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Abstract

An academic journal's *impact factor* (hereafter JIFs) is an average measure of the citation count of individual articles published in that journal. JIF is used to assess merit, predict impact, and allocate resources, but the actual number of citations to individual articles is only modestly correlated with the JIFs of the journals in which they are published. We counted *Psycinfo* citations to 1,134 papers published in nine leading psychology journals (1996-2005). Both article length, $r = .31$, and reference list length, $r = .41$, predicted log-transformed citation counts better than JIF, $r = .27$. Articles with fewer graphs and more structural equation models were more frequently cited. Citation count was better predicted by a model based on article length and citation count rather than JIF. When JIF was used to predict citation count, the impact of women authors and social science research was underestimated. These findings distinguish impact in science, as measured by JIF, from actual impact in psychology, and show the unintended consequences of using a measure of the former to predict the latter.

An academic journal's *impact factor* (hereafter, JIF) is an average measure of the frequency with which articles within that journal are cited. For any given year, JIF is defined as the ratio of the number of citations to articles published in the previous two years in that journal, to the total number of articles published in the journal over that same two year period. JIFs were originally developed to allow different journals to be ranked by relative impact within a discipline (Garfield, 1972). Individual scientists can readily access JIFs through the ISI Web of Science to assess both the merit of colleagues' work, and the likely impact of publishing their own work in a particular journal. Institutional policy makers can also use such information when evaluating individuals for academic appointments and promotions. Some national and institutional policies that allocate resources to individuals and to departments on the basis of the quality of their publications have considered using citation count and JIF in their decision making (Haslam & Koval, 2010; Norris & Oppenheim, 2003; Seglen, 1997). This article describes the limits of assessing the merit of individual psychology articles on the basis of the JIF of the journal in which they were published.

We examined the extent to which JIF was predictive of individual article's *citation counts* within psychology. Psychologists rarely cite each other's work with the goal of critique; and so citation counts largely reflect positive regard between authors (Shadish, Tolliver, Gray, & Gupta, 1995). As JIF is an average citation count measure, it is not surprising that it is positively, but modestly correlated with individual articles' citation counts in such fields as physics (Dahwan & Gupta, 2004), biomedicine (Seglen, 1994), social work (Holden, Rosenberg, Barker, & Onghena, 2006), and social and personality psychology (Haslam, Ban, Kaufman, Loughman, Peters, Whelan, & Wilson, 2008). However, there are several problems inherent in using JIF to predict an article's citation count. First, citation counts are not normally distributed; a minority of articles tend to garner a majority of the citations in any given journal or scientific field. JIF is a *mean* measure extracted from a highly skewed distribution that overestimates the impact of the numerical majority of articles in a given journal (Adler, Ewing & Taylor, 2008; Garfield, 2006). Second, the Web of Science database includes some journal matter as 'citable' and excludes other matter as 'magazine content' for the purpose of calculating JIF, but the inclusion rules are not completely transparent (PLoS Medicine Editors, 2006). Third, Web of Science provides

incomplete coverage of social science and humanities disciplines, and of journals that are published in languages other than English (Nederhof, 2006). For example 12% of the publications that sociologists submitted as their best work to the United Kingdom's 2001 national Research Assessment Exercise were not archived on Web of Science (Norris & Openheim, 2007). For such reasons, the European Association of Science Editors (2008) has publicly cautioned against using JIF to evaluate the merits of individual research articles.

In this article, we compare the consequences of using JIF to predict impact within psychology to its alternatives. We aimed to clarify what decision makers might unintentionally do when they rely on JIF to allocate resources such as jobs, promotions, and funding. The bibliometric literature on academic citation motivated several hypotheses about alternative predictors of citation counts in psychology (see Bornman & Daniel, 2008 for a review). First we predicted that more recent articles would be cited more often because science is growing over historical time (Cawkell, 1976). Second and third, we predicted that papers which were longer, in pages, and those which listed more references would be more frequently cited themselves, as several earlier studies have shown (Bornman & Daniel, 2008). In social psychology, both length of articles and length of reference sections partially mediate the difference in impact between articles in top-tier and second-tier journals (Haslam et al., 2008). Some scholars consider the trend toward longer reference lists in psychology to be a problematic consequence of a harsh culture of peer review (Adair & Vohra, 2003), and others have urged psychologists to adopt the more terse style of the natural sciences (Park, 2009; Taylor, 2009). Our fourth prediction was made on normative grounds. We predicted that articles that reported on more *participants* would be more frequently cited because larger samples should provide a sounder basis for inductive inference (see Osherson, Smith, Wilkie, Lopez, & Shafir, 1990).

Our fifth and sixth predictions concerned academic authors. Papers with more co-authors are typically more frequently cited (Bornman and Daniel, 2008). Collaborative research combines input from several individuals drawing on multiple skills and resources and may broaden informal networks of communication and trust about a research project (Quiñones-Vidal, López-García, Peñaranda-Ortega & Tortosa-Gil, 2004). Indeed, psychologists consider the more important citations in their own papers to be to their own work and that of their associates (Tang & Safer, 2008; Safer & Tang, 2009). We also examined author gender. Studies of citation patterns in other science have reached mixed conclusions as to whether papers authored by men garner more citations than those authored by women or not (Baldi, 1998; Haslam et al., 2008; Over, 1982). Several forms of sexism in psychological science have been reduced in recent decades (Gannon, Luchetta, Rhodes, Prdie, & Segrist, 1992), but sexist bias has subsequently been observed in peer review processes (Petty, Fleming, & Fabrigar, 1999), and the confinement of research on women to lower impact journals (Lee & Crawford, 2007). We assumed that any metric used to predict impact and assess merit ought not to be unintentionally biased against authors on the basis of their gender.

Our last three predictions were informed by the *graphism thesis*; a provocative relativist claim that the presence of graphs makes a scientific paper appear to be presenting 'hard science' (Latour, 1990). Graphs are more common in natural science disciplines cognate to psychology than in cognate social sciences (Cleveland, 1984). Psychology journals which are rated by psychologists as publishing 'harder' science contain a greater density of graphs and a lower density of tables than psychology journals deemed to publish 'softer' science (Smith, Best, Stubbs, Johnson, & Archibald, 2000). Accordingly we assessed separately the number of graphs and tables in the articles in our corpus to assess whether each was related to citation count. Following Hegarty (2011), we defined *tables* as spatial arrangements of numbers representing empirical observations, and *graphs* as relational displays in which spatial extension

on the journal's page represented a quantity that is not distributed in space, such as time. Structural Equation Modelling (SEM) uses model diagrams to display hypothetical relationships between latent variables (Herschberger, Marcoulides & Parramore, 2003). These diagrams use space to represent abstract properties, as graphs do, and display specific numerical information, as tables do. We categorized models separately from graphs and tables. Thus our final three hypotheses were exploratory, and we aimed to examine the relationship between graphs, tables, models, and citation count.

Method

We sampled all articles published in the first issue of each calendar year from 1996 to 2005 within each of nine high-impact psychology journals. Each journal represented one of the ten sub-disciplines of psychology defined by the ISI Web of Knowledge. The areas and journals sampled were Psychology, Applied (*Journal of Applied Psychology*, $n = 133$), Psychology, Biological (*Psychophysiology*, $n = 133$), Psychology, Clinical (*Journal of Consulting and Clinical Psychology*, $n = 168$), Psychology, Developmental (*Developmental Psychology*, $n = 151$), Psychology, Educational (*Child Development*, $n = 178$), Psychology, Experimental (*Journal of Cognitive Neuroscience*, $n = 102$), Psychology, Mathematical (*Psychological Methods*, $n = 72$), Psychology, Multidisciplinary (*Psychological Bulletin*, $n = 62$), and Psychology Social (*Journal of Personality and Social Psychology*, $n = 147$). We excluded psychoanalysis from the study because of previous analysis showing that articles in this area are cited less often than articles from other fields (Robins, Gosling & Craik, 1999). Articles were also excluded from the analysis if they reported no new empirical findings, other than in the journals *Psychological Bulletin* and *Psychological Methods*, wherein only a minority of sampled articles reported original empirical studies. This sampling procedure yielded 1147 articles. We excluded 7 articles which were not archived on *Psycinfo*, and a further 7 published in *Psychological Methods* in 1996, as there was no impact factor available for this journal for this year. The analysis below is based on the remaining 1133 records.

Each article was initially coded for the impact factor of its journal of publication in the relevant year, its year of publication, the number of references it cited, the whole number of journal pages that it covered, the number of human participants described in its studies, the number of co-authors who wrote the paper, and the gender of its first author. Two papers published under the authorship of the National Institute of Child Health and Human Development were attributed the number of participating co-authors mentioned in the author note. As most of these credited co-authors were women, we coded both articles as authored by women. The 1133 articles cited a mean of 60.61 references ($SD = 43.71$), covered a mean of 13.34 journal pages ($SD = 5.94$), reported on a mean of 1,233 human participants ($SD = 21,909$), and were authored by a mean of 2.29 co-authors ($SD = 2.08$). More papers had a first author who was a man rather than a woman ($N = 661, 472$ respectively), $\chi^2(1, N = 1,133) = 31.53, p < .001$. The raw number of pages, references, participants, and co-authors of each article were non-normally distributed, with absolute values of kurtosis and skew being >2.6 in all cases. All four variables were log-transformed, with 1 added to the number of participants prior to transformation to avoid zero values. After transformation, all absolute kurtosis and skew values were less than 1.96 for all variables.

The articles contained a mean of 3.29 tables ($SD = 2.47$), 1.53 graphs ($SD = 2.15$), and 0.12 models ($SD = 0.49$). The distribution of graphs showed high kurtosis and skew (2.40, 9.41 respectively). The distribution of tables showed a normal level of kurtosis (1.11) but this distribution was also skewed (2.57). We quantified the density of both tables and graphs on a 0-8 point scale representing articles by the raw number of each representation within them, and

representing those articles containing more than eight graphs or tables with a score of eight. This transformation rendered both distributions normal, with absolute values of kurtosis and skew being <1.96 . Only eighty-six articles (7.6%) contained models, and we coded articles for the absence [0] or presence [1] of models.

Finally, we used the *Psycinfo* database to determine the citation count of each article by counting the number of citations to each article in the five years following its publication. For each article, we began the five year period on January 1st of the calendar year following the date of the article's publication. The articles in this corpus were each cited an average of 29.49 times ($SD = 37.45$) by publications archived on *Psychinfo* in the five years after their publication. These citation counts were also non-normally distributed, skew = 5.66, kurtosis = 55.39. We added 1 to each citation count and log-transformed the resulting values which were normally distributed, skew = -0.31, kurtosis = 0.34.

Results

The correlations between citation count and each of the article attributes are shown in Table 1. Consistent with earlier studies, JIF and citation count were moderate correlated. In addition, year of publication, number of pages, and number of cited references were all stronger predictors of citation count than JIF. These three factors were strongly positively correlated. Longer psychology articles contained more references. Over time, both psychology articles and their reference lists have become longer.

The first two rows of Table 1 show convergence and divergence in the relationship between citation count and JIF and other article attributes. Notably, papers in higher impact journals tended to be more often authored by men and to report on fewer participants. However, neither of these factors was significantly correlated with actual citation count. Papers with fewer tables were reported in higher impact journals, but the most cited papers included more tables. More frequently cited papers included more model diagrams but fewer graphs, but neither of these factors was related to JIF. Finally, we note that the correlations between the density of graphs and tables in psychology articles and those articles' citation counts were the opposite of that suggested by the graphism hypothesis; articles were more frequently cited when they included models, included many tables, and included fewer graphs.

As many of these variables were substantially correlated with each other, we conducted a regression analysis next to examine which factors predicted unique variance in citation count. We regressed citation count on the nine other variables displayed in Table 1. The model was highly significant and explained over one-quarter of the total variance in citation count, $F(10, 1122) = 46.32$, $p < .001$, $R^2 \text{ adj.} = .29$ (see Table 2). JIF predicted unique variance in citation count, but was not the only factor to do so. Year of publication, number of references, number of journal pages, number of participants and number of co-authors all explained unique variance, and the first two of these factors were better single predictors of unique variance in citation count than JIF. The regression models confirmed our rejection of the graphism thesis. A large number of graphs in these articles predicted lower citation count, while the presence of models predicted higher citation counts. The density of tables did not predict unique variance.

Recall that we relaxed the criterion that articles must report original empirical data to be included in the corpus for the journals *Psychological Bulletin* and *Psychological Methods*. As a check on our conclusions, we re-ran the regression analysis excluding all articles from the journals *Psychological Bulletin* and *Psychological Methods*. The second regression analysis showed that our inclusion criteria were not responsible for our statistical conclusions. This

second model was highly significant, $F(10, 996) = 30.81, p < .001, R^2 \text{ adj.} = .22$. Using the conventional .05 criterion of statistical significance, we reached identical statistical conclusions for each predictor in this second model to those reported in Table 2.

These correlational and regression analyses showed that JIF is not the only metric that can predict citation count in psychology. Accordingly, we compared two models for predicting citation count, one that relied on JIF, and another that relied on both the number of pages and the number of citations. We conducted two linear regression models. In the first model, citation count was predicted from JIF, $F(1, 1131) = 91.08, p < .001, R^2 \text{ adj.} = .07$. In the second model, citation count was predicted from article length and number of references, $F(2, 1130) = 115.46$, both $p < .001, R^2 \text{ adj.} = .17$. For both models we calculated the standardized predicted scores, the best possible predictions of actual citation count that could be made on the basis of the metrics included in each model, and standardized the actual citation counts for purposes of comparison.

We conducted three analyses. First we examined the simple correlations between the two sets of predicted citation count and the actual standardized citation counts. The model based on length and citations made predictions that were closer to actual citation counts than the model based on JIF, $r(1132) = .41, .27$ respectively, Fisher's $Z = 3.75, p < .001$. Second, we examined if these two sets of predictions had different implications for articles first-authored by women and by men. The predicted citation counts from the JIF model were higher for articles first-authored by men than for articles first-authored by women ($M_s = .07, -.10$ respectively), $t(1131) = -2.81, p = .005$. In contrast, the length and citations model predicted equivalent citation counts for papers authored by men and women ($M_s = -.05, +.04$ respectively), $t(1131) = 1.37, p = .19$. As the correlational analysis suggests, the standardized citation count scores did not vary according to whether the first author was a man or a woman ($M_s = +.01, -.01$ respectively), $t < 1$. In other words, the model based on JIF alone introduces an erroneous gender bias into the prediction of citation counts that is not present when predictions are made on the basis of page count and citation count.

Finally, we calculated the mean standardized impact scores and the mean standardized predicted scores from both models (see Figure 1). Both models overestimated the scientific impact of articles in *Psychological Bulletin* and *Psychophysiology*. The model based on length and citations overestimated the impact of articles in the *Journal of Applied Psychology*, and underestimated the impact of articles in *Journal of Clinical and Consulting Psychology*. In contrast, the model based on JIF overestimated the impact of *Journal of Cognitive Neuroscience* articles, and underestimated the impact of articles published in *Journal of Personality and Social Psychology*, *Child Development*, *Developmental Psychology*, and *Journal of Applied Psychology*.

Discussion

JIF appears to be a face valid way to look across the articles published in leading psychology journals and to estimate which articles will have the most impact in our field. However, predictions and decisions that are made solely on this basis are not ideal. Citation counts are better predicted by readily available bibliometric variables such as article length, the number of cited references, and the format in which data is visualized. Relying on JIF underestimates the impact of social science relative to natural science research and leads to a subtle bias against women authors in psychology.

We are not the first to show that the JIF of psychology journals that are closer to the natural sciences are higher than those closer to the social sciences. Haslam and Koval (2010) note that in the Excellence in Research in Australian journal rankings many more journals in biological and experimental psychology are highly ranked as A and A* than are journals that publish research in other areas of psychology. These authors do not label this matter as a 'bias' but rather call for the hierarchy of journals to be 'recognized, justified, and if necessary, corrected' (Haslam & Koval, 2010, p. 114). Our analysis contributes to the recognition of how such journal ranking systems can become skewed toward natural sciences when they rely on JIF. The distortion most likely occurs because the Web of Science database, from which JIF is calculated, has much more comprehensive coverage of the natural sciences than of the social sciences (Nederhof, 2006; Norris & Opeenheim, 2007), while the range of psychology articles archived on *Psycinfo* spans both areas. Indeed, this matter may also explain why the JIF-based model introduced a gender bias. The proportion of articles first-authored by women and men varied across the journals we sampled. The highest proportions of articles authored by women were in two journals whose impact JIF underestimated; *Child Development* and *Developmental Psychology*. This reliance on JIF to allocate resources might contribute to the "Matilda effect" by which women's achievements in science lead to career advantage less reliably than men's do (Rossiter, 1993). Moreover, as people tend to believe that sexism is waning over time (Deikman & Eagly, 2000), gender bias in evaluating scientific merit based on a modern metric like JIF might be particularly likely to evade detection.

Our analysis gave reason to doubt the claim that graphs are the insignia of 'hard science' in psychology. Why would psychologists consider journals that typically include papers that contain more graphs than tables as reporting 'harder' science (Smith et al., 2002), but also be more likely to cite articles that contain fewer graphs than tables, and more model diagrams? The graphism thesis contains an internal contradiction; it assumes that scientists frequently use graphs to convince their peers of the strength of their findings, and also are routinely duped by this same persuasion technique. Such effects might occur where people are communicating across hierarchies of expertise, as when irrelevant brain images appear to increase the scientific validity of psychological arguments, for example (McCabe & Castel, 2008). The graphism thesis might also apply when people in one scientific discipline aim to persuade members of another discipline of the 'truth' of something, because neighbouring disciplines can have qualitatively different graphing conventions (see also Roth, 2003). The latter process may explain the impact of the small proportion of articles containing structural equation modelling diagrams in the corpus of articles analyzed here. However, we think it unlikely that psychologists are routinely duped by graphs of the sort that they routinely construct themselves, just as neuroscientists are less frequently baffled by technical jargon about neuroscience than are members of the public (Weisberg, Keil, Goodstein, Rawson, & Gray, 2008).

In conclusion, we would like to clarify that we are not urging policy makers to disregard JIF altogether, or to reify the length of either articles or reference lists as ideal measures of merit. Rather, we urge deeper thinking about prevailing methods for assessing scientific merit in psychology using bibliometrics. JIF may well lead individual psychologists and the policy makers who allocate resources to them to overestimate the impact of natural science articles relative to social science articles in psychology because of a difference between the content that Web of Science defines as 'science' and the content that *Psycinfo* defines as psychology. Our analysis of citation patterns in contemporary psychology cannot inform the question of how to allocate such resources, but we hope to have shown how priorities can be set unintentionally when JIF is used uncritically as a measure of scientific merit.

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References

- Adair, J.G. & Vohra, N. (2003). The explosion of knowledge, references, and citations: psychology's unique response to a crisis. *American Psychologist*, 58, 15-23.
- Adler, R.J., Ewing, J., & Taylor, P. (2008). Citation statistics: A report from the International Mathematical Union in cooperation with the International Council of Industrial and Applied Mathematics and the Institute of Mathematical Statistics. *Statistical Science*, 24, 1-14.
- Baldi, S. (1998) Normative versus social constructivist processes in the allocation of citations: A network-analytic model. *American Sociological Review*, 63, 829-846.
- Bornman, L., & Daniel, H.-D. (2008). What do citation counts measure? A review of studies on citing behaviour. *Journal of Documentation*, 64, 45-80.
- Cawkell, A. E. (1976) Documentation note - citations, obsolescence, enduring articles, and multiple authorships. *Journal of Documentation*, 32, 53-58.
- Cleveland, W. S. (1984). Graphs in scientific publications. *American Statistician*, 38, 261-269.
- Cronbach, L., & Meehl, P. (1955). Construct validity in psychological tests. *Psychological Bulletin*, 52, 281-302.
- Dahwan, S.M., & Gupta, B.M. (2004). Comparative evaluation of Indian physics research: Impact factor vs. citations frequency. *Current Science*, 86, 1194-1195.
- Diekman, A. B., & Eagly, A. H. (2000). Stereotypes as dynamic constructs: Women and men of the past, present, and future. *Personality and Social Psychology Bulletin*, 26, 1171-1188.
- European Association of Science Editors. (2008). EASE statement on inappropriate use of impact factors. http://www.ease.org.uk/artman2/uploads/1/EASE_statement_IFs_final.pdf Downloaded 31/01/2011.
- Gannon, L., Luchetta, T., Rhodes, K., Pardie, L., & Segrist, D. (1992). Sex bias in psychological research: Progress or complacency? *American Psychologist*, 47, 389-396.
- Garfield, E. (1972). Citation analysis as a tool in journal evaluation. *Science*, 178, 471-479.
- Garfield, E. (2006). The history and meaning of the Journal Impact Factor. *Journal of the American Medical Association*, 295 (1), 90-93.
- Gilbert, G. N. (1977) Referencing as persuasion. *Social Studies of Science*, 7, 113-122.
- Hansen, H.B., & Henriksen, J.H. (1997). How well does journal "impact" work in the assessment of papers on clinical physiology and nuclear medicine. *Clinical Physiology*, 17, 409-418.
- Haslam
- Haslam, N., Ban, L., Kaufman, L., Loughnan, S., Peters, K., Whelan, J., & Wilson, S. (2008). What makes an article influential? Predicting impact in social and personality psychology. *Scientometrics*, 76, 169-185.
- Haslam, N., & Koval, P. (2010). Possible research area bias in the Excellence in Research in Australia (ERA) draft journal rankings. *Australian Journal of Psychology*, 62, 112-114.
- Hegarty, M. (2011). The cognitive science of visual-spatial displays: Implications for design.

- Trends in Cognitive Science*, 3, 446-474.
- Herschberger, S.L. Marcoulides, G.A. & Parramore, M.M. (2003). Structural equation modelling: an introduction. In Pugesek, B.T. Adrian VonEye, A (Eds). *Structural Equation Modelling: Applications in Ecological and Evolutionary Biology*. Cambridge University Press.
- Holden, G., Rosenberg, G., Barker, K., & Onghena, P. (2006). An assessment of the predictive validity of impact factor scores: Implications for academic employment decisions in social work. *Journal of Social Work Practice*, 16, 613-624.
- Latour, B. (1987). *Science in action*. Cambridge, MA: Harvard University Press.
- Latour, B. (1990). Visualisation and cognition: drawing things together. In M. Lynch & S. Woolgar (Eds.). *Representation in Scientific Practice* (pp. 19-68). Cambridge, MA: MIT Press.
- Lee, I.C., & Crawford, M. (2007). Lesbian and bisexual women in the eyes of scientific psychology. *Feminism & Psychology*, 17, 109-127.
- McCabe, D.P., & Castel, A.D. (2008). Seeing is believing: The effects of brain images on judgments of scientific reasoning. *Cognition*, 107, 343-352.
- Merton, R. K. (Ed.) (1973) *The sociology of science: theoretical and empirical investigations*, Chicago, USA, University of Chicago Press.
- Nederhof, A.J. (2006). Bibliometric monitoring of research performance in the social sciences and the humanities: A review. *Scientometrics*, 66, 81-100.
- Norris, M. & Oppenheim, C. (2001). Citation counts and the research assessment exercise V: archaeology and the 2001 RAE. *Journal of Documentation*, 59, 709-730.
- Osherson, D., Smith, E.E., Wilke, O., Lopez, A., & Shafir, E. (1990). Category-based induction. *Psychological Review*, 97, 185-200.
- Over, R. (1982). Research productivity and impact of male and female psychologists. *American Psychologist*, 37, 24-31.
- Park, D. (2009). Publishing in the psychological sciences: Enhancing journal impact while decreasing author fatigue. *Perspectives on Psychological Science*, 4, 36-37.
- Petty, R.E., Fleming, M.A., & Fabrigar, L.R. (1999). The review process at *PSPB*: Correlates of interreviewer agreement and manuscript acceptance. *Personality and Social Psychology Bulletin*, 25, 188-203.
- PLoS Medicine Editors (2006). The impact factor game. *PLoS Medicine*, 3, e291.
- Quiñones-Vidal, E., López-García, J.J., Peñaranda-Ortega, M., & Tortosa-Gil, F. (2004). The nature of social and personality psychology as reflected in *JPSP*, 1965-2000. *Journal of Personality and Social Psychology*, 86, 435-452.
- Racine, E., Bar-Ilan, O. and Illes, J. (2005). fMRI in the public eye. *Nature Reviews Neuroscience*, 6, 159-164.
- Robins, R., Gosling, S.D., & Craik, K.H. (1999). An empirical analysis of trends in psychology. *American Psychologist*, 54, 117-128.
- Rossiter, M. W. (1993). The Matthew Matilda effect in science. *Social Studies of Science*, 23, 325-341.
- Roth, W.M. (2003). *Toward an anthropology of graphing: Semiotic and activity-theoretic perspectives*. Berlin: Springer.
- Safer, M.A. & Tang, R. (2009). The psychology of referencing in psychology journal articles. *Perspectives in Psychological Science*, 4, 51-53
- Seglen, P.O. (1994). Causal relationship between article citedness and journal impact. *Journal of the American Society for Information Science*, 45, 1-11.
- Seglen, P. O. (1997). Why the impact factor of journals should not be used for evaluating research. *British Medical Journal*, 314, 497.

- Shadish, W.R., Tolliver, D., Gray, M. & Gupta, S.K.S. (1995). Author judgements about works they cite: three studies from psychology journals. *Social Studies of Science*, 25, 477-498.
- Smith, L.D., Best, L.A., Stubbs, A.D., Archibald, A.B. & Roberson-Nay, R. (2002). Constructing knowledge: the role of graphs and tables in hard and soft psychology. *American Psychologist*, 57, 749-761.
- Tang, R., & Safer, M.A. (2008). Author-rated importance of cited references in biology and psychology publications. *Journal of Documentation*, 64, 246–272.
- Taylor, S. (2009). Publishing in scientific journals: We're not just talking to ourselves anymore. *Perspectives in Psychological Science*, 4, 38-39.
- Weisberg, D.S., Keil, F.C., Goodstein, J., Rawson, E. & Gray, J.R. (2008). The seductive allure of neuroscience explanations. *Journal of Cognitive Neuroscience*, 20, 470-477.

Table 1: Correlational Analysis: Scientific Impact and Article Attributes

	JIF	Year	^a Refs.	^a Pages	^a Authors	Gender	^a Particpts	Graphs	Tables	Models
Impact	.27***	.30***	.41***	.31***	.10***	.01	.01	-.14***	.13***	.15***
JIF		.18***	.35***	.31***	.06*	.08*	-.39**	.04	-.14***	-.03
Year			.14***	.08**	.13***	-.05	.04	.09**	.02	.02
^a Refs				.63***	-.02	-.03	-.19***	-.04	.11**	.11***
^a Pages					-.14*	-.06*	-.22***	.13***	.29***	.10***
^a Authors						-.03	-.13***	-.02	.06*	.07*
Gender							.13***	.05	-.11***	.03
^a Particpts								-.12***	.21***	.14***
Graphs									-.21***	-.13***
Tables										.02

* $p < .05$, ** $p < .01$, *** $p < .001$. *Impact* = Five-Year Scientific Impact, *JIF* = Journal Impact Factor, *Refs* = Cited References, *Pages* = Journal Pages, *Authors* = Co-Authors, *Gender* = Author Gender (Female = 0, Male = 1), *Particpts* = Human Participants, *Graphs* = Graph Density, *Tables* = Table Density, *Models* = Model Density. ^aLog Transformed Variable.

Table 2: Predictors of Article Citation Count

Predictor	β	t	p
Journal Impact	.15	4.93	<.001
Year	.23	8.82	<.001
References	.25	7.35	<.001
Journal Pages	.12	3.37	.001
Participants	.10	3.31	.001
Co-Authors	.07	2.48	<.02
Author Gender	.05	1.87	.06
Graphs	-.14	-5.11	<.001
Tables	.04	1.37	.17
Models	.07	2.61	.009

Figure 1: Scientific Impact in Psychology by Journal Publication; Predicted by Article Length and Citations, by Journal Impact Factor, and Actual Scientific Impact.