = empiricalforums.Where(r => r.T1 == true || r.T3
== true || r.T4 == true || r.T5 == true);

      var isAnecdotal = forumrecords.Select(
        r => new CrossTableKey(r.DE2a, r.DE12a));
      var isExperiment = empiricalforums.Select(
        r => new CrossTableKey(r.DE2a, r.T2 == false && r.T6 == false));
      var isExplanatory = empiricalforums.Select(
        r => new CrossTableKey(r.DE2a, (r.T2 == true || r.T6 == true) && r.T1
== false
                                    && r.T3 == false && r.T4 == false && r.T5 ==
false));
      var isAttitude = forumrecords.Select(
        r => new CrossTableKey(r.DE2a, r.D1 == true && r.D2 == false && r.D3 ==
false
                                    && r.D4 == false && r.D5 == false && r.D6 ==
false
                                    && r.D7 == false && r.D8 == false && r.D9 ==
false
                                    && r.D10 == false && r.D11 == null));
      var isPosttest = experimentalrecords.Select(
        r => new CrossTableKey(r.DE2a, r.RD11));

      // Write results to a file.
      AppendResults(CrossTable.Create(isAnecdotal, "Forum", "Anecdotal"),
false);
      AppendResults(CrossTable.Create(isExperiment, "Forum", "Experimental"),
false);
      AppendResults(CrossTable.Create(isExplanatory, "Forum", "Explanatory"),
false);
      AppendResults(CrossTable.Create(isAttitude, "Forum", "Attitude-only"),
false);
      AppendResults(CrossTable.Create(isPosttest, "Forum", "Posttest-only"),
false);
    }

    /// <summary>
    /// Appends the results to a CSV file for analysis.
    /// </summary>
    /// <param name="table">The table to draw.</param>
    /// <param name="isOrdinal">if set to <c>true</c> report M-square.</param>
    private static void AppendResults(CrossTable table, bool isOrdinal)
    {
      using (var writer = File.AppendText("crosstables.csv"))
```

```
        {
          writer.WriteLine(table.ToString());
          if (isOrdinal)
          {
            writer.WriteLine(table.MSquare.ToString());
          }
          else
          {
            writer.WriteLine(table.ChiSquare.ToString());
          }

          writer.WriteLine();
        }
      }
    }
  }
```