# THE VALUE OF SCMC IN SLA: COMMENTS ON LIN, HUANG & LIOU (2013)

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Meta-analytic methods are often used to determine the effectiveness of certain treatments across studies. However, we are often unaware of how a meta-analysis can provide value to researchers and practitioners. This paper offers a brief commentary on a meta-analysis conducted by Lin, Huang and Liou (2013) in LLT, providing further statistical evidence of the importance of their results.

**Keywords:** Computer-Mediated Communication, Research Methods, Computer-Assisted Language Learning, Language Learning Strategies.

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## INTRODUCTION

Since meta-analytic research can provide robust conclusions about experimental treatments and their effects across studies, I found of great interest the recent LLT article by Lin, Huang and Liou (2013). More importantly, I think it can be very helpful to our field because it provides further evidence for improving L2 learning through computer-assisted language learning.  The value of meta-analytic methods was effectively shown in their study because, at first glance, the results of the studies do not seem substantial but they turn out to be so if we look more closely at the statistics reported in the study. I would like to further demonstrate the value of meta-analysis by shedding more light on their results.

### Meta-Analytic Methods

Meta-analysis has the benefit of allowing practitioners to look across experiments to see the overall effectiveness of particular treatments.  In the medical field, meta-analytic methods are very important because the effects of certain treatments on patients can determine the health of an individual.  Similarly, when certain techniques or treatments in second language (L2) settings are applied, sometimes they are viewed with either evangelical fervor or deep suspicion.  Occasionally, practitioners will cite different studies on the same experimental question to justify their own results.  Meta-analyses address such situations because they provide a more general statistical perspective only a synthesis of studies can provide.

One of the major benefits of meta-analytic methods is their use of the *effect size*.  The effect size is hugely important because it essentially takes the idea of significance and *p*-values and renders them almost useless.  The major weakness in using a *p*-value in determining the importance of a study lies in the box score nature of them.  In other words either a study has obtained significance below the .05 level (or. 01, depending on who is setting the level of significance) or not.  This is a somewhat unhelpful method of looking across studies at the overall effectiveness of a treatment. In the early 1980s, two statisticians, Hedges and Olkin (1980) demonstrated that, statistically, if we were to only consult statistical tests such as *p*-values, more often than not, we would arrive at the wrong conclusion as to the effectiveness of a particular treatment.

Because *p*-values are outdated, we should use a more modern statistic such as an effect size.  An effect size is basically the standardized difference between two means.  To calculate the effect size, we use the following equation:

$$d = \frac{\overline{X}_E - \overline{X}_C}{s_P}$$

These are, in essence, adjusted normal curve deviants of the differences between the averages of the experimental and comparison groups divided by the pooled natural standard deviations of the two groups, where *d* is the effect size estimate, $\overline{X}_E$ is the mean of the experimental group, $\overline{X}_C$ is the mean of the comparison group, and $s_P$ is the pooled average standard deviation,

$$s_P = \sqrt{\frac{(n^e - 1)(s^e)^2 + (n^c - 1)(s^c)^2}{(n^e + n^c - 2)}}$$

where $n$ is the sample size and $s$ is the standard deviation of the respective experimental or control group (Hedges & Olkin, 1980, p. 79). The *d*, along with the sample sizes were taken from Lin, Huang, and Liou (2013) and entered into the software Comprehensive Meta-Analysis (2001) from which all other statistics were calculated.

If we look closely at the statistics in Lin, Huang and Liou (2013), we can see that the authors are correct in commenting that there are generally quite small effect sizes for synchronous computer mediated communication (SCMC). Further, we can ascertain the benefits of meta-analytic methods by noting the overall effect size of .33, which means that on average, those with SCMC treatment will perform approximately one third of a standard deviation higher than those without such treatment. Moreover, if we assume that 34% of variance occurs in the first standard deviation of a standardized scale on which a score such as an effect size is based, and if we further assume that an effect size of .0 would mean that 50% of learners with treatment performed as well as those without treatment (no effect, in other words), then an effect size of 1 (one standard deviation above a .0, that is) would indicate that 84% of learners with the treatment should perform higher on test tasks than those without such treatment (50% + 34% =84%). Similarly, an effect size of .5 would indicate that 67% (50%+17%) of learners would perform higher. Thus, using proportions, we can assume that an average overall effect size of .33 would be approximately 61%. Thus, we can suggest that approximately 61% of L2 learners provided with SCMC treatment will perform higher than those without such treatment. In order to more accurately demonstrate the benefits of the use of effect sizes in meta-analysis, I extracted *p*-values from each study report using the following methods:

For each study and its effect size estimate, equation (16-6) can be used from Cooper and Hedges (1994) to convert an effect size (d) to a *t* statistic from which a *p*-value can be extracted. Essentially, we start out with the following formula:

$$t = d * \frac{(\sqrt{n_1} n_2)}{(n_1 + n_2)} * \sqrt{df}$$

Once we have the *t* statistic and degrees of freedom *df*, we can obtain a *p*-value using the *t* distribution function TDIST function in Excel: pval = TDIST(t,df,2). A *t* distribution function, otherwise known as a *t value*, is often used to determine the statistical significance of the difference between two sample means.

Example from our data: For instance, let us take the example of Sequiera (2009) from Table 1 below, whose study obtained an effect size (*d)* of .86 with a sample size of 56. Using the above formula, we would have the following calculations:

$$\frac{\sqrt{28*28}}{(28\ +28\ )}*\sqrt{55}$$

which in turn, produced the following calculations:

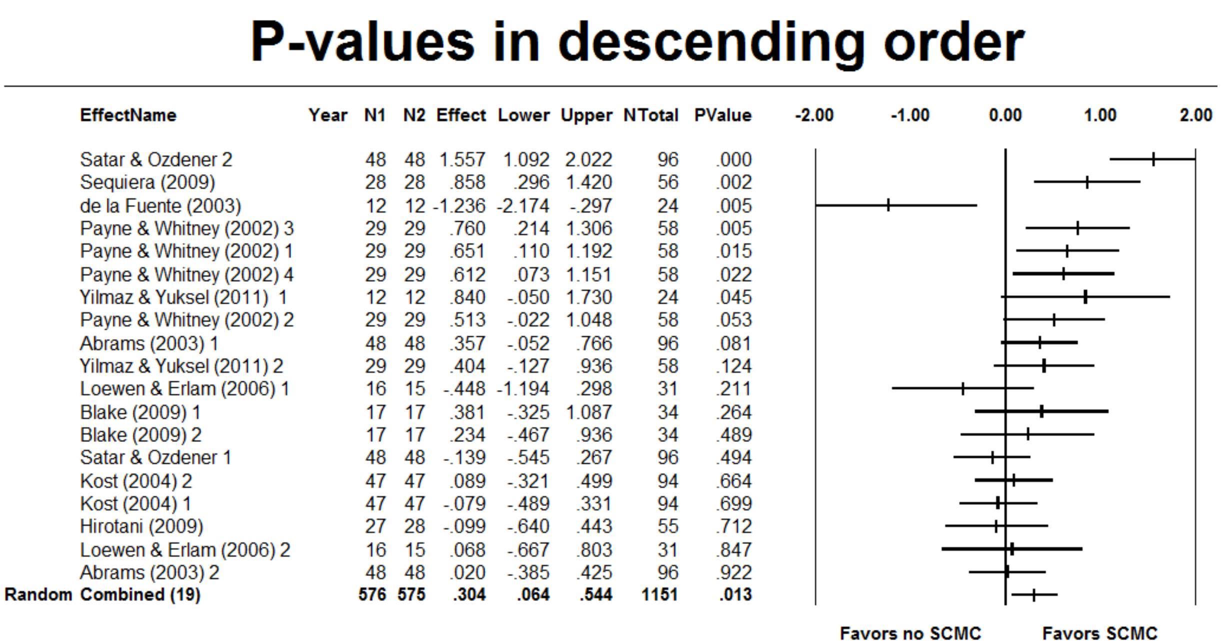
$$\frac{28}{56}*(7.41)$$

which equals 3.705. We then multiply 3.705 by the Cohen's *d* which, in this case is .86 and we obtain the *t* value of 3.19 which is easily converted into a *p*-value via Excel, which in turn reveals the *p*-value to be significant at the .02 level.

Given the statistics provided by Lin, Huang and Liou (2013), I observed the *p*-values of each study and found that, out of the 19 outcomes, only 6 actually had significant results. That is, only 6 studies (32%) obtained a significant *p*-value result at the .05 level or lower in favor of the treatment.[1] Thus, the researcher who does not have access to Lin, Huang and Liou's (2013) meta-analysis may incorrectly conclude, based on the number of *p*-values showing significant results, that SCMC may not be effective. Of course, with the use of effect sizes and especially the combining of them, Lin, Huang and Liou's study generally suggests otherwise. Please see Figure 1 taken from the software program Comprehensive Meta-Analysis.

## CONCLUDING REMARKS

In sum, because of their methods and what we have demonstrated above, Lin, Huang and Liou (2013) are to be commended on a study that not only has shown the potential of SCMC learning, but also more generally how computer assisted language learning may be even more effective than otherwise thought to be in certain contexts. Meta-analysis, by combining results and not using *p*-values as the final word in determining the effects of a particular treatment, should be used more to show the effects of experimental results that can, in turn, greatly empower the L2 learner and teacher.




| | EffectName | Year | N1 | N2 | Effect | Lower | Upper | NTotal | PValue |
|---|---|---|---|---|---|---|---|---|---|
| | Satar & Ozdener 2 | | 48 | 48 | 1.557 | 1.092 | 2.022 | 96 | .000 |
| | Sequiera (2009) | | 28 | 28 | .858 | .296 | 1.420 | 56 | .002 |
| | de la Fuente (2003) | | 12 | 12 | -1.236 | -2.174 | -.297 | 24 | .005 |
| | Payne & Whitney (2002) 3 | | 29 | 29 | .760 | .214 | 1.306 | 58 | .005 |
| | Payne & Whitney (2002) 1 | | 29 | 29 | .651 | .110 | 1.192 | 58 | .015 |
| | Payne & Whitney (2002) 4 | | 29 | 29 | .612 | .073 | 1.151 | 58 | .022 |
| | Yilmaz & Yuksel (2011) 1 | | 12 | 12 | .840 | -.050 | 1.730 | 24 | .045 |
| | Payne & Whitney (2002) 2 | | 29 | 29 | .513 | -.022 | 1.048 | 58 | .053 |
| | Abrams (2003) 1 | | 48 | 48 | .357 | -.052 | .766 | 96 | .081 |
| | Yilmaz & Yuksel (2011) 2 | | 29 | 29 | .404 | -.127 | .936 | 58 | .124 |
| | Loewen & Erlam (2006) 1 | | 16 | 15 | -.448 | -1.194 | .298 | 31 | .211 |
| | Blake (2009) 1 | | 17 | 17 | .381 | -.325 | 1.087 | 34 | .264 |
| | Blake (2009) 2 | | 17 | 17 | .234 | -.467 | .936 | 34 | .489 |
| | Satar & Ozdener 1 | | 48 | 48 | -.139 | -.545 | .267 | 96 | .494 |
| | Kost (2004) 2 | | 47 | 47 | .089 | -.321 | .499 | 94 | .664 |
| | Kost (2004) 1 | | 47 | 47 | -.079 | -.489 | .331 | 94 | .699 |
| | Hirotani (2009) | | 27 | 28 | -.099 | -.640 | .443 | 55 | .712 |
| | Loewen & Erlam (2006) 2 | | 16 | 15 | .068 | -.667 | .803 | 31 | .847 |
| | Abrams (2003) 2 | | 48 | 48 | .020 | -.385 | .425 | 96 | .922 |
| **Random** | **Combined (19)** | | **576** | **575** | **.304** | **.064** | **.544** | **1151** | **.013** |

*Figure 1.* P-values in descending order.

**NOTE**

1. There are actually 7 studies that obtained significant results but one actually had significant results *against* the treatment in question. In other words, the control group significantly outperformed the experimental group.

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