

Unethical Numbers? A Meta-analysis of Library Learning Analytics Studies

M. Brooke Robertshaw, Oregon State University*
Andrew Asher, Indiana University, Bloomington

ABSTRACT

Following trends in higher education that emphasize quantitative analytical approaches to assess educational outcomes, academic libraries are increasingly attempting to quantify their impacts on student learning and demonstrate their value to the university's educational mission. By applying learning analytics techniques to library use and instructional data, libraries have especially focused on attempting to measure the impact of the library on student GPA, retention, and attainment measures.

Because learning analytics studies typically require large datasets of personally identifiable information (PII), they present inherent risks to the privacy, confidentiality, and autonomy of research subjects, who often are unaware and uninformed of the data collected.

This paper presents the results of a meta-analysis of learning analytics studies in libraries that examine the effects of library use on measures of student success. Based on the aggregate results, we argue that outcomes of these studies have not produced findings that justify the loss of privacy and risk borne by students. Moreover, we argue that basing high-impact decisions on studies with no, or low, effect sizes, and weak correlation or regression values, has the potential to harm students, particularly those in already vulnerable populations. Finally, we believe that these studies also have the potential to harm institutions that rely on these particular analytical approaches to make crucial business and educational decisions.

INTRODUCTION

Since at least the late 1980s, universities have faced increasing pressure to assess and quantify their impact on students' educational outcomes (Worthen, 2018). While this work was initially housed primarily in offices of institutional research, efforts to quantify the student experience have expanded beyond central administrations to include nearly all areas of campus life, from academic departments, to advising, support services, extracurricular activities, and even housing, food, and health services. It is, therefore, unsurprising that academic libraries have also become entwined in this work. The influential 2010 ACRL *Value of Academic Libraries: A Comprehensive Research Review and Report* (Oakleaf et al. 2010, henceforth the VAL Report), advocated for academic libraries to develop ways to better capture and assess their impact on their institutions, and especially on student outcomes such as retention, attainment (e.g. graduation rates), success (including career placement, earnings, graduate/professional acceptance, etc.), achievement (e.g. GPA, test scores, etc.) and learning (Oakleaf et al. 2010, 17-19; Oakleaf & Kyrillidou 2016, 757), and suggested specific methods and measures that might be used (Oakleaf et al. 2010, 101-140). While not exclusively quantitative, these recommendations emphasized computational methods and correlational data. In response many libraries developed quantitative studies examining the relationships between the use of library resources and services to student outcomes, particularly as related to grades, retention, and attainment.

Falling broadly under the umbrella of universities' learning analytics (LA) efforts, or "the collection, measurement, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs" (LAK 2011), these studies indicate a trend in academic libraries to expand their infrastructural capabilities to collect more detailed types of transactional and behavioral student data to support arguments about library impact and library value (see Jones & LeClare 2018,6). Many librarians and library administrators (see Oakleaf et. al 2017) continue to argue for the necessity of robust library participation in universities' learning analytics programs in order to ensure their relevancy to increasingly metric-driven institutions. Similarly, ACRL recently commissioned a new research agenda, "Academic Library Impact: Improving Practice and Essential Areas to Research" (Connaway et al. 2017) to specifically examine student learning and the impact of the library on student educational outcomes. Building on work completed by early adopters of learning analytics in academic libraries, such as the University of Minnesota in the United States (Soria et al. 2013, 2014, 2017; Nackerud et al. 2014), Huddersfield University in the United Kingdom (Goodall & Pattern 2011; Stone & Ramsden 2012; Stone et al. 2012), and Wollongong University in Australia (Cox & Jantti 2012), this report calls for additional studies and continuing the alignment of the library with the quantification of institutional impacts on student outcomes (Connaway et al. 2017).

Despite this enthusiasm, other librarians, administrators, and researchers have questioned the efficacy of libraries' participation in learning analytics on ethical grounds, both as it relates to the values of librarianship (Jones & Salo 2018) and to the principles of ethical research design (Asher 2017; Prinsloo & Slade 2013). Because they often require detailed and personally identifiable records that can be linked to other information sources, participation in learning analytics initiatives creates tension between librarians' service ethic, which encourages them to create and gather data in order to deliver the best services to their constituents, and their privacy ethic, which demands that patrons' library activities be kept private and confidential (Asher 2017, see also the ALA Code of Ethics¹)

Researchers have additionally questioned how meaningful the information collected for learning analytics purposes is, the rigor of the work, and, by extension, the validity of the findings, and even whether improvements to student outcomes are the result of the intervention studied or attributable to other causes (Eubanks 2017; Worthen 2018). The answers to these questions are critical to evaluating the ethical efficacy of research designs. If research is not sufficiently rigorous or meaningful, it is unlikely to meet the beneficence standard required for ethical research, which requires researchers to weigh studies' risks against their potential benefits to research participants and the common good.

As a means of engaging with this debate, this article utilizes a meta-analysis of learning analytics studies that examine the effects of library use and instruction on students' educational outcomes to address the ethical questions posed by this mode of research. Based on the results of these analyses, we evaluate whether the outcomes of libraries' learning analytics studies have produced sufficient findings to meet the beneficence standard and to sufficiently justify the risks, such as the loss of privacy and autonomy, that this research requires students to bear.

¹ <http://www.ala.org/tools/ethics>

ETHICS & LIBRARY LEARNING ANALYTICS

As a relatively new and developing field, learning analytics in higher education is characterized by a high degree of experimentation and a wide range of methods. Initially, uses of LA were mainly for the purposes of academic analytics, or the use of large datasets married with data mining and statistical techniques to draw conclusions directed at the institutional level, rather than at practices aimed at directly impacting students' learning or faculty teaching (Campbell et al. 2007; Siemens & Long 2011). Drawing on an array of academic disciplines, including learning sciences, sociology, computer science, and information science, LA has now expanded to include interventions aimed at the level of individuals, while also attempting to describe and explain entire systems and support decision-making (Bienkowski et al. 2012).

Academic libraries have tended to slightly trail their institutions in implementing learning analytics practices, partly due to the availability of data stemming from institutional barriers and insufficient infrastructure (Oakleaf et al. 2017), but also due to privacy concerns, policies, and regulations. Nevertheless, the number of library-sponsored and library-focused learning analytics studies endeavoring to link library use and instruction measures to student grades, attainment, and retention increased dramatically after the release of the VAL Report. The results of these studies provide intriguing, but inconsistent statistical findings, making it difficult not only to interpret the real-world effect of library practices on student outcomes, but also the benefit versus risk evaluations necessary to meet the beneficence standard of ethical research practice.

Ethical standards for data collection involving human subjects oblige researchers to comply with three guiding principles: respect for persons, which establishes principles for informed consent and disclosure of the data collected; justice, which requires the selection of research subjects and the burden of research participation to be equitably distributed; and beneficence, which requires research to maximize benefits and minimize risks (Schrag 2010, 87-88). Asher (2017) and Briney (forthcoming) have already suggested that libraries' participation in learning analytics data collection may not meet these standards, particularly in matters of consent and disclosure. In this article, we focus explicitly on the principle of beneficence by asking, "Do the benefits and new knowledge derived from libraries' learning analytics efforts justify the risks to students about whom the data is collected?"

Proponents of library-based learning analytics argue that the potential benefit of improving educational approaches justifies, or even obligates, data collection. These proponents list numerous benefits, including demonstrating the library's value and contribution to students' educational outcomes, helping to determine students at risk of dropping out or in need of additional support, identifying and providing better services, making more efficient use of resources, and improving collections management. While these are all important goals driven by a desire to improve educational experiences and practices, there is presently little critical work evaluating whether library learning analytics is actually delivering on these promises.

The risks presented by library learning analytics data are likewise myriad, including risks to students' privacy, confidentiality, autonomy, and intellectual property, as well as the potential for creating self-censorship and limitations on academic freedom (Asher et al. 2018; Jones & Salo 2018; Rubel & Jones 2016). Moreover, the collection of fine-grained library use data through tools such as EZProxy log files (as many of the studies included in this analysis did) over

extended periods of time makes weighing the long-term risks of creating and maintaining these data difficult to assess at the time of collection. Datasets created for learning analytics activities are particularly vulnerable to re-identification, even after de-identification and anonymization techniques have been utilized. (Asher 2017; Briney forthcoming; Metcalf & Crawford 2016). This vulnerability potentially exposes these datasets' constituent individuals and populations to unintended disclosures and insufficiently considered reuse or misuse by unexpected actors, including commercial, governmental, or law enforcement interests, such as for investigatory requests and subpoenas. In most cases, minority groups that are already more economically underprivileged, socially marginalized or discriminated against, and surveilled, are at greater risk of unintended identification due to their smaller numbers and subsequent greater visibility in systematically collected datasets, a situation that also brings into question the justice of creating these data (Asher 2017).

The individuals who provide library learning analytics data are often also poorly positioned to directly benefit from the findings of these studies. Since educational outcomes must usually be known in order to draw meaningful conclusions, almost any intervention based on these findings will occur too late to benefit research participants. As Rubel & Jones rightly observe, data obtained from individual students is usually far more valuable to institutions when aggregated than to the subjects themselves (2016, 147). The parties likely to incur the benefits of library data analyses are, therefore, more likely to be not only universities, but also third-party educational service providers, including for-profit corporations whose primary responsibility is to their shareholders rather than students.

Because individuals bear most of the risk while institutions gain most of the benefit, library learning analytics studies may not meet the beneficence requirement of ethical research practice, and, at a minimum, should justify these initiatives by conducting methodologically rigorous research designs and by demonstrating clear outcomes and effects derived from the data collected. This article attempts to engage in this debate by conducting a review and meta-analysis of published studies by examining the effect of library instruction and use on student attainment, retention, and grade outcomes. By providing a summary effect size for library learning analytics studies, this meta-analysis can help clarify the benefit side of the risk versus benefit equation. A summary effect size is a measure of the amount of observed variability that can be attributed to a theoretical model that links library use and instruction to measures of student success.

METHODS

What is a meta-analysis, and why perform it?

A meta-analysis is a statistical procedure for synthesizing quantitative studies that investigate the same intervention on the same outcome. Meta-analyses are used to determine an overall effect size of the intervention in order to assess the efficacy of interventions on populations. A large effect would support the argument that a strong real-world association exists between library services and interventions and student outcomes, while conversely, a small effect size suggests that no such relationship exists. Meta-analyses are advantageous because, in essence, they allow researchers to investigate interventions across larger populations than they would have access to in a traditional study. They also allow for investigation across time and geography and an

evaluation of the consistency of findings across multiple studies. Finally, in comparison to narrative reviews, meta-analyses allow for additional transparency in research synthesis because of the use of specific statistical procedures rather than relying only on evaluation decisions made by researchers (Borenstein et al. 2009).

Defining the meta-analysis corpus

Library LA studies were selected for inclusion in this review and meta-analysis if they (1) addressed the impact of library use or instruction on undergraduate GPA, retention, or attainment, (2) utilized quantitative methods so that effect size calculations were possible, (3) were available in an English-language version, and (4) were published since 2000.

Studies were initially identified via recent literature reviews (Jones & Salo 2018; Jones & LeClare 2018; Briney forthcoming; Kogut 2016; Oliveira 2017) and from the personal research bibliographies maintained by the authors. To ensure comprehensive coverage of published library LA materials, a literature search was conducted in ProQuest's Library and Information Science Abstracts (LISA) database for peer-reviewed articles that met the inclusion criteria using the keywords "GPA, retention, graduation, or persistence" that co-occurred with "libraries or library" and "student or students."² The search was not date-limited to ensure that a study that was published before 2000 would not be excluded automatically without review, if it met the other criteria.

Forty four studies were identified that met the requirements for inclusion (Table 1). The majority of these studies were published after 2010, indicating both the growth in interest in applying learning analytics in libraries and the agenda-setting influence of the VAL Report (in fact, many of the studies specifically mention the VAL report as their inspiration) (Fig. 1). Thirty five addressed the relationship between libraries and grade outcomes, 15 addressed the relationship between libraries and student retention, and 10 examined the relationship between libraries and measures of attainment (some studies examined more than one outcome). In the case of the attainment studies, the outcome variables used were judged too heterogeneous to provide a sufficient basis for a meta-analysis. These studies were, therefore, excluded from further review and 'completion' was eliminated as a topic of analysis for this review.

² The exact syntax used for the LISA search was as follows:
`{(NOFT(Libraries OR Library) AND NOFT(GPA OR Retention OR Graduation OR Persistence) AND NOFT(Student OR Students)) AND (sttype.exact("Scholarly Journals" NOT ("Trade Journals" OR "Magazines"))) AND la.exact("ENG") AND PEER(yes))`

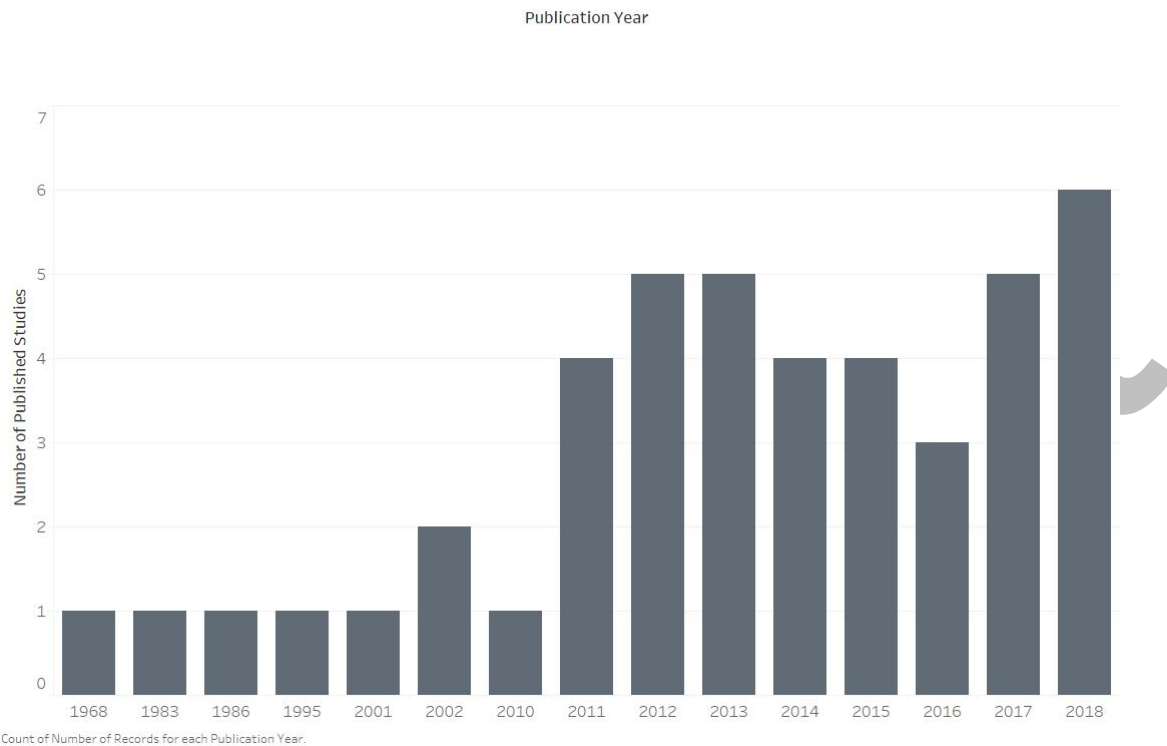


Table 1. Library Learning Analytics Studies Reviewed for this Analysis

Study Type	Citations
Attainment	Cook (2014) Crawford (2015) Goodall & Pattern (2011) Greater Western Library Alliance (2017) LeMaistre et. al. (2018) Selegan et. al. (1983) Soria et. al.(2017) Stemmer & Mahan (2016) Stone & Ramsden (2012) Stone et. al.(2012)
Grade	Allison (2015) Asher (2017) Black & Murphy (2017) Bowles-Terry (2012) Cherry et. al. (2013) Chodock et. al. (2018) Cook (2014)

	<p>Cox & Jantti (2012)</p> <p>Davidson et. al. (2013)</p> <p>Gaha et. al. (2018)</p> <p>Garipey et. al. (2017)</p> <p>Greater Western Library Alliance (2017)</p> <p>Hiscock (1986)</p> <p>Kot & Jones (2015)</p> <p>Kramer & Kramer (1968)</p> <p>Krieb (2018)</p> <p>LeMaistre et. al. (2018)</p> <p>Moore et. al. (2002)</p> <p>Nackerud et. al. (2013)</p> <p>Nurse et. al. (2018)</p> <p>Renaud et, al (2015)</p> <p>Renaud et. al. (2015)</p> <p>Samson (2014)</p> <p>Scott (2014)</p> <p>Selegan et. al. (1983)</p> <p>Soria et. al. (2014)</p> <p>Soria, et. al. (2013)</p> <p>Stemmer & Mahan (2016)</p> <p>Thorpe et. al. (2016)</p> <p>Vance et. al. (2012)</p> <p>Wells (1995)</p> <p>Whitmire (2001)</p> <p>Wong & Cmor (2011)</p> <p>Wong & Webb (2011)</p> <p>de Jager (2002)</p> <p>de Jager et. al. (2018)</p>
Retention	<p>Allison (2015)</p> <p>Black & Murphy (2017)</p> <p>Crawford (2015)</p> <p>Greater Western Library Alliance (2017)</p> <p>Haddow & Joseph (2010)</p> <p>Haddow (2013)</p> <p>Kramer & Kramer (1968)</p> <p>Krieb (2018)</p> <p>LeMaistre et. al. (2018)</p> <p>Murray et. al. (2016)</p>

Soria et. al. (2014)
Soria, et. al. (2013)
Stemmer & Mahan (2016)
Thorpe et. al. (2016)
Vance et. al. (2012)

Three grade studies (Selegan et al. 1983; Kramer & Kramer 1968; Hiscock 1986) and one retention study (Kramer & Kramer 1968) met the inclusion criteria, but were published outside the time period specified. After review, the authors decided that the age of these studies, as well as their publication before the digitization of library holdings, likely makes both the data collection methods used and students' experience of the library sufficiently different from more recent studies to warrant their exclusion from this analysis.

The heterogeneity of research designs and statistical methods utilized by the remaining studies required further exclusions as follows:

Two grade studies (Allison 2015; Wong & Webb 2011) and one retention study (Allison 2015) were excluded due to designs that mixed undergraduate and graduate outcomes.

One grade study did not include individual-level measures (Crawford 2015), making it unsuitable for inclusion in this meta-analysis, and another only presented descriptive information about the research (Nackerud et al. 2013).

Four grade studies did not provide enough information in the published report to calculate an effect size (Davidson et al. 2013; deJager 2002; Moore et al. 2002; Scott 2014). Three grade studies (Chodock 2018; Stemmer & Mahan 2016; Wells 1995) and one retention study (Stemmer & Mahan 2016) were excluded due to self-reported independent variables in their research design. Methodologically, we do not consider these variables equivalent to independently observed measures of library use and they cannot, therefore, be included in this meta-analysis.

Three grade studies (Black & Murphy 2017; Krieb 2018; Wong & Cmor 2011) and one retention study (Black & Murphy 2017) were excluded because their independent variables were sufficiently different from other studies to render them incompatible for meta-analysis. Black & Murphy (2017) used an assignment-based design that was too specific to compare to other studies; Krieb (2018) only considered outcomes in five courses; and Wong & Cmor (2011) divided their analysis into complex subgroups that make it impossible to calculate an overall effect size for the entire study.

Three grade studies (Cox & Jantti 2012; Soria 2014, Vance et al. 2012) and one retention study (Soria 2014) were excluded because their statistical approaches were not sufficiently comparable with those utilized in other studies to include them in the meta-analysis. Soria et al. (2014) used an ordinary least squares regression, while Vance et al. (2012) used probit and tobit regressions. Neither of these approaches allows a calculation of effect size that is compatible with the regression techniques used in other studies for meta-analysis purposes. Cox & Jantti (2012) used a logarithmic correlation on average student grade outcomes, also rendering their study incompatible with more common linear correlation approaches.

After these exclusions, 17 grade and six retention studies remained for this meta-analysis (Table 2). Unfortunately, the six viable retention studies (Haddow 2013; Haddow & Joseph 2010; LeMaistre et al. 2018; Murray et al. 2016; Soria et al. 2013; Thorpe et al. 2016), did not contain a sufficient number of comparable statistics to produce a reliable meta-analysis, forcing the authors to proceed with only the studies that examined the relationship between library use and instruction with students' grade outcomes. While the current corpus of retention studies did not allow us to complete a meta-analysis, we did observe that almost all (9 of 11) of the retention studies reviewed focused on retention in the first-year or first-to-second year, indicating a gap in the literature on potential library impacts on later-year retention of undergraduates.

Table 2: Studies Included in the Meta-Analyses

Meta-Analysis Group	Citations
Library Instruction by GPA	Asher (2017) Bowles-Terry (2012) Chodock et. al. (2018) Cook (2014) Gaha et. al. (2018) Garipey et. al. (2017) Soria, et. al. (2013) Whitmire (2001)
Library Use By	Allison (2015) Cherry et. al. (2013) Kot & Jones (2015) LeMaistre et. al. (2018) Nurse et. al. (2018) Renaud et. al. (2015) Samson (2014) Soria, et. al. (2013) Thorpe et. al. (2016) de Jager et. al. (2018)

Meta-analysis groupings

In order to maximize the number of studies that could be included, we decided to group all types of library instruction and all types of library usage together creating two meta-analysis groups: “Instruction by GPA” and “Library Use by GPA.” Given the complexity of library instructional approaches, any two studies (and even instruction sessions recorded with a given study) are unlikely to be absolutely comparable. However, since they all share similar instructional goals and content (e.g. information fluency), we believe they are sufficiently comparable to justify inclusion in the same meta-analysis. Similarly, the usage measures utilized in the included studies also vary between libraries, and many studies treat use as a composite variable that includes many inputs, such as e-resource access, checkouts of physical materials, interlibrary loan use, and use of physical space (e.g. counts derived from swipe-card access). The principle component of use that all of these studies contained was either e-resource use or checkouts,

which we believe produce sufficiently comparable measures of engagement with library materials to be included in the same meta-analysis.

Once the two groups were created based on type of interaction with the library, a decision was made to group means comparisons and correlations together to increase the analysis group size. To do this, effect sizes calculated for means comparisons were converted into correlations according to the procedure described in Lenhard & Lenhard (2016). The final article groupings that were used for this meta-analysis examined studies that looked at library instruction by GPA and library use by GPA. Nevertheless, the decision to be maximally inclusive in the meta-analysis may tend to increase the uncertainty and amplify the results of the combined effect size.

To examine for potential publication bias, an Egger's Test was conducted. This test was not statistically significant ($p > 0.05$), meaning that there was not a positive bias in the studies included in the meta-analyses. The Egger's Test did, however, indicate that deJager et al. (2018) could be an outlier, possibly due to the study's use of categories rather than absolute values for its usage variable (49). For this reason, the library use by GPA analysis was run both with and without that study, as described below.

Meta-analysis limitations

These meta-analyses contain several limitations due to the nature of the underlying studies providing data. First, the precise definitions of both dependent and independent variables were often not entirely consistent among studies. For example Bowles-Terry (2012) examined the impact of one-shot library instruction on cumulative GPA, whereas the Greater Western Library Alliance (2017) investigated the impact of multiple types of instruction on first year GPA. Similarly, in examining library use, LeMaistre et al. (2018) investigated the impact of using electronic resources on term and year-to-year GPA, while Thorpe et al. (2014) investigated the impact of service points on term GPA. These differences make it difficult to answer questions such as which type of library instruction or usage is most associated with the student outcomes. Second, the regression models presented in these studies included different combinations of variables in almost every instance. This makes it difficult to compare across studies in order to better understand the library impact on student outcomes.

Third, because of the designs of the included studies, potential sampling bias is extremely difficult to avoid, and might skew results. For example, many studies used counts based on EZProxy logs as a library uses measure, which may be systematically biased depending on how these logs are set up. Furthermore, e-usage and physical usage are not necessarily directly comparable even though they are treated as a composite in this analysis.

Finally, publication and confirmation bias may be contained in the studies included in this meta-analysis. It is more likely that the studies included in this meta-analysis show an effect, because studies that demonstrate impact are more likely to be published than those that do not (Borenstein et al. 2009). Furthermore, in many of the studies reviewed, the introductions stated explicitly that the authors were seeking to confirm the same results as previous studies that ostensibly demonstrated that libraries have a positive impact on student outcomes (Chodock et al. 2018; deJager et al. 2018; Haddow & Joseph 2010; Nurse et al. 2018; Thorpe 2016). For this reason, meta-analyses in general are likely to overestimate the effect size compared to its theoretical true value.

Obtaining effect sizes

The effect size chosen for this meta-analysis is the correlation coefficient, or r . This statistic was utilized rather than the more common Cohen's d because the majority of the studies used in this analysis utilized correlation and regression calculations, and thus a Pearson's r statistic was already present. When non-parametric Spearman's rho (ρ) correlations were used, values with sample sizes above 1000 were included in the analyses and treated as equivalent to parametric Pearson's r correlations (no comma) since there is statistically little difference between Pearson's r and Spearman's rho once sample size is larger than 1000 (deWinter et al. 2016). When published results included effect sizes, these values were used. However, only five studies of the 18 included in the final meta-analysis contained an effect size measure. For studies that did not report an effect size, effect sizes were calculated using established methods (Borenstein et al. 2009) (no comma) through the use of the "Practical Meta-Analysis Effect Size Calculator" (Wilson 2010)³, and the use of the "Calculating Effect Sizes" website (Landon & Landon 2016).⁴

Since correlation and means comparison studies were grouped as discussed above, effect sizes for means comparisons (Bowles-Terry 2012; Cook 2014; Gaha et al. 2018; Garipey et al. 2018; LeMaistre, 2018; Soria, 2014; Thorpe, 2014) were calculated using Cohen's d and then converted to correlation values using the procedure described in Borenstein et al. (2009) via the Landon & Landon (2016) website. Finally, for studies that reported multiple correlations using the same or similar research designs (e.g. a correlation calculated yearly for multiple years) (deJager et al. 2018; LeMaistre et al. 2018; Thorpe 2014) a single weighted mean correlation coefficient was calculated using a Fisher's z transformation according to the procedure outlined in Bobko (2001,48-53). The effect sizes used are shown in column 1 of Tables 3, 4, and 5. (An r -value of 0-0.2 should be interpreted as no effect; 0.2-0.4, a small effect; 0.5-0.7, a medium effect; and above 0.7, a large effect).

Fisher's z transformations, confidence intervals around correlations and Fisher's z transformations, and variance calculations were then computed using the "Practical Meta-Analysis Effect Size Calculator" website (Wilson 2010).

RESULTS

Analysis

The two meta-analyses were completed using the Comprehensive Meta-Analysis software, and a random effects model was used for both groupings. A random effects model assumes there is no theoretical "true" effect shared by all of the studies analyzed and is, therefore, more appropriate to this analysis than a fixed effects model that assumes that the factors that influence the effect size are the same in every study (Borenstein et al. 2009, 63,69).

Instruction by GPA

³ <https://campbellcollaboration.org/escalc/html/EffectSizeCalculator-Home.php>

⁴ https://www.psychometrica.de/effect_size.html

The instruction by GPA analysis included eight studies which examined the impact of different types of library instruction on grade point average. As stated above, both library instruction and grade point average variables were figured differently in nearly all the studies, which potentially impacts the validity of the findings of this meta-analysis. These findings, therefore, should be understood as an approximation of an overall effect size for these studies. The null hypothesis that there is no effect in these studies was accepted, ($z=1.807$, $p=0.07$), and there was no aggregate effect across the studies, ($r=0.127$, $CI= -0.011- 0.26$). However, it should be noted that the precision of this analysis is lower than we would like, as indicated by the confidence interval, which ranges from a negative no effect to a positive small effect. This is due to the small number of studies included in this analysis (see Table 3).

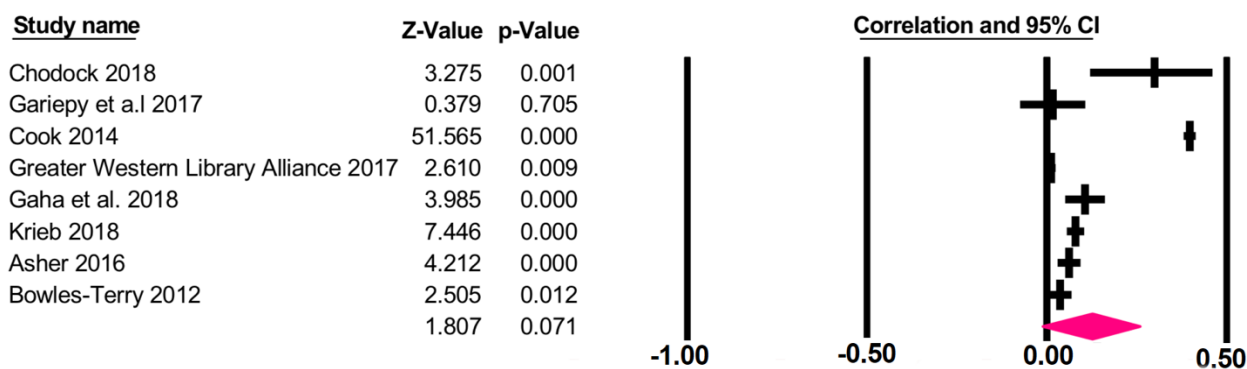


Table 3. Instruction by GPA correlations and study size

Study authors (year)	Effect size (r)	95% CI -	95% CI +	N
Chodock (2018)	0.300	0.124	0.458	115
Gariepy et al. (2017)	0.017	-0.071	0.105	500
Cook (2014)	0.398	0.384	0.411	15012
Greater Western Library Alliance (2017)	0.013	0.003	0.022	42899
Gaha et al. (2017)	0.107	0.055	0.159	1380
Krieb (2018)	0.080	0.059	0.101	8623
Asher (2016)	0.062	0.033	0.091	4545
Bowles-Terry (2012)	0.0374	0.008	0.067	4489

Note: 0-0.2=no effect, 0.2-0.4=small effect, 0.5-0.7=medium effect, 0.7-1.0=large effect

Library Use by GPA

The library use by GPA analysis included 10 studies that examined the impact of different types of library use on grade point average. The null hypothesis that there is no effect across these studies was rejected, ($Z=2.324$, $p=0.002$) as there was a small effect, $r=0.229$, ($CI=0.036$ - 0.405). Again, the precision of this analysis is relatively low, as indicated by a fairly wide confidence interval around the effect size, which ranges from no effect ($r=0.036$) to a small effect ($r=0.405$) (see Table 4).

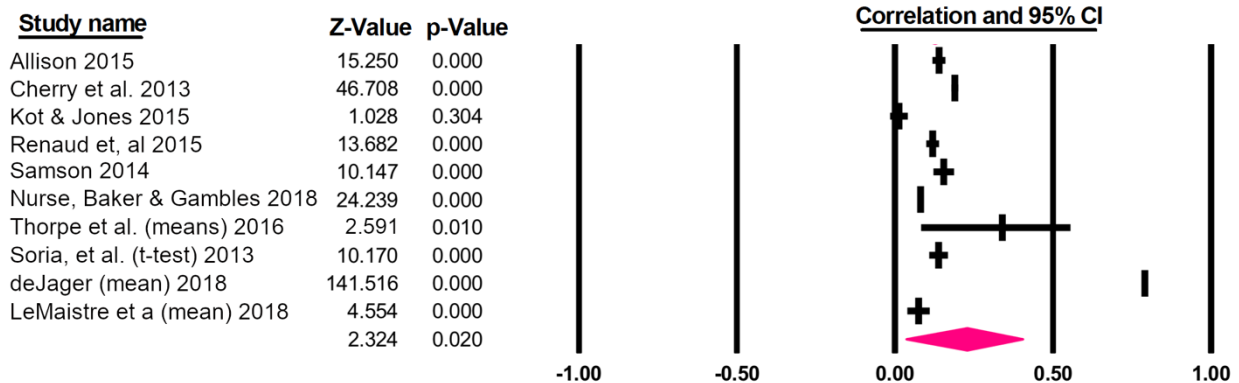


Table 4. Results for Use by GPA with deJager (2018) included

Study authors (year):	Effect size	CI-	CI+	N	Z	Sig
Allison (2015)	0.140	0.122	0.158	11718	15.250	0.000
Cherry et al. (2013)	0.190	0.182	0.198	59000	46.708	0.000
Kot & Jones (2015)	0.013	-0.012	0.038	6073	1.028	0.304
Renaud et al. (2015)	0.120	0.103	0.137	12873	13.682	0.000
Samson (2014)	0.155	0.125	0.184	4218	10.147	0.000
Nurse, Baker & Gambles (2018)	0.082	0.075	0.089	86954	24.239	0.000
Thorpe et al. (mean) (2016)	0.340	0.086	0.553	57	2.591	0.001
Soria et al. (2013)	0.139	0.112	0.165	5318	10.170	0.000
de Jager (mean) (2018)	0.791	0.785	0.797	17362	141.516	0.000
LeMaistre (mean) (2018)	0.075	0.043	0.107	3661	4.455	0.000
Total for group (with de Jager, 2018)	0.229	0.036	0.405	207233	2.324	0.002

Note: 0-0.2=no effect, 0.2-0.4=small effect, 0.5-0.7=medium effect, 0.7-1.0=large effect

Because the deJager et. al. (2018) study is a noticeable outlier on the Egger's test, we decided to run the analysis a second time, without including the outlying study. This analysis was still significant ($Z=53.886$, $p=0.000$), but the effect was small ($r=0.123$), however, there is much more precision to this analysis, with the confidence interval ranging from 0.119-0.127. For transparency, both versions of this meta-analysis are included, but if the authors had to rely on one particular model, we would argue that the second analysis is a more precise measure of population effect (see Table 5).

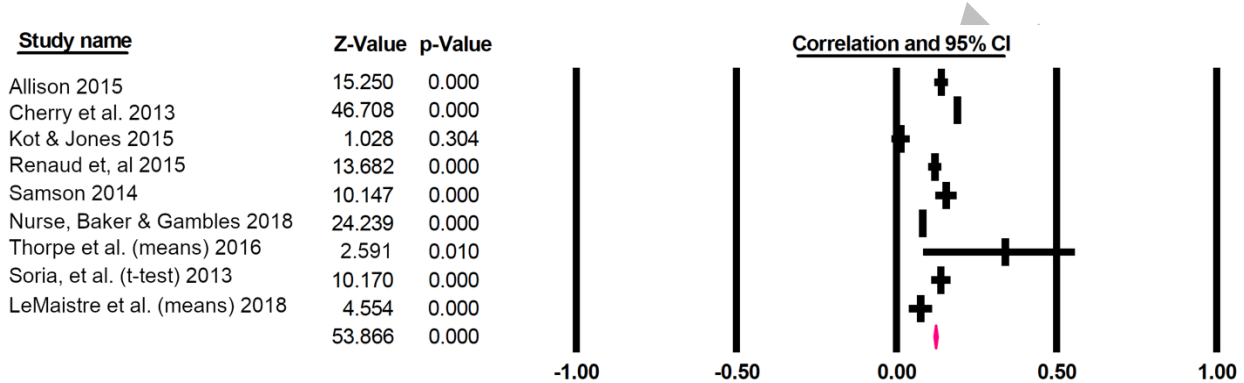


Table 5. Results for Use by GPA without de Jager (2018) included

Study authors (year)	Effect size	CI-	CI+	N	Z	Sig
Allison (2015)	0.140	0.122	0.158	11718	15.250	0.000
Cherry et al. (2013)	0.190	0.182	0.198	59000	46.708	0.000
Kot & Jones(2015)	0.013	-0.012	0.038	6073	1.028	0.304
Renaud et al. (2015)	0.120	0.103	0.137	12873	13.682	0.000
Samson (2014)	0.155	0.125	0.184	4218	10.147	0.000
Nurse, Baker & Gambles (2018)	0.082	0.075	0.089	86954	24.239	0.000
Thorpe et al. (mean) (2016)	0.340	0.086	0.553	57	2.591	0.001
Soria et al. (2013)	0.139	0.112	0.165	5318	10.170	0.000
LeMaistre (mean) (2018)	0.075	0.043	0.107	3661	4.455	0.000
Total for group (without de Jager, 0.123 2018)		0.119	0.127	189871	53.886	0.000

Note: 0-0.2=no effect, 0.2-0.4=small effect, 0.5-0.7=medium effect, 0.7-1.0=large effect

Because of the low number of studies included in this analysis, however, as well as the differences in how each study measures library use, the authors generally recommend caution drawing conclusions from results designed to approximate overall effect sizes in order to avoid over-interpretation. We view these findings as an indication that additional meta-analyses should be completed, and that future library learning analytics studies should consider both the methodological and ethical problems revealed by these results.

DISCUSSION

Overall findings

This meta-analysis had two main goals: to evaluate the overall impact of academic library services on measures of student success, and to use the outcomes of that analysis to examine the ethical implications of library learning analytics research. Rather than being satisfied simply with statistically significant findings--which is unfortunately often the case with library impact studies, as well as in reviews investigating common statistical errors found in library science publications (Van Epps, 2012; Zhang, Wang, & Zhao, 2017)-- we sought to conduct a more complete analysis by measuring the overall effect indicated by these studies. Demonstrating a large effect would support tolerating a higher level of potential risk posed by connecting library data to student outcome data. This is because the larger the effect indicates greater benefit, thus generating findings that are more meaningful and support more confident decisions by library and university administrations. A larger effect size also diminishes the chance of type I error--observing a relationship when none exists-- an error that is extremely important to avoid when considering high impact interventions.

Unfortunately, both meta-analyses presented here indicate that there is either no, or a very small, effect of library use or instruction on student GPA outcomes. While the data provided by the corpus of library LA studies prevented evaluating other outcome variables, such as retention and attainment, these findings nevertheless have important ethical implications for all types of personal data-intensive library learning analytics research. In short, do studies that, when aggregated, produce a null result in a meta-analysis (no comma) justify students' loss of privacy and autonomy, as well as re-identification risks students are forced to bear, often without their explicit consent (see Asher 2017)? From the standpoint of meeting the beneficence standard of ethical research, we would submit that the answer is no.

Moreover, given the inherent risks of using student data, the beneficence standard of ethical research demands that researchers endeavor to follow statistical best practices. Regrettably, many library LA studies fail to meet the minimum standards for statistical reporting. For example (and *egregiously*), studies sometimes reported "significant" results, but not the actual values of statistical tests, nor the basic descriptive statistics required to evaluate the quality of the study, such as means, standard deviations, and sample sizes. Others inappropriately described small p-values with adjectives like "massive" significance, which is an incorrect characterization since, as p-values indicate probability, they do not have size values attached to them. These types of incorrect descriptions contribute to confirmation bias, over-interpretation of results, and reporting correlation as implied causation (Wasserstein & Lazar 2016). Additional common errors observed repeatedly in this review included the use of an incorrect statistic for the analysis undertaken, particularly using parametric statistics when non-parametric statistics are required (e.g. for ordinal data or data that is not normally distributed). Types of

errors and statistical problems have been documented in earlier library literature citing the need for librarians to have a greater understanding of, and more training in, the use of inferential statistics (Dilevko 2007; Wallace 1985; Van Epps 2012). At a minimum, articles utilizing inferential statistics should include descriptive statistics required to reproduce the test statistic (typically the mean, standard deviation, and sample size), the value of the test statistic, the significance (p-value) and a measure of effect-size (often Cohen's *d*, but various measures are appropriate) for the key findings being reported.

Perhaps due to librarians' enthusiasm for their work, there is often a tendency within these studies to overinterpret results and overstate the library's contribution to student outcomes, leading to relatively small statistical differences being misleadingly or hyperbolically reported. Large datasets are more likely to produce statistically significant results when comparing means and distributions between populations, as well as spurious correlations between variables, especially for complex, real-world observations (Calude & Longo 2016, 600-602). As Calude & Longo observe, "The more data, the more arbitrary, meaningless and useless (for future action) correlations will be found in them that do not reflect real-world differences in the groups under study" (2016:600). Routinely calculating and reporting effect size statistics is one check on these errors, and is probably an ethical imperative if interventions are planned based on these studies.

Nevertheless, very few of the studies we reviewed reported an effect size, which is an extremely important complementary measure to the more common null-hypothesis statistical test (NHST, p-value). Effect sizes are required for evaluating the likely real-world impact represented by statistical models. This is especially true of relatively large-sample-size studies (as most LA studies are), which are likely to obtain statistically significant findings in relatively small variations in measures such as GPA (Field 2017; Salkind 2017; Wasserstein & Lazar 2016).

These errors of method and interpretation are also indications that library LA research is not presently sufficiently meeting the beneficence standard. By conducting research that potentially puts subjects at risk-- even if that risk is small-- it is the responsibility of the researcher to conduct the highest quality research possible. To do otherwise because of insufficient methodological proficiency is not ethically defensible. These persistent problems in analysis and communication suggest that the library community needs to have a more extensive conversation about data collection and analysis standards, and about the ethical implications of these decisions, particularly since it is unlikely that pressures to provide quantitative impact of library services on student success measures will decrease in the foreseeable future. As discussed above, calls for the library community to become more proficient in the application of inferential statistics have appeared in library science literature for at least the last 4 decades (Dilevko 2000; Dilevko 2007; Wallace 1985; Wyllys 1978; Van Epps 2012). The development of an ethical code for librarians conducting research that addresses topics such as training, treatment of subjects, research integrity, researcher responsibility, supervision, communication, and peer review, similar to those developed by other scholarly associations (The American Educational Research Association (2011), The American Sociological Association (2018), The American Psychological Association (2016)) might assist in addressing these issues and provide a unified front to prevent a race to the bottom in ethical standards for library LA data collection and use.

Finally, because these meta-analyses are based on correlation values, we are obligated to consider the inverse of our results, which is that it is just as likely that whatever positive association we observe between library use or instruction and grade outcomes is as attributable to

high-performing students being more likely to utilize these services than these interventions contributing to students' better performance. If this is the case, many library LA studies are simply confirming findings that we already know, that is, better students tend to use the library resources available. This type of reproduction of known information does not justify the risk of the data collected, and, therefore, neither meets the beneficence standard nor contributes effectively to administrative decisions about library services and resources, nor to arguments supporting the value of libraries to their institutions.

Recommendations for practice

Given the continued pressure on libraries to quantitatively demonstrate their value and contribution to students' learning outcomes, and the increasing use of inferential statistics in the library science literature (Wallace 1985; Zhang, Wang, & Zhao 2017; Zhang, Wang, Zhao, & Cai 2018), it is vital for librarians and library administrators to increase their fluency in the application of these methods and techniques to library-centered research questions. This increased fluency should not just include the use of inferential statistics, but also, as Van Epps (2012) notes, in the use of survey methodologies as well.

This article echoes previous findings of common errors in application of statistical techniques in library-based research, such as Van Epps' (2012) review of survey research. Additionally it asserts the necessity of routinely reporting effect sizes in addition to measures of statistical significance (p-values) in order to more effectively assess the actual real-world impacts suggested by statistical models. Specifically, we believe the following actions might be taken by the library community to help limit statistical errors in its research literature and improve the overall quality of quantitative methods utilized in libraries: As is suggested by previous studies, (Dilvelko 2000; Dilevko 2007; Wallace 1985; Wyllys 1978; Van Epps 2012) we believe that statistical methods training needs greater emphasis in the curricula of Master of Library Science degree programs. This emphasis might take the form of increased attention to and integration in existing course syllabi. The statistical methods addressed should not be limited to basic inferential statistics, but should include more advanced techniques that are commonly employed in libraries such as regression and survey methodologies. While we believe that additional training in assessment, evaluation, and research methods will help improve the quality of librarians' own research, and their peer-review of others' work, it will also help librarians better serve patrons who have questions about the use of statistics in the news, in research articles, and in other information sources. Even if librarians do not intend to conduct their own research studies, as Divilko (2007) points out, librarians with this knowledge will be better positioned to help students, faculty, and staff with questions about analysis, interpretation, and visualization of statistics.

Journal editors and peer reviewers should increase their scrutiny of statistics reported in submitted articles. Many of the errors and omissions documented in this article could have been corrected easily during peer review. Journals that commonly publish articles using inferential statistics should have quantitative methodologists specifically review the quality of these statistics as a part of the peer review process, and changes requested by these methodologists should be required by the editors of those journals. Likewise, peer-reviewers of articles should carefully consider if they have the statistical expertise to fully evaluate the specific methods used in a study, and, if not, should request the editor employ a specialist to review those sections of the work.

Librarian practitioners should both seek and provide mentorship and training in research methods and statistics. Mentorship might be provided by library colleagues who are experienced with the use of inferential statistics in social and behavioral sciences, by faculty members in social science departments, by institutional research offices, or by library programs and associations (the Library Research Round Table, The Institute for Research Design in Librarianship; Note: the first author of this paper is a mentor in this program).

Finally, the original impetus for this meta-analysis was to investigate the ethical implications of the use of student data in library impact studies. While we have argued these studies do not meet the beneficence standard set by the Common Rule, we acknowledge that these studies will continue to be undertaken. That given, libraries participating in learning analytics studies should take specific measures to minimize the potential risks to students whose data is used in these studies, and to inform students of these risks. In particular, libraries should take steps to mitigate risks by 1) limiting the collection of demographic data not specifically required by a study, 2) aggregating data at the highest level possible when conducting an analysis, 3) avoiding collecting transaction-level data that identifies both an item accessed or used and an individual, and 4) implementing a destruction plan for data once analysis is complete (Asher 2017). Libraries should also be transparent about the data they are collecting by developing notification practices that are easily scanned and understood by busy users and that occur in locations where they are likely to be seen and read. At minimum, libraries should put in place clear and easily enacted opt-out procedures for students who do not wish to have information about them collected, and, as a best practice, utilize active opt-in procedures to ensure students' consent whenever possible.

CONCLUSIONS

Because of the myriad of factors that affect grade, retention, and attainment outcomes, library use or instruction is unlikely to be able to statistically demonstrate a meaningful real-world affect on these outcomes (Garipey et al. 2017,104), and almost certainly not a strong enough relationship to responsibly intervene on, effectively act on, or conclusively demonstrate the value of libraries. In fact, to take the findings of the studies included in this meta-analysis at statistical face value, they do as much, if not more, to support an argument that libraries are contributing very little to overall student success. While we as educators, librarians, and researchers, believe this argument to be wrong, it does indicate that library LA studies may have problems with validity in their design, in that they do not adequately describe students' educational experiences, outcomes, and behaviors. As LeMaistre et al. (2018) suggest, while there is potentially great value in quantitatively investigating the impact of the library on student outcomes, there are obviously many other factors and confounding variables that impact student success that lie well beyond the library. For this reason, focusing only on the impact of the library on student outcomes artificially inflates its contribution, for better or for worse, an approach that presents both methodological and ethical problems.

Since we are presently in an era where the businessification of higher education is quickening, academic libraries will likely find it difficult to completely resist the quantification of their impacts. However, it is necessary to approach this work differently. As Tinto (2006) points out, what makes a student successful in education is complex, and cannot be whittled down to any

particular lens, or a simplistic set of factors. Rather, student success is the result of the entirety of what makes the university a worthwhile environment for further learning—from the experience of living (or not) in a residence hall to the political environment in which higher education is situated. As academic libraries are working to make their way in this context we must avoid tunnel vision and instead look outward to partners across our institutions who have been investigating what makes students successful for decades. In fact, the authors believe that academic libraries are in a unique position to take a leading role in creating new models for student success because of their focus on providing safe and free environments for inquiry of all types to occur. As the #RealCollege movement is showing (Alon & Tienda 2007; Goldrick-Rab 2016; Guinier 2015), education is still very much the same false meritocracy described by Erickson & D. Robertshaw (1983), one that asserts the potential for upward social class attainment through education, as defined by grades, test scores, and class rank, but in fact continues to benefit the already-privileged. Libraries have been at the forefront of innovating new ways to meet community needs. They have a unique lens through which to look at student success because of their focus on the complex needs of their communities. Using this lens, rather than a lens based on the quantification of “value” measures, can help libraries lead higher education in creating the complex and multi-faceted models that show how students are successful. The authors believe that these models can be created without the overt violation of student privacy rights, and strict adherence to rigorous research methods.

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AUTHOR BIOGRAPHIES

M. Brooke Robertshaw serves as the Assessment Librarian and is an Assistant Professor at Oregon State University Libraries & Press. She is a white, European, documented, cis-gender, straight, academic class, second generation PhD, woman. Dr. Robertshaw acknowledges that what she has written in this article and how she has worked with the statistics involved in this meta-analysis are influenced by her cultural context and position in the world. Her research interests involve research ethics, big data, and the cultural nature of statistics. She can be emailed at brooke.robertshaw@oregonstate.edu.

Andrew Asher is the Assessment Librarian at Indiana University Bloomington, where he leads the libraries' qualitative and quantitative assessment programs and conducts research on the anthropology of information. Asher's most recent work examines search and discovery workflows of students and faculty, information fluency development, and the ethical dimensions of library assessment and social science research data. Asher holds a PhD in sociocultural anthropology from the University of Illinois at Urbana-Champaign, and has written and presented widely on using ethnographic methods in academic libraries, including the co-edited volume, *College Libraries and Student Culture*.

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