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Statistical Literacy Among Applied Linguists and Second Language Acquisition Researchers

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Abstract
The importance of statistical knowledge in applied linguistics and second language acquisition (SLA) research has been emphasized in recent publications. However, the last investigation of the statistical literacy of applied linguists occurred more than 25 years ago (Lazaraton, Riggenbach, & Ediger, 1987). The current study undertook a partial replication of this older work by investigating (a) applied linguists' general experiences with statistics, (b) underlying factors that constitute applied linguists' knowledge about and attitudes toward statistics, and (c) variables that predict attitudes toward statistics and statistical self-efficacy. Three hundred thirty-one scholars of applied linguistics and SLA completed a questionnaire. Eighty percent had taken a statistics class; however, only 14% of doctoral students and 30% of professors felt that their statistical training was adequate. A factor analysis of participants' knowledge of statistical terms revealed three factors: common inferential statistics knowledge, advanced statistics knowledge, and basic descriptive statistics knowledge. An analysis of participants' attitudes toward statistics revealed two factors: statistics are important and lack of statistical confidence. Regression analyses found that a quantitative research orientation was the strongest predictor of positive attitudes toward statistics; nevertheless, participants also expressed support for qualitative research. Recommendations for improving quantitative methods in our field are made based on our findings.

Keywords
linguistics, second language, foreign language, SLA, language learning

Disciplines
Applied Linguistics | English Language and Literature | First and Second Language Acquisition | Linguistics | Modern Languages | Other Languages, Societies, and Cultures | Reading and Language

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Abstract

The importance of statistical knowledge in applied linguistics and second language acquisition research has been emphasized in recent publications. However, the last investigation of the statistical literacy of applied linguists occurred over 25 years ago (Lazaraton, Riggenbach, & Ediger, 1987). The current study undertook a partial replication of this older work by investigating (a) applied linguists' general experiences with statistics, (b) underlying factors that constitute applied linguists' knowledge about and attitudes toward statistics, and (c) variables that predict attitudes towards statistics and statistical self-efficacy. Three hundred and thirty-one applied linguistics/SLA scholars completed a questionnaire. Eighty percent had taken a statistics class; however, only 14% of doctoral students and 30% of professors felt that their statistical training was adequate. A factor analysis of participants' knowledge of statistical terms revealed three factors: common inferential statistical knowledge, advanced statistical knowledge, and basic descriptive statistic knowledge. An analysis of participants' attitudes towards statistics revealed two factors: statistics are important and lack of statistical confidence. Regression analyses found that a quantitative research orientation was the strongest predictor of positive attitudes towards statistics; nevertheless, participants also expressed support for qualitative research. Recommendations for improving quantitative methods in our field are made based on our findings.

Statistical Literacy among Applied Linguists and Second Language Acquisition Researchers

In 1987, *TESOL Quarterly* published a study by Anne Lazaraton, Heidi Riggenbach, and Anne Ediger examining applied linguists' quantitative literacy titled "Forming a Discipline: Applied Linguists' Literacy in Research Methodology and Statistics." They concluded that professionals in the field of applied linguistics came from a variety of educational backgrounds and had diverse statistical training. Over the past 25 years, the fields of applied linguistics and, more specifically, second language acquisition (SLA), have grown and changed; nonetheless, no subsequent research investigating the state of statistical literacy in the field has been published. That is not to say, however, that the field has not been concerned with quantitative analysis. Indeed, evidence suggests that quantitative analysis is very important in applied linguistics and SLA (e.g., Lazaraton, 2000; Loewen & Gass, 2009), particularly because the quality of conducting and reporting quantitative studies affects, at the core, the epistemological claims made both in individual and synthetic studies (Ellis, 2006; Larson-Hall & Herrington, 2009; Norris & Ortega, 2000; Plonsky & Gass, 2011, *inter alia*). Given the demonstrable importance and predominance of quantitative research in our field, the current study investigates the statistical literacy of established researchers as well as those who are being trained to enter the field in an effort to contribute to the continued development of high quality statistical analyses in applied linguistics and SLA.

Reviews of Statistical Literacy in Related Fields

Although the assessment of statistical knowledge is relatively rare in applied linguistics/SLA, more established fields such as psychology and education have a tradition of such inquiry, particularly in relation to graduate student education, because such training affects the quality of future research (e.g., Aiken, West, & Millsap, 2008; Aiken, West, Sechrest, & Reno, 1990; Alder & Vollick, 2000; Henson, Hull, & Williams, 2010). One study of psychology PhD programs in North America revealed that, on average, graduate students were required to complete three semesters of statistics courses (Aiken et al., 2008). In addition to inquiring about the statistical requirements of psychology programs, Aiken et al. (2008) also asked program directors about the ability of their recent graduates to apply various statistical techniques. The study found that competence in most traditional techniques such as analysis of variance (ANOVA) and multiple regression was perceived to be high, while competence in less common techniques such as structural equation modeling and logistic regression was perceived to be considerably lower. Note, however, that graduates themselves were not asked to rate their own abilities; rather, the researchers relied on the perceptions of the program directors.

The study by Aiken et al. (2008) sparked a debate regarding the optimal amount of training necessary for psychology graduate students. Specifically, Zimiles (2009) wondered if (a) too much time was being devoted to statistical training, (b) such training would skew research in favor of areas in which such statistical knowledge could be applied, and (c) the need for advanced statistical knowledge would serve as a gatekeeping mechanism in the field. Aiken, West, and Millsap (2009) responded that (a) individual departments and concentrations should be able to determine the amount of statistical training they deem appropriate, (b) important questions in the field drove the development of the new methodologies, rather than the reverse, and (c) although the need for advanced statistical knowledge might exclude some researchers, such knowledge was necessary to avoid the stagnation of psychology as a science.

The field of education has also investigated statistical training within the discipline, with several studies surveying the amount of statistical training required of doctoral students. Studies have found a range of requirements. Curtis and Harwell (1996) examined the quantitative methods requirements of 21 doctoral programs in the United States for both students that specialized in quantitative methods and those that did not. They found that 43% of institutions did not require students to take statistics courses if they were not specializing in quantitative research. Nevertheless, Curtis and Harwell’s study showed that over 40% of the faculty thought that these students should have taken at least one, if not more, statistics courses. Furthermore, faculty believed that their quantitatively oriented students also were not well prepared, with 44% of faculty stating that more than half of their students would benefit from one or two additional statistics courses. Finally, 11% of respondents believed that students should take both quantitative and qualitative methods courses. In a similar survey of 100 education doctoral programs in the United States, Leech and Goodwin (2008) found that 63% of programs required students to take basic statistics and that 54% required intermediate statistics. Their study did not explore the competence of students in the programs.

While the studies reviewed above have relied on faculty impressions of students’ statistical knowledge, other studies have measured student knowledge directly. Within educational psychology, Finney and Schraw (2003) developed a measure of current statistics self-efficacy to measure the development of students’ statistical knowledge during a semester-long statistics course. The questionnaire, which was found to reliably measure a single underlying construct, showed that undergraduate students made substantial and significant improvements in their statistical self-efficacy in their first statistics course. In addition, Finney and Schraw found that the questionnaire correlated positively with a measure of attitudes towards statistics.

Finally, it is important to briefly consider the causes of statistical advancement. Of course, additional statistical training is important; however, the question of what constitutes effective training needs to be clearly answered (Beyth-Marom, Fidler, & Cumming., 2008; Fidler, Thomason, Cumming, Finch, & Leeman, 2004). Moreover, although sending students to nondiscipline-specific statistics courses is a common practice, bridging the divide between statistics and other disciplines is not always easy (Henson, Hull, & Williams, 2010). One discipline-specific practice is that of journal editors requiring higher standards in conducting and reporting of statistics. Several studies have documented the influence that a journal editor can have, but they also noted that advancements may not endure beyond the tenure of a specific editor (Cumming et al., 2007; Fidler et al., 2004). In sum, multiple avenues are necessary to increase the statistical literacy of a discipline.

Reviews of Statistical Literacy in Applied Linguistics and SLA

In comparison to education and psychology, the field of applied linguistics and SLA has seen little research regarding the statistical knowledge and training of its established and developing researchers, despite the clear importance of quantitative analysis in applied linguistics/SLA research. For example, Lazaraton (2000) found that almost 90% of studies published between 1991 and 1997 in four of the field's leading journals (*Language Learning*, *The Modern Language Journal*, *Studies in Second Language Acquisition*, and *TESOL Quarterly*) were quantitative in nature. In a subsequent study of the same journals, Lazaraton (2005) found very similar trends. Additional insight into the role of statistics in SLA is found in Author (2009), which traces the development of statistical use in SLA. Although there is some evidence that more advanced statistical techniques, such as structural equation modeling and mixed-effects methods, are finding their way into SLA research (Author, 2009; Cunnings, 2012), other studies (e.g., Gass, 2009; Plonsky, in press; Plonsky & Gass, 2011) have not documented an increase in the use of more sophisticated statistical techniques over the past 20 years, although they did find an increase in the number of statistical tests used in individual studies. Along with the reliance on more numerous and sometimes more complex statistical analyses, there has been a concomitant concern for rigor in the conducting and reporting of statistics, expressed in editorial pieces such as Brown's (1990) warning against the use of multiple *t*-tests and Ellis's (2000) call for the reporting of effect sizes. Additionally, Chapelle and Duff (2003) issued a detailed set of guidelines for both quantitative and qualitative studies submitted to *TESOL Quarterly*.

Along with the handful of publications from the 1990s and 2000s, there has been an upturn in the number of publications concerned with the quality of statistical knowledge and quantitative methodology in the field. One important example is Larson-Hall's (2010) text, *A Guide to Doing Statistics in Second Language Research Using SPSS,* which provides the first discipline-specific manual for using SPSS to conduct statistical analyses. It contains examples and datasets from existing studies in applied linguistics/SLA. Another example is the investigation into the quality of quantitative research studies, particularly as it relates to the ability to conduct secondary, synthetic research of primary studies (Plonsky, in press; Plonsky & Gass, 2011). In their review of 174 interaction studies published between 1981 and 2009, Plonsky and Gass (2011) found some improvement in research design and reporting practices over time; however, they pointed out that further improvement in quality is still necessary. Related to study design, they recommended more random group assignment and larger sample sizes. In regard to reporting practices, they suggested that researchers report basic means and standard deviations, along with effect sizes, statistical power, and exact *p*-values, *t*-values, and *F*-values. Plonsky (in press) found similar results in his examination of all quantitative studies published between 1990 to 2010 in two SLA journals: *Language Learning* and *Studies in Second*

Language Acquisition. He attributed some of the weaknesses in quantitative design and analysis to a lack of statistical knowledge on the part of researchers; consequently, he called for improvement in the training of graduate students in statistical procedures.

Of course, calls for the improved use and reporting of statistics assume that statistical training is available in the field, but only a handful of studies have investigated this issue. For example, Brown and Bailey have conducted surveys of language testing course instructors, regarding their own statistical knowledge and the statistical information provided in their courses (Bailey & Brown, 1996; Brown & Bailey, 2008). They found that instructors had taken an average of four statistics or testing courses and that more than 90% of instructors covered basic statistical concepts, such as mean, median, and standard deviation, in their own courses. Brown and Bailey (2008) did not find substantial differences from their 1996 study on these items. Additionally, Brown (2001) reported that just over 50% of TESOL members had taken a testing course and that roughly 60% had taken a statistics course.

The most detailed study of statistical knowledge among applied linguistics/SLA professionals is Lazaraton et al.'s (1987) study, which reported the results of a survey of the statistical background, knowledge, and attitudes of 121 TESOL members, of whom 69% indicated that they were professors and 34% researchers. Most participants (68%) held doctoral degrees, while a smaller number (24%) had obtained masters degrees. On average, participants had taken two statistics or research methods courses, with a range from 0 to 12. Only 26% of participants reported that their statistical coursework had been adequate, while 67% felt that it had not. To assess familiarity with statistical concepts and procedures, Lazaraton et al. asked participants to rank their confidence in interpreting and using 23 statistical terms. Participants reported being more confident interpreting terms such as mean, median, validity, reliability, standard deviation, null hypothesis, correlation, standardized score, and random assignment; however, they were less confident interpreting terms such as statistical power, Rasch model, Scheffé test, and implicational scaling. In regards to attitudes, participants responded to 18 statements about statistics, ranging in topic from participants' confidence using statistics to participants' perception of the value of statistics in applied linguistics. Many participants strongly believed that (a) statistics are important to the field, (b) courses in statistics should be required, (c) the appropriateness of applying certain statistics is often open to interpretation, and (d) research findings are often useful for practical purposes like teaching.

In sum, Lazaraton et al. (1987) provide a useful picture of statistical knowledge and attitudes in the field of applied linguistics. Nonetheless, considerable time has passed since their study was conducted, and several studies have reported some improvement in the use and reporting of statistics (e.g., Author, 2009; Plonsky & Gass, 2011). The current study seeks to partially replicate Lazaraton et al.'s study in an attempt to assess the current state of statistical knowledge and training in applied linguistics and SLA.[1] To that end, the following research questions were posed:

1. What are applied linguists' general experiences with statistics?
2. What underlying factors support applied linguists' (a) knowledge about statistics, and (b) attitudes towards statistics?

[1] A full replication and comparison was not undertaken due to some modifications in the current methodology, as well as to the lack of inferential statistics in the former study. Nevertheless, direct comparisons are made when possible.

3. Which variables predict (a) attitudes towards statistics and (b) statistical self-efficacy?

Method

Participants

Over 1,000 surveys were emailed to scholars in applied linguistics/SLA programs around the world. A total of 331 people responded to all or part of the survey, for a respectable return rate of just over 30%. Sixty-two percent of respondents were female, and 37% were male. Most were located in North America (79%), although Australasia (6%), Europe (7%), and Asia (5%) were also represented.[2] Exactly 50% of participants were working on a doctoral degree, while the other 50% had already obtained one: 99% were affiliated with a university. The average age of PhD students was 34 (*SD* 8.4), while for professors it was 47 (*SD* 11.5). More than half of the participants identified themselves as being in either the field of SLA (35%), applied linguistics (27%), or TESOL (8%). Other disciplines included linguistics (7%), foreign languages (4%), education (3%), and psychology (3%).

Participants were asked to indicate on a scale from 1 (not at all) to 6 (exclusively) how strongly they identified as being a researcher. Professors and doctoral students scored similarly (4.5 and 4.3, respectively). Participants were also asked to rate, on the same scale, how frequently they conducted both quantitative and qualitative research. Professors and doctoral studies were similar in reporting conducting quantitative research (3.9 and 3.9, respectively)

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[2] Although we acknowledge that there are differences in educational systems around the world, we felt it was important to include participants from outside of North America in keeping with the international composition of our field.

more frequently than qualitative (3.4 and 3.3, respectively).

Instruments

A questionnaire was created to assess participants' knowledge of and attitudes towards quantitative research and statistics. The questionnaire was divided into four sections: statistical background (Appendix A), knowledge of statistics (Appendix B), attitudes towards statistics (Appendix C), and statistical self-efficacy (Appendix D). The first three sections were based on Lazaraton et al.'s (1987) questionnaire, while the final section consisted of Finney and Schraw's (2003) statistical self-efficacy survey. Each section will be described briefly.

In addition to asking about basic demographic information, Section 1 elicited information about participants' previous experiences with statistical analysis by requesting information concerning the number of statistics courses taken, the methods used to compute statistics, and the ways in which participants sought statistical assistance.

Section 2, based closely on Lazaraton et al.'s (1987) questionnaire, examined participants' knowledge of 28 statistical concepts. Participants were asked to indicate, on a six-point Likert-scale, their ability to both interpret and use the concepts. Several terms were added to those of Lazaraton et al. to reflect developments in the field; these terms were *discriminant function analysis*, *effect sizes*, *nonparametric tests*, *MANOVA*, and *structural equation modeling*. In addition, the term *Scheffé*, which refers to a specific type of post-hoc test, was replaced with the more generic term *post-hoc tests*. The reliability of this section was high, Cronbach's $\alpha = .97$.

Section 3 used a six-point Likert scale to rate participants' attitudes towards statistics as expressed in a series of 20 statements. Again, these statements came primarily from Lazaraton et al.'s (1987) questionnaire; however, the wording of several items was changed slightly to address concerns raised by Lazaraton et al. themselves and by the results of our own piloting. Specifically, the term *research method*s was replaced with *statistics*, and several double-barreled questions were simplified. The reliability of the questionnaire items was good, Cronbach's α = .88.

Section 4 consisted of Finney and Schraw's (2003) Current Statistics Self-Efficacy measure, which uses a six-point Likert scale (1 = no confidence at all, 6 = complete confidence) to examine "confidence in one's abilities to solve specific tasks related to statistics" (Finney & Schraw, 2003, p. 164). Although several of the items overlapped somewhat with those in previous sections of the questionnaire, we used the instrument *in toto* because it is a recent, validated instrument. The reliability of this section was high, Cronbach's α = .96.

Procedure

After developing and piloting the entire questionnaire and obtaining Institutional Review Board consent, the questionnaire was emailed to roughly 1,000 people who would potentially self-identify as applied linguists or SLA researchers. Email addresses were obtained from the webpages of known applied linguistics/SLA programs and from recent applied linguistics/SLA conference programs. Links to the questionnaire were also posted on several social media sites, such as Facebook. A snowball approach was used in which participants were encouraged to send the link to anyone whom they felt might be interested. The questionnaire took roughly 15 minutes to complete.

Analysis

To answer Research Question 1, descriptive statistics for the statistical background questions were tabulated. For Research Question 2, separate exploratory factor analyses were conducted on two sections of the questionnaire: knowledge of statistical terms and attitudes towards statistics. Note that the statistical knowledge section of the questionnaire followed Lazaraton et al.'s (1987) design of asking participants about their ability to both use and interpret specific statistics; however, because the results of the two statistical analyses were roughly identical (suggesting that the abilities of interpreting and using statistical terms are potentially the same construct), only the results for the ability to interpret statistics are presented to avoid redundancy. To answer Research Question 3, regression analyses were conducted with the factor scores from the previously mentioned factor analyses as outcome variables. The demographic variables of research orientation (quantitative and qualitative), number of statistics classes taken, and academic status (PhD student or professor) were used as predictor variables.

Assumption Testing

To compute the factor analyses and regressions, the statistical assumptions for each were investigated. These results are detailed below.

Knowledge of statistics factor analysis. A principal component analysis was conducted on the 28 statistical terms (Section 2 of the questionnaire). The sample size of 272 proved sufficient based on the rule of thumb of 10 participants per variable and a KMO sampling adequacy value of .960 (Field, 2009). Bartlett's test of sphericity yielded $\chi^2(378) = 7767.738$, $p < .001$, indicating that the correlations between items were sufficiently large for the analysis. The Kaiser criterion of using eigenvalues over 1 for retaining factors was used, and .30 was used as a cut-off point for factor loadings (Field, 2009). An oblique rotation was used because it was assumed that the factors would be related.

Attitudes factor analysis. A principal component analysis was conducted on the data from the attitudes questionnaire (Section 3). A reliability analysis showed that five items (Items 8, 9, 10, 17, 20) had item-total correlations below .30; therefore, they were not included in the factor analysis. The KMO sampling adequacy coefficient for the 270 participants was .892, and Bartlett's test of sphericity yielded $\chi^2(105) = 1899.540$, $p < .001$. An oblique rotation was used, and participant scores were calculated for each factor.

Regression analyses. Two multivariate regression analyses were conducted. The outcome variable for the first analysis, 'Statistics are important,' came from the factor analysis of the statistical attitudes questionnaire. A hierarchical method of entering the predictor variables was used, with the variables being entered in descending order of hypothesized impact on the outcome variable. The predictor variables, in order of entry, were quantitative orientation, number of statistics classes taken, qualitative orientation, and academic rank. A sample size of 261 was used for the regression, exceeding even the most conservative recommendation of 30 participants per predictor variable (Porte, 2010). Tests investigating multicollinearity and autocorrelation did not reveal violations of these assumptions; however, nine outlying participants were removed from the analysis for a sample size of 254 (Field, 2009; Larson-Hall, 2010).[3]

The outcome variable for the second analysis was the statistical self-efficacy factor

[3] In an effort to model good practice, our initial manuscript reported the exact tests and statistics used to investigate the statistical assumptions of regression. An anonymous reviewer suggested (and we believe rightly so) that the average reader might find such detail overwhelming. We highlight this point as an example of the tensions related to the detailed reporting of statistical information.

scores. Similar to Finney and Schraw's (2003) study, an initial factor analysis of the self-efficacy questionnaire indicated a unified construct with only one factor. As a result, we only present the descriptive statistics for this part of the questionnaire (Appendix D). Again, a hierarchical method of entering the predictor variables was used, with the same predictor variables entered in descending order of hypothesized impact. An adequate sample size of 263 was used. Again, the assumptions of regression were investigated and met, although 15 outliers were identified and removed for a sample size of 254.

Results

The results for Research Question 1 revealed several findings regarding participants' experiences with statistics. First, 81% of individuals reported having taken a statistics class (Table 1), and although the median number of classes taken for both PhD students and professors was two (Table 2), a Mann-Whitney test revealed that a statistically higher number of classes had been taken by professors, U = 14,231.50, z = 2.31, p = .021, r = .013.

Insert Table 1 Here

Insert Table 2 Here

Most statistics courses were taken in education departments, followed closely by psychology and applied linguistics (Figure 1). Combining all of the language-related departments indicates that over 40% of participants had taken classes in applied linguistics, linguistics, or SLA departments.

Insert Figure 1 Here

In terms of adequacy of statistical training, 13% of doctoral students felt that their training was adequate, while almost 30% of professors felt this way. Conversely, 40% of PhD students felt that their training was not adequate, while 30% of professors felt that way (Figure 2).

Insert Figure 2 Here

Participants were asked to indicate on a scale of 1 (never) to 6 (very frequently) how often they sought statistical help from various sources: the most frequent source was the internet, followed closely by colleagues and textbooks (Table 3).

Insert Table 3 Here

In response to being asked about how they computed statistics, over 65% said that they used SPSS, and 55% said Excel (Table 4), while roughly 15% used R or calculated statistics by hand.

Insert Table 4 Here

The second research question asked about the underlying factors found in two sections of the questionnaire: knowledge of statistics and attitudes towards statistics. These analyses are reported in turn, with the descriptive statistics for the individual items reported in Appendices B and C.

For the factor analysis of knowledge of statistical terms, three factors had eigenvalues over 1, accounting for 72% of the variance in scores (Table 5). We consider the first factor to represent common inferential statistical knowledge, with terms such as *ANOVA*, t-*test*, p *value*, *post-hoc test*, and *chi-square* loading at .30 or higher on this factor (Table 5). We describe the second factor as advanced statistical knowledge, with terms such as *Rasch analysis*, *discriminant function analysis*, and *structural equation modeling* loading highly on it. We describe the final factor as basic descriptive statistic knowledge, containing terms such as *mean*, *median*, and *standard deviation*.

Insert Table 5 Here

The analysis of participants' attitudes towards statistics, presented in Table 6, revealed two factors, accounting for 53% of the variance. In looking at the first factor, it is clear that the main theme of all the items loading on it is "Statistics are important." We interpret the second factor as "Lack of statistical confidence."

Insert Table 6 Here

The third research question investigated which variables predict attitudes towards statistics and statistical self-efficacy. From the attitude factors, the scores from the first factor, "Statistics are important," were used as the outcome variable. A hierarchical method of entry was used. The predictor variables, in descending order of hypothesized impact, were Quantitative Orientation, Number of Statistics Classes Taken, Qualitative Orientation, and Academic Position. The strongest predictor was Quantitative Orientation, accounting for 34% of the variance in the "Statistics are important" variable. Qualitative Orientation contributed only 1%, with a p value of .037 (Tables 7 and 8). Not surprisingly, the more quantitative research one did, the greater importance one attributed to statistics.

Insert Table 7 Here

Insert Table 8 Here

The multivariate regression for the self-efficacy questionnaire scores used the same four predictor variables as the previous analysis, entered in the same way. Tables 9 and 10 show that Quantitative Orientation was the strongest predictor, accounting for roughly 30% of the variance in self-efficacy scores (R^2 = .318). The number of classes an individual had taken accounted for an additional 10% of the variance, while academic position added less than 2%. Academic position was coded as a binary variable, with the positive coefficient indicating that being a professor was statistically more predictive of self-efficacy. Qualitative Orientation was not a significant predictor and was therefore not included in the model.

Insert Table 9 Here

Insert Table 10 Here

Discussion

In their 1987 article, Lazaraton et al. discussed how a developing discipline approached quantitative research methodology. Now, over 25 years later, we revisit the status of quantitative analysis in a discipline that has undergone considerable development. The importance of statistics and quantitative analysis was reaffirmed throughout the current survey, even by those who identified themselves as more qualitatively oriented. Most respondents had had some experience with statistics, with over 80% of PhD students and professors taking at least one statistics course. This percentage is somewhat higher than the 60% that Brown (2001) found in his survey of TESOL members, although the stronger pedagogical focus of TESOL might partially explain this difference. The current study also found that both professors and doctoral students had taken an average of two statistics classes. Lazaraton et al. found a similar number of courses reported; however, they inquired about research methods courses as well as quantitative methods courses, so the current study might reflect a small increase in quantitative training. When looking at related disciplines, the average number of required statistics courses in psychology was found to be three (Aiken et al., 2008), while in education 50 out of 100 programs required two courses (Leech & Goodwin, 2008). Finally, in the field of language testing, Brown and Bailey (2008) found that instructors of testing courses averaged four statistics or testing courses. Thus, it seems that applied linguists are at the lower end of statistical training.

Ideally, statistical training should result in people who are confident in interpreting and using quantitative methods. Lazaraton et al. (1987) found that 26% of their respondents, the majority of whom were professors, felt that their statistical training had been adequate. In the current study, 29% of professors and 13% of doctoral students felt that way. Conversely, in the 1987 study, 67% felt that their training was not adequate, compared to only 30% of professors and 40% of students in the current study. It should be noted that, unlike the current study, Lazaraton et al. did not appear to have a *somewhat adequate* category, which may partially explain the differences in numbers. Still, it is encouraging that roughly two-thirds of the current participants felt that their statistical training was somewhat adequate or better; however, the lower confidence level of doctoral students compared to professors is noteworthy. The statistical difference in the number of quantitative methods classes undoubtedly accounts for some of the greater confidence, although the effect size is quite small. It is also possible that professors may have continued developing their statistical confidence after obtaining their doctoral degrees by the ongoing use of quantitative research methods during their careers. Indeed, it seems that informal statistical education may be taking place as seen in respondents’ reports of greater reliance on the internet, colleagues, and textbooks for statistical assistance than on workshops or seminars.

In considering the composition of statistical knowledge, three distinct areas appeared: basic descriptive statistics, common inferential statistics, and advanced inferential statistics. These groupings are largely consistent with the familiarity rankings in Lazaraton et al.'s (1987) study. Additionally, the basic descriptive statistics contained many of the same terms that Brown and Bailey (2008) found to be covered by 90% of language testing instructors. These results also echo the findings of Aiken et al. (2008) in their study of familiarity with statistical terms in psychology. Finally, it is encouraging that statistical tests such as *t*-test, chi-square and ANOVA, which comprise the majority of those used in SLA research (Gass, 2009; Plonsky & Gass, 2011), occur together in what could be considered the common inferential statistics

A question raised by these results is how participants gain this statistical knowledge. It may be that doctoral students enter their programs with knowledge of basic descriptive statistics. They may gain some understanding of common inferential statistics in general research methods courses, while learning advanced inferential statistics in quantitative methods classes. However, these suggestions are speculative because the current study did not address these questions directly. Nonetheless, the results of the current statistics self-efficacy questionnaire indicate that the number of statistics courses taken and the possession of a doctoral degree were positive predictors of confidence. Little is known about the content of research methods courses taken in applied linguistics/SLA programs. Furthermore, there is limited information regarding the cause of the professors' greater statistical confidence. These topics are fundamental starting points for further investigation because understanding how researchers increase their statistical knowledge is crucial for improving the quality and reporting of quantitative research.

One small insight into the development of statistical knowledge provided by the current study relates to effect sizes. The term was not even included in the 1987 questionnaire, but in

2012, it grouped with the common inferential statistics. It seems that the recommendations of journal editors and other researchers (e.g., Ellis, 2000; Norris & Ortega, 2000; Plonsky, 2011) have been effective in raising awareness of the importance of effect sizes. Although such advances are encouraging, evidence from other disciplines suggests that such gains can be lost without continued vigilance (Cumming et al., 2007; Fidler et al., 2004).

Another important finding is that attitudes towards statistics and quantitative research have remained largely positive over the past 25 years. Statistics are viewed as an important and necessary component of applied linguistic/SLA research, although more so by quantitatively oriented participants than by qualitatively oriented ones. In part, these positive feelings may be overrepresented in the current study because quantitatively oriented researchers may have been more inclined to participate in the survey. However, even participants who were more qualitatively oriented researchers acknowledged the importance of statistics. Conversely, many participants made comments about the value of both types of research (Author). Indeed, it is not our intention to suggest that quantitative methods should have priority over qualitative ones. Rather, because of the preponderance of quantitative studies (Gass, 2009; Lazaraton, 2000, 2005; Plonsky, 2011), it is necessary to understand the statistical literacy of the field and how it is acquired in order to improve and ensure research quality.

Several limitations of the study should be mentioned. First, the survey relied on self-report measures of participants' ability to interpret and/or use quantitative methods. No direct evidence of participants' ability to perform statistical analyses was obtained, and yet such information is necessary to better understand the effectiveness of statistical training. Future research should triangulate self-report data with measures of statistical capability. Second, we acknowledge that the survey results may be biased by a higher response rate from enthusiastic quantitative researchers and therefore portray a more positive picture of quantitative methodology than exists in the broader applied linguistics/SLA community. Although numerous researchers with self-reported higher qualitative orientation completed the survey, an indication of such bias is found in the following statement from a qualitative researcher who did not complete the survey, but nevertheless felt compelled to share his views: “I have absolutely zero interest in the idea that statistical methods could have any intellectually productive role in the analysis of linguistic conduct.”

In spite of these limitations, the current study demonstrates that quantitative methodology remains an important component of applied linguistics/SLA. In many respects, the findings are not sharply different from those found by Lazaraton et al. over 25 years ago, even though numerous recent publications have highlighted the importance of sound quantitative methodology (e.g., Cunnings, 2012; Ellis, 2000; Larson-Hall, 2010; Plonksy & Gass, 2011). Evidence from other disciplines suggests that continuous effort by multiple entities is necessary to achieve and maintain lasting methodological improvements (Cumming et al., 2007; Fidler et al., 2004). As a contribution toward that goal, we would like to offer several recommendations.

- For researchers: It is clear that little is known about statistical training in our field, including how many applied linguistics/SLA programs offer or require quantitative methods classes, and what is taught and/or learned in those classes. Furthermore, we know little about how professors maintain or improve their statistical knowledge. It is vital to understand the current state of statistical training in our field, and it is also imperative to have evidence regarding what constitutes effective statistical instruction (Fidler et al., 2004). Drawing upon the insights of statistics education in other fields can provide additional evidence regarding best practices in research and instruction.

- For applied linguistics/SLA programs: Because statistical literacy is an important part of the field, doctoral students should receive the best possible training even if not all students will conduct quantitative research. Programs should therefore consider (a) how students will obtain basic statistical knowledge, (b) what additional training is needed for quantitatively oriented students, (c) in which departments students should take quantitative methods courses, and (d) what qualifications are necessary for teaching discipline-specific statistics courses. Answers to these questions will differ depending on the size and emphasis of the program; however, research can help inform the various options. Again, information from related disciplines such as education and psychology can also be instructive.

- For journal editors: The role of editorial leadership in improving and maintaining statistical standards is crucial, as is evidenced by the current familiarity with effect sizes in our field. Nonetheless, experiences from other disciplines indicate that gains in statistical literacy and reporting are not necessarily permanent. Researchers need detailed guidelines, such as those provided by the APA manual or *TESOL Quarterly* (Chapelle & Duff, 2003) and examples of good practice. Journals and journal editors are well-placed to provide such guidance (Cumming et al., 2007).

In summary, statistical knowledge clearly continues to be critical for applied linguistics research because the conclusions that are drawn about the nature of language learning and language use are based on the implementation of such knowledge. If theoretical insights and pedagogical recommendations are to be trusted, they must come as the result of the accurate use of appropriate methods. It is encouraging that the necessity of sound quantitative methodology is receiving more attention in our field; however, continuous effort is needed to train new researchers and to ensure that established researchers are able to stay abreast of statistical advancements.

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Appendix A

Quantitative Research Survey

1. Age ____________

2. Gender: ☐ Male ☐ Female

3a. What is your current academic position?

☐ B.A. Student ☐ Assistant Professor

☐ M.A. Student ☐ Associate Professor

☐ PhD Student ☐ Professor

☐ Other (Please specify) ____________________

3b. In what year did you obtain your ***highest*** degree? _________________

3c. If you are ***currently*** working on a degree, how many years have you been working on it?

__________________ years ☐ I'm not currently working towards a degree

3d. What is your major field of study?

☐ Applied Linguistics ☐ Foreign Languages

☐ TESOL/TEFL ☐ Education

☐ Second Language Acquisition ☐ English

☐ Psychology ☐ Other (Please specify) ___________________

☐ Language Testing

3e. What type of academic institution are you at?

☐ University ☐ Other (Please specify) ____________________

☐ Language School

3f. Where is your academic institution located?

☐ North America ☐ Australasia

☐ Europe ☐ Asia

☐ Other (Please specify) __________________________

4. To what extent do you identify yourself as a researcher? (circle one)

Not at all

1 2 3 4 5

5. To what extent do you conduct ***quantitative*** research? (circle one)

Not at all

1 2 3 4 5

6. To what extent do you conduct ***qualitative*** research? (circle one)

Not at all

1 2 3 4 5

7a. Have you ever taken a course that focused specifically on quantitative analysis/statistics?

☐ Yes ☐ No

7b. If yes, how many courses have you taken? ______________________

7c. Which department(s) offered the quantitative analysis/statistics course(s) that you took?

(Please select all that apply.)

☐ Psychology ☐ Linguistics ☐ Applied Linguistics

☐ Education ☐ Other (Please specify)_____________________

7d. Are you ***currently*** enrolled in a quantitative analysis/statistics course?

☐ Yes ☐ No

If so, what is the title of that course? _________________________

8. Do you feel that the amount of statistical training you have received is adequate?

☐ Yes ☐ Somewhat ☐ No

9. How frequently do you use the following sources for statistical assistance?

	Never					Very Frequently
Statistical Textbooks	☐	☐	☐	☐	☐	☐
University Statistics Help Center	☐	☐	☐	☐	☐	☐

Statistics Seminar	☐	☐	☐	☐	☐	☐
Statistics Workshops	☐	☐	☐	☐	☐	☐
Professional Consultants	☐	☐	☐	☐	☐	☐
Internet	☐	☐	☐	☐	☐	☐
Other Colleagues	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐

Other:______________________

10. How do you compute your statistics? (Please select all that apply.)

☐ SPSS ☐ Excel

☐ R ☐ By hand

☐ SAS ☐ Other: ____________________

☐ AMOS

☐ I don’t compute statistics.

Appendix B

Ability to Interpret Different Statistical Terms

Statistical Term	*Mean*	*SD*
Mean	5.65	.927
Median	5.51	1.15
Null Hypothesis	5.29	1.42
Standard Deviation	5.26	1.31
Correlation	5.08	1.40
t-test	4.99	1.60
p-value	4.90	1.61
Reliability	4.78	1.53
ANOVA	4.71	1.66
Validity	4.67	1.54
Random Assignment	4.65	1.84
Variance	4.53	1.54
Chi-square	4.22	1.81
Effect Size	4.17	1.75
Confidence Interval	4.16	1.82
Standardized Scores	4.16	1.76

Degrees of Freedom	4.14	1.71
Power	4.08	1.83
Regression	4.06	1.67
Post-hoc Tests	4.02	1.91
Nonparametric Tests	3.68	1.97
Item Analysis	3.63	1.92
MANOVA	3.60	1.85
Factor Analysis	3.53	1.78
Implicational Scaling	2.31	1.67
Discriminant Function Analysis	2.27	1.62
Structure Equation Modeling	2.20	1.65
Rasch Analysis	2.07	1.57

Note. n = 306

Appendix C

Attitudes Towards Statistics

	Mean	*SD*
11. A course in statistics should be required for students in applied linguistics/SLA.	5.29	1.187
15. It is important for me to understand statistics.	5.26	1.160
12. In quantitative research, there are rules that have to be followed.	5.17	1.034
2. Researchers in applied linguistics/SLA need to be knowledgeable about statistics.	5.14	1.219
13. It is important for me to be able to use statistics in my research.	4.90	1.524
14. There are strict standards of appropriateness in statistics.	4.70	1.220
7. Statistical findings are useful for practical things (e.g., teaching, designing tests).	4.51	1.346
18. The field of applied linguistics/SLA should have more rigorous standards for the use of statistics.	4.29	1.347
5. I feel comfortable working with statistics in research.	3.83	1.596

20. The appropriateness of applying certain statistical procedures is open to interpretation.	3.81	1.386
3. I trust others for advice about statistics more than myself.	3.80	1.596
10. Researchers in applied linguistics/SLA misuse statistics.	3.71	1.432
8. It is acceptable to use intuition as well as statistics in the interpretation of research results.	3.39	1.457
16. I feel confident giving advice about statistics to others.	3.27	1.642
6. I have more faith in the results of quantitative studies than those of qualitative studies.	3.12	1.721
1. I skim over statistics in result sections of research reports.	2.97	1.614
9. Statistics intimidate me.	2.85	1.591
17. It is difficult to apply research findings on a practical level.	2.71	1.394
4. It is possible to be well informed about research without knowing anything about statistics.	2.51	1.447
19. There is no need for me to be knowledgeable about statistics.	1.51	1.067

Note. n = 292

Appendix D

Statistics Self-Efficacy

	Mean	*SD*
1. Identify the scale of measurement for a variable	4.11	1.87
2. Interpret the probability value (*p*-value) from a statistical procedure	4.67	1.73
3. Identify if a distribution is skewed when given the values of three measures of central tendency	4.08	1.79
4. Select the correct statistical procedure to be used to answer a research question	3.72	1.64
5. Interpret the results of a statistical procedure in terms of the research question	4.20	1.57
6. Identify the factors that influence power	3.61	1.71
7. Explain what the value of the standard deviation means in terms of the variable being measured	4.55	1.53
8. Distinguish between a Type I error and a Type II error in hypothesis testing	3.93	1.87
9. Explain what the numeric value of the standard error is measuring	3.33	1.75
10. Distinguish between the objective of descriptive versus	4.18	1.89

inferential statistical procedures		
11. Distinguish between the information given by the three measures of central tendency	4.15	1.95
12. Distinguish between a population parameter and a sample statistic	3.97	1.93
13. Identify when the mean, median, and mode should be used as a measure of central tendency	4.36	1.63
14. Explain the difference between a sampling distribution and a population distribution	4.36	1.76

Note. n = 261

Table 1

Number of Participants Who Had Taken a Statistics Course

Position	*n*	Taken a Stats Course	%
PhD Student	163	131	80
Professor	162	132	81
Total	325	263	81

Table 2

Number of Statistics Courses Taken

Position	*n*	Mean	*SD*	Median	Minimum	Maximum
PhD Student	158	1.88	1.78	2	0	10
Professor	157	2.78	3.31	2	0	20
Total	315	2.33	2.70	2	0	20

Table 3

Frequency of Statistical Assistance

Source	Mean	*SD*
Internet	3.77	1.74
Colleagues	3.71	1.64
Statistical textbooks	3.63	1.84
Professional consultants	2.05	1.55
University statistics help center	1.95	1.44
Statistics workshops	1.67	1.15
Statistics seminars	1.57	1.11
Other	1.85	1.70

Table 4

Statistical Computation

	n	%
SPSS	228	69
Excel	186	56
By Hand	56	17
R	51	15
SAS	26	8
AMOS	20	6
Don’t Compute Stats	33	10

Note. Respondents could choose more than one method. Consequently, the percentages do not total 100.

Table 5

Factor Analysis of Statistical Terms

	Component		
	1	2	3
p-value	**.944**	−.263	.054
ANOVA	**.933**	−.114	.031
Post-hoc Tests	**.882**	.042	−.059
Chi-square	**.806**	.106	−.060
t-test	**.800**	−.175	.237
MANOVA	**.775**	.241	−.144
Nonparametric Tests	**.773**	.192	−.093
Degrees of Freedom	**.746**	.075	.093
Confidence Interval	**.721**	.084	.086
Variance	**.714**	.053	.184
Effect Size	**.701**	.052	.151
Regression	**.639**	.245	.088
Power	**.590**	.166	.200
Standardized Scores	**.488**	.286	.163
Item Analysis	**.441**	**.412**	.062
Rasch Analysis	−.109	**.856**	.119

Structure Equation Modeling	.131	**.800**	−.054
Discriminant Function Analysis	.119	**.733**	.003
Implicational Scaling	.076	**.708**	.030
Factor Analysis	**.489**	**.501**	−.016
Median	−.070	−.025	**.906**
Mean	.021	−.091	**.872**
Random Assignment	.050	.260	**.665**
Standard Deviation	.400	-.078	**.617**
Validity	.128	**.305**	**.607**
Null Hypothesis	**.525**	−.196	**.535**
Reliability	.239	**.317**	**.489**
Correlation	**.436**	.075	**.487**
Eigenvalue	16.296	2.620	1.073
% of Variance	58.201	9.358	3.831
Cumulative %	58.201	67.559	71.390

Table 6

Factor Analysis of Attitudes Towards Statistics

	Factor	
	1	2
11 A course in statistics should be required for students in applied linguistics/SLA.	.846	.153
15 It is important for me to understand statistics.	.829	−.124
12 In quantitative research, there are rules that have to be followed.	.827	.230
2 Researchers in applied linguistics/SLA need to be knowledgeable about statistics.	.724	.026
13 It is important for me to be able to use statistics in my research.	.700	−.261
14 There are strict standards of appropriateness in statistics.	.683	.125
19 There is no need for me to be knowledgeable about statistics.	−.631	.101
7 Statistical findings are useful for practical things (e.g., teaching, designing tests).	.605	−.156
6 I have more faith in the results of quantitative studies than those of qualitative studies.	.452	−.195

18 The field of applied linguistics/SLA should have more rigorous standards for the use of statistics.	.437	−.309
3 I trust others for advice about statistics more than myself.	.170	.861
16 I feel confident giving advice about statistics to others.	.193	−.749
5 I feel comfortable working with statistics in research.	.245	−.716
1 I skim over statistics in result sections of research reports.	.048	.703
4 It is possible to be well informed about research without knowing anything about statistics.	−.308	.311
Eigenvalue	6.121	1.915
% of Variance	40.807	12.763
Cumulative Variance	40.807	53.570

Table 7

Regression Model Summary for the Importance of Statistics

Model	R	R^2	Adjusted R^2	SEE	F Change	$df1$	$df2$	Sig. F Change
1	.58	.34	.34	.781	128.636	1	252	.000
2	.59	.35	.34	.777	4.38	1	251	.037

Table 8

Model Data

		Std.				95% CI	
Model	*B*	Error	*β*	*t*	Sig.	Lower	Upper
(Constant)	−.983	.28		−3.49	.00	−1.54	−.428
Quantitative Orientation	.327	.04	.502	7.92	.00	.245	.408
Qualitative Orientation	−.090	.04	−.133	−2.09	.037	−.175	−.005

Table 9

Regression Model Summary for Statistical Self-efficacy

Model	R	R^2	Adjusted R^2	SEE	F Change	*df1*	*df2*	Sig. F Change
1	.530[a]	.281	.278	.803	98.47	1	252	.000
2	.638[b]	.407	.403	.731	53.56	1	251	.000
3	.655[c]	.429	.422	.719	9.24	1	250	.003

Note. [a] Quantitative Orientation. [b] Quantitative Orientation, Number of Classes. [c] Quantitative Orientation, Number of Classes, Academic Position

Table 10

Model 3 Data

Model	*B*	Std. Error	*β*	*t*	Sig.	95% CI Lower	95% CI Upper
(Constant)	−1.80	.186		−9.05	.00	−1.65	−1.06
Quantitative Orientation	.26	.03	.40	7.88	.00	.197	.329
Number of Classes	.18	.03	.35	6.87	.00	.127	.229
Academic Position	.248	.09	.15	3.04	.00	.098	.458