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Review

Statistical procedures for analyzing mental health services data

Jon D. Elhai [a,*], Patrick S. Calhoun [b], Julian D. Ford [c]

[a] *Disaster Mental Health Institute, The University of South Dakota, 414 East Clark Street, Vermillion, SD 57069-2390, USA*
[b] *Mental Health Service, Durham VA Medical Center, USA and Department of Psychiatry, Duke University Medical Center, Durham, NC, USA*
[c] *Department of Psychiatry, University of Connecticut School of Medicine, Farmington, CT, USA*

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Abstract

In mental health services research, analyzing service utilization data often poses serious problems, given the presence of substantially skewed data distributions. This article presents a non-technical introduction to statistical methods specifically designed to handle the complexly distributed datasets that represent mental health service use, including Poisson, negative binomial, zero-inflated, and zero-truncated regression models. A flowchart is provided to assist the investigator in selecting the most appropriate method. Finally, a dataset of mental health service use reported by medical patients is described, and a comparison of results across several different statistical methods is presented. Implications of matching data analytic techniques appropriately with the often complexly distributed datasets of mental health services utilization variables are discussed.

Keywords: Mental health services research; Service utilization; Skewed distributions; Health care costs; Statistics

Contents

* Corresponding author. Tel.: +1 605 677 6575/+1 800 522 9684.
E-mail addresses: jonelhai@fastmail.fm, jelhai@usd.edu (J.D. Elhai).

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1. Introduction

A large body of research has examined variables associated with the previous use of mental health services, using various conceptual frameworks (Bruce et al., 2002). Among large-scale community surveys, recent results have demonstrated that mental health service use is significantly associated with a number of variables including demographic characteristics, attitudes toward treatment, mental health diagnoses, and access variables (Bland et al., 1997; Kessler et al., 1998; Lin and Parikh, 1999; Parslow and Jorm, 2000; Lewis et al., 2005; Oliver et al., 2005; Wang et al., 2005; Elhai et al., 2006a; Elhai and Ford, 2007).

Several recent reviews have discussed a number of important methodological issues that have limited the literature examining the use of mental health services, including design-specific problems in querying about service use and in measuring utilization (Walker et al., 2004; Elhai et al., 2005). However, in addition to methodological and design issues, there are also important data analysis issues that warrant consideration. The current article aims to briefly present the problems inherent in analyzing data on mental health service use and costs, and discusses in non-technical terms several alternative statistical methods that represent the state of the art in handling such data, with an empirical comparison of the performance of these methods.

2. Complexities in mental health service use and cost data

Mental health services researchers often gather data on the intensity of services used by participants (typically in the form of visit counts), and sometimes the resulting costs incurred (in dollars). Such data are most often gathered over a recent time period (e.g., past 12 months), since research demonstrates that subjects' recall accuracy substantially decreases when estimating visit counts over longer time frames (Roberts et al., 1996). Medical chart reviews also tend to focus on short time frames, since conducting such reviews can be quite costly when focusing on longer time periods.

During any short time frame, most individuals, even those with mental disorders, have not accessed mental health treatment, highlighting the gap between the need for and actual use of services (Aoun et al., 2004). As a result, data on mental health treatment visit counts and costs typically have substantial positive skews in their distributions, with only a small proportion of participants having more than a few recent treatment visits or dollars incurred. Additionally, reporting means for such variables is not meaningful, without reporting other indices of central tendency that are less biased by skewed distributions (e.g., medians or quartiles), and ranges of the values.

Under these conditions, several problems occur when attempting to analyze correlates of mental health service use or costs with general linear model (GLM) analyses (e.g., ordinary least-squares linear regression). First, the linear model can yield expected values that have a negative sign, which is impossible since visit counts and costs in reality must be "0" or higher. Additionally, GLM's requirement that data are normally distributed will be violated, which can distort true relationships and significance test results. Finally, the assumption that residual variance is equally distributed within a variable (i.e., homoscedasticity) is likely to be violated (called heteroscedasticity), resulting in distortions of the estimated variance, deflated regression coefficient standard errors, and more inflated coefficient t test values than would be expected (potentially yielding Type I errors). Such problems with count data have been extensively reviewed elsewhere (Gardner et al., 1995).

3. Data transformations

Perhaps as a result of these data problems, the actual analyses presented in mental health service use studies most often involve logistic regression, by reducing visit counts and costs to dichotomous categories (e.g., "use"/"non-use"; "0–9 visits"/"10 or more visits"; "above"/"below median costs"). While this approach may seem to solve the problems discussed above, because logistic regression does not have the same restrictive assumptions that linear regression has, new problems are introduced. Specifically, analyzing discrete categories results in the loss of rich information about service use intensity and cost; for example, it can place individuals who had one mental health visit into the same category as those who had 300 visits! Additionally, such reduction to categories may reduce statistical power. Finally, even when criteria are based on empirically-defined benchmarks (e.g., prior studies' cutpoints; points along the distribution of the current dataset), results can be influenced by the specific arbitrary cutoff points chosen to define visit and cost categories. Problems inherent in reducing dimensional variables to discrete categories are discussed in detail elsewhere (MacCallum et al., 2002).

An alternative solution to analyzing such skewed data is to first conduct data transformations on the skewed variable, after adding a constant to all cases (e.g., "1" or "5" added visit counts, because of problems transforming zero values). For example, conducting square root (for "moderate" skewness), logarithmic (for "substantial" skewness), or inverse (for "severe" skewness) transformations are commonly accepted statistical methods to normalize skewed distributions (Tabachnick and Fidell, 2001). However, this transformation solution too is problematic. First, in our experience working with numerous datasets, mental health visit counts are often too skewed for data transformations to result in normalized distributions; in fact, after transformation the modal value often still appears in the bottom range of the distribution. Additionally, conducting such a data transformation results in a loss of the data distribution's integrity. As a result, examining the amount of change in visit counts (the dependent variable) that is associated with a unit change in each predictor variable may yield uninterpretable results, since after transformation the dependent variable no longer represents the true visit count.

4. Count regression models

When analyzing predictors of such skewed service use and costs data, the best solution is to use a non-linear, count regression model. Such models require that the dependent variable is a non-negative integer, and as in ordinary linear regression, the predictor variables must be either continuously-scaled, binary-coded or a mixture. Count models use maximum likelihood procedures, and implement transformations to make the non-linear count dependent variable linear. Count models are specific cases of the *generalized* linear model (McCullagh and Nelder, 1989) (which is a different family of statistical analyses than the more commonly used *general* linear model, GLM), but specifically deal with a count dependent variable. We will discuss two types of generalized linear count models, Poisson regression and negative binomial regression. We then will discuss modifications that may be applied to these models with datasets that have either a large proportion of zero values (zero-inflated regression), or no zero values (zero-truncated regression).

4.1. Poisson regression

Poisson regression is the simplest count regression model. Coefficients are exponentiated, since counts must be 0 or greater. Poisson regression assumes a Poisson distribution, often characterized by a substantial positive skew (with most cases falling at the low end of the dependent variable's distribution) and a variance that equals the mean. Because count data distributions (e.g., visit counts) often have a Poisson distribution, Poisson regression tends to fit these data better than linear regression does (which assumes a normal distribution). As a result, predictive relationships with a dependent variable (e.g., visit counts) can be examined as in ordinary linear regression, but without the problems from having the non-normal distributions and heteroscedasticity that are expected with visit counts and costs.

However, Poisson regression has an important restriction in its own right. It requires that the count variable's variance is not greater than its mean. Violating this assumption, known as "overdispersion," results in deflated standard errors and inflated z values, yielding Type I errors and thus making Poisson regression contraindicated. Several tests are available in software programs to assess if significant overdispersion is present (Long, 1997). Unfortunately, overdispersion is quite likely to occur with mental health visit counts (Calhoun et al., 2002), making Poisson regression often untenable for mental health services researchers. Nonetheless, the interested reader is referred to several sources for more detailed information on Poisson regression (Gardner et al., 1995; Long, 1997; Cameron and Trivedi, 1998).

4.2. Negative binomial regression

Like Poisson regression, negative binomial regression also can examine predictive relationships with a count dependent variable, despite non-normal, heteroscedastic distributions. However, unlike Poisson regression, negative binomial regression can be used if the count variable's data are overdispersed. While Poisson regression accounts for observed differences among cases, negative binomial regression also includes a random component that involves unobserved variance among cases. The inclusion of this random component helps prevent the incorrect (Poisson) assumption that all differences among subjects in the dependent variable are *equally* explained by the process of making the non-linear dependent variable linear. This random component results in more accurate standard errors and z-statistics for the regression coefficients than by using Poisson regression with overdispersed data. Negative binomial regression typically assumes a gamma distribution, although other distributions have been proposed as well. More detailed information is available to the reader (Gardner et al., 1995; Long, 1997; Cameron and Trivedi, 1998).

4.3. Zero-inflated regression

Despite their advantages in being able to model non-normal data distributions, Poisson and negative binomial regression do not fully address the requirements of modeling mental health visit counts. Quite often, in addition to being skewed and overdispersed, such visit counts and cost data have an excess of "0" values, since most participants have not visited a mental health professional within a recent time frame (Elhai et al., 2006b). Therefore, neither Poisson nor negative binomial regression will be appropriate, and if used, the maximum likelihood procedures may not converge on a solution when a data distribution has a preponderance of zero values. Zero-inflated regression was specifically designed to address the problem of excess zeros in the dependent variable, and is therefore a very likely candidate in analyzing mental health service use and costs data.

Using data reduction methods, zero-inflated regression estimates two latent (or unobserved) groups. The "Always Zero" group has a score of 0 on the dependent count variable, while the "Not Always Zero" group can have a score of 0 or any positive integer. This essentially produces a logistic component, such as in logistic regression, where the predictor variables are examined in predicting group status (Always Zero, and Not Always Zero groups). Based on the results of this logistic component, cases are weighted (with less weight given to Always Zero group members) in order to determine the prediction of visit counts or costs, which could be a 0 or any positive number.

Zero-inflated regression has been available for over a decade, with the first papers detailing its use published in the early 1990s (Lambert, 1992; Heilbron, 1994). In fact, few published reports have yet implemented this method in analyzing mental health service use data (Powers et al., 2002; Elhai et al., 2006b), but some evidence exists supporting this method as superior to traditional statistical methods in modeling mental health visit counts (Bao, 2002). The zero-inflated analysis is available using Poisson methods (for non-overdispersed data) or negative binomial methods (for overdispersed data), as recently reviewed (Hall and Zhengang, 2004). Moreover, statistical tests have been developed to assess whether a zero-inflated model should be used instead of a standard Poisson or negative binomial model, and to test whether zero-inflated Poisson vs. zero-inflated negative binomial regression should be used (Long, 1997). The interested reader is referred to several key resources (Long, 1997; Cameron and Trivedi, 1998; Hall and Zhengang, 2004).

4.4. Zero-truncated regression

Finally, it should be noted that some mental health services researchers have a different data problem than that presented in the previous section — namely, a lack of zero values on the dependent count variable (Powers et al., 2002). For example, an investigator may wish to examine correlates of prospective visit counts at a particular mental health facility, but using records of those who visited the facility at least once. Thus visit counts will have a minimum score of 1. This type of data is referred to as "zero-censored" or "zero-truncated" data.

Zero-truncated regression allows the investigator to estimate the number of visit counts or costs in the entire population of patients, rather than simply among those with at least one visit or dollar incurred. It can also provide results on the expected number of visit counts or costs specifically among those with at least one visit/dollar. As with zero-inflated regression, two forms of this method are available: a Poisson method (for non-overdispersed data), and a negative binomial method (for overdispersed data). Testing for overdispersion is quite important, since overdispersion causes especially problematic effects in truncated models. The interested reader is referred elsewhere for more detail (Gurmu and Trivedi, 1992; Long, 1997; Cameron and Trivedi, 1998).

5. Decisions in analyzing count regression models

In Fig. 1, we present a flowchart to assist the reader in selecting the most appropriate regression model, given characteristics of the dependent variable.

At the time of this writing, two statistical packages include standard modules for Poisson, negative binomial, and the zero-inflated and zero-truncated methods: Stata (Statacorp, 2005) and LIMDEP (Econometric Software, 2002). Gauss (Aptech Systems Inc., 2005) offers (but does not include as standard) a Maximum Likelihood application which includes all but the zero-inflated methods, and a Discrete Choice application that

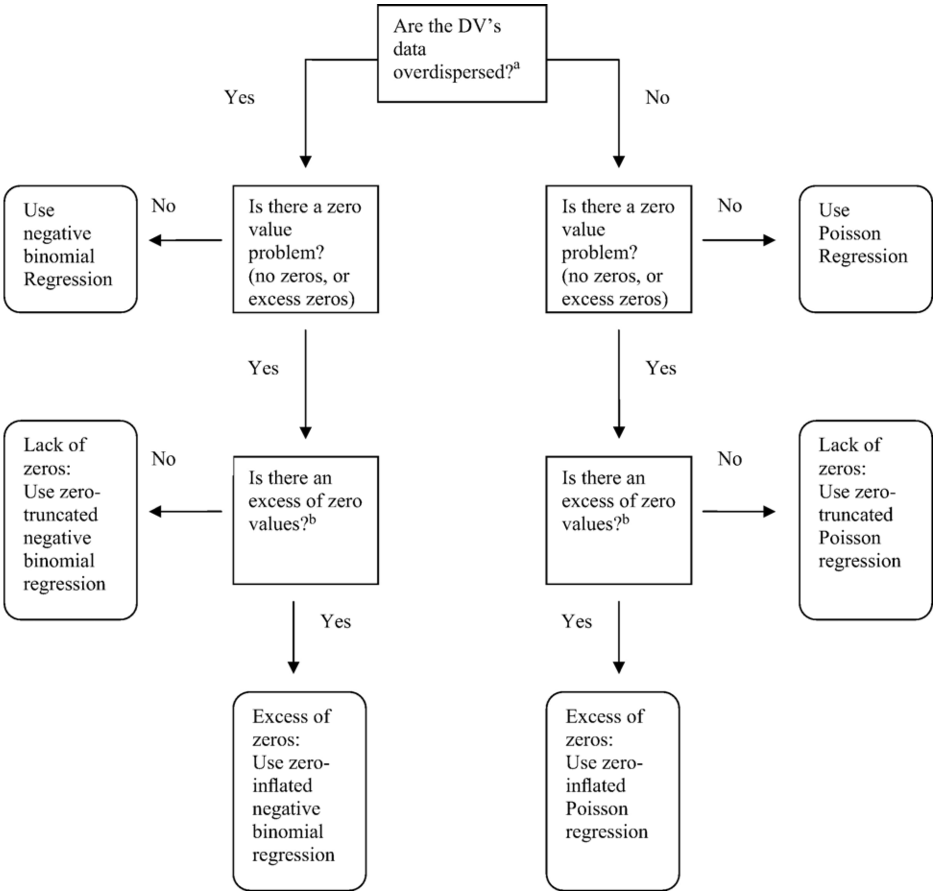

Fig. 1. Flowchart for selecting a count regression model in analyzing mental health services research. Assuming a) a non-negative integer, count dependent variable, and b) predictor variables that are continuously-scaled, binary-coded, or a mixture. Note. DV = dependent variable. [a] = Testable with a likelihood ratio test. [b] = Testable with the Vuong test for non-nested data.

includes all methods. SPSS (SPSS Inc., 2006) now offers an Advanced Models module for Poisson and negative binomial regression only StatSoft (2007) allows for Poisson regression. Mplus (Muthén & Muthén, 2008) includes modules to analyze Poisson and zero-inflated Poisson regression, negative binomial and zero-inflated and zero-truncated negative binomial regression, including for structural equation and multi-level (or hierarchical linear) modeling. HLM (Scientific Software International, 2005) allows for multilevel Poisson regression.

Several additional software packages offer only some of these methods as standard, but these packages include matrix language programming, so any absent modules can be programmed, if not found as macros via the internet. For example, SAS (SAS, 2006) includes standard modules for all but the zero-truncated methods. TSP (TSP International, 2005), Matlab (Mathworks, 2006), and S-Plus (Insightful Corporation, 2005) include modules for Poisson and negative binomial regression.

6. Applying the models to a dataset of mental health visit counts

Recently, we examined mental health treatment use intensity among 186 Midwestern U.S. primary care patients (Elhai et al., 2006b). We assessed the relationship of gender, attitudes toward mental health treatment, violent-crime and non-crime trauma frequency (log-transformed due to substantial skewness), and a probable posttraumatic stress disorder (PTSD) diagnosis with self-reported mental health visit counts from the past 6 months. We now present a comparison of the above-mentioned statistical methods to this dataset. Our original analyses examined blocks of predictor variables (assessing the incremental contribution of the trauma and PTSD variables above gender and mental health

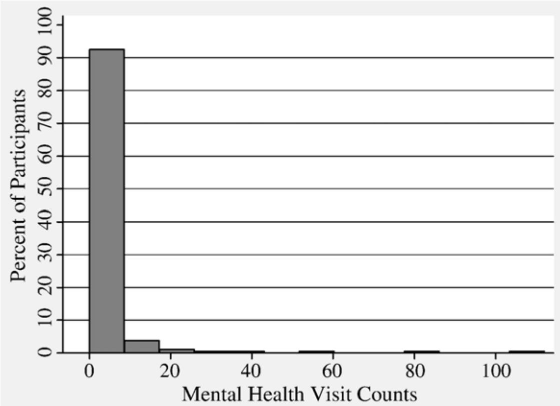

Fig. 2. Histogram of mental health visit counts variable.

treatment attitudes). However, for the sake of simplicity the present report will examine each regression model with the variables simultaneously entered.

First, it should be noted that the dependent variable, mental health visit counts, was substantially positively skewed (skewness = 6.78), and kurtotic (kurtosis = 51.83), severely violating GLM assumptions (with absolute values greater than 1 or 2 typically considered problematic).[1] Fig. 2 displays a histogram, demonstrating pictorially the skewness of the mental health visit count variable. Even when applying data transformations to the dependent variable, skewness and kurtosis were still substantial. For example, applying a logarithmic transformation resulted in skewness of 3.48 and kurtosis of 13.34; an inverse transformation resulted in skewness of −2.17 and kurtosis of 3.69. Thus, even with data transformations GLM procedures would be contraindicated for these data.

Referring to the flowchart in Fig. 1, first we assess for overdispersion. Using a likelihood ratio test to assess for overdispersion, the variable's data were significantly overdispersed, LR $\chi^2(1) = 1031.69$, $P < 0.001$ (rejecting a Poisson model, and favoring a negative binomial model). The next step in the flowchart involves assessment for problems with zero values, referring to the left half of the flowchart because of overdispersion found. As expected, most participants ($n = 141$, or 76%) denied using mental health services in the previous 6 months, making excess zero values (rather than the lack of zero values) a significant problem. Using the Vuong test for non-nested models, we determine that this excess of zeros results in the rejection of a standard negative binomial model (in favor of a zero-inflated negative binomial model), $z = 2.63$, $P < 0.01$ (see Long, 1997, for a review of tests comparing the count regression models, including the overdispersion likelihood ratio test and Vuong test).

Given the significant overdispersion and excess of zero values, zero-inflated negative binomial regression appears to be the most appropriate analysis, which accounted for 29% variance in the dependent variable (visit counts), with only non-crime trauma frequency resulting in a significant regression coefficient in the model. Table 1 presents a comparison of the different models' results in predicting mental health visit counts, using Stata 9.0 SE software. In addition to presenting results from the zero-inflated negative binomial regression model (using Stata's ZINB analysis), we also present Poisson and standard negative binomial regression results (using Stata's Poisson and NBREG analyses, respectively). R^2 values were computed using Stata's Fitstat post-estimation command.

In comparison to the zero-inflated negative binomial regression, standard negative binomial regression underestimated the amount of variance (0.20), yielding one additional statistically significant variable, thus

Table 1
Comparison of regression models in predicting mental health visit count data, with non-standardized beta coefficients, standard errors of beta, statistical significance, and model R-squared values ($N = 186$)

Variables	Zero-inflated negative binomial regression[a]	Poisson regression	Negative binomial regression[b]
	($R^2 = .29$)	($R^2 = 1.00$)	($R^2 = .20$)
	b (SE b)	b (SE b)	b (SE b)
Gender	−0.19 (0.81)	−0.49 (0.10) ***	1.08 (0.61)
Mental health treatment attitudes	0.00 (0.05)	0.12 (0.01) ***	0.06 (0.05)
Violent-crime trauma frequency	2.09 (1.26)	2.98 (0.26) ***	4.50 (1.35) **
Non-crime trauma frequency	4.05 (2.02) *	2.00 (0.31) ***	5.02 (1.94) *
PTSD Diagnosis	−0.22 (0.69)	0.06 (0.11)	−0.90 (0.77)

Note. R^2 values are standardized (Nagelkerke's R^2), ranging from 0 to 1. P values represent z test (for count regression) comparisons of regression coefficient being significantly different from 0. [a]Test results for an excess of zero values (compared to negative binomial regression), Vuong test for non-nested data $z = 2.63$, $P < 0.01$. [b]Test results for significant overdispersion (compared to Poisson regression), LR $\chi^2(1) = 1031.69$, $P < 0.001$.

* $P < 0.05$.
** $P < 0.01$.
*** $P < 0.001$.

[1] A more precise method for judging significant skewness is to estimate the standard error of skewness (SE Skewness), multiply this value by 2, and then derive the range of (− 2 × SE Skewness) to (+ 2 × SE Skewness). If the skewness value falls outside of this range, then the variable's distribution can be considered significantly skewed. A similar process can be used to determine if kurtosis is significant.

likely committing Type I error. Additionally, Poisson regression yielded a non-sensical amount of variance accounted for (1.00), and designated all variables but the PTSD variable as statistically significant.

Last, it should be noted that the Poisson analysis yielded a significant regression coefficient that was negative in sign. Thus, the Poisson analysis found greater treatment use among men than women. This finding is opposite of what has typically been found previously in mental health service use research (discussed above).

7. Conclusions

This paper presented a review of the data analysis problems that are inherent when analyzing mental health service use data. Several solutions were presented, including Poisson and negative binomial, zero-inflated, and zero-truncated regression models. Quite different results were observed when alternative statistical solutions were used to handle a typical dataset with mental health service use as the outcome variable. The results demonstrate the potential danger of using analytic methods whose assumptions are violated by a data distribution that is non-normal and zero-inflated, which commonly occurs with datasets representing mental health services utilization.

We believe that mental health service use studies with complexly distributed data will present much more compelling and accurate results if the assumptions of the analytic techniques are carefully matched to the nature of the data distribution, instead of relying on logistic or linear methods, or data transformations. As shown in the sample analyses in this paper, analytic techniques whose assumptions are violated by the actual distribution of mental health services utilization data are likely to yield results that: (a) over- or under-state the actual variance accounted for in the overall model, (b) identify predictor/correlate variables as significantly associated with utilization when in fact they are not, and (c) actually reverse the direction of associations between predictor/correlate variables and mental health utilization. Such results can mislead researchers, clinicians, and policymakers in a number of ways that are potentially detrimental to the development and deployment of effective and accessible mental health services.

When study results suggest stronger relationships by specific (or sets of) predictor/correlate variables with mental health services utilization that are accurate, service providers and funders may falsely assume that services should be geared to address the specific characteristics or features represented in a predictor/correlate variable set. For example, in the present dataset, findings associating higher levels of utilization with men might be interpreted as indicating that women are under-utilizing mental health services. Or the findings might be interpreted as indicating that men might be over-utilizing mental health services. Neither of these sets of conclusions is borne out by the present or many prior studies (discussed above) of the determinants of mental health services utilization. Furthermore, these spurious associations can obscure a meaningful relationship, such as the association between non-violent trauma and mental health services utilization which was present in all of the analyses (and is consistent with prior studies) (Elhai et al., 2005) but which only emerged as the sole viable correlate of utilization in the zero-inflated regression analysis.

Alternately, when the data analyses under-estimate the true overall association between a set of predictor/correlate variables and mental health services utilization (e.g., negative binomial regression results in the present dataset), the importance of the predictor/correlate variables to the planning of mental health services may be correspondingly under-valued. This could lead to false assumptions such as that characteristics including gender can be ignored in developing or delivering mental health services, because it (even if showing a statistically significant beta weight) appears to contribute very little to the variance in mental health services utilization. Anomalous findings, such as a reversal of the direction of association between service use and PTSD (in negative binomial regression)—while not of import in the present analyses due to a non-significant beta weight—might emerge as significant in large datasets (due to the increased power to detect significant relationships) as the apparently "true" direction of meaningful relationships (as noted above).

Thus, the selection of data analytic techniques whose assumptions are appropriate for the distribution of mental health services utilization data is not a trivial statistical matter. Using an approach such as that which we have schematically identified in Fig. 1 can enable mental health services researchers to maximize the accuracy and utility of their findings concerning the factors that are of great importance in large-scale clinical, policy, and fiscal decisions as well as to produce a consistent body of research that can validly inform these critical decisions.

References

Aoun, S., Pennebaker, D., Wood, C., 2004. Assessing population need for mental health care: a review of approaches and predictors. Mental Health Services Research 6, 33–46.

Aptech Systems Inc., 2005. Gauss. Author, Black Diamond, WV.

Bao, Y., 2002. Predicting the use of outpatient mental health services: do modeling approaches make a difference. Inquiry 39, 168–183.

Bland, R.C., Newman, S.C., Orn, H., 1997. Help-seeking for psychiatric disorders. Canadian Journal of Psychiatry 42, 935–942.

Bruce, M.L., Wells, K.B., Miranda, J., Lewis, L., Gonzalez, J.J., 2002. Barriers to reducing burden of affective disorders. Mental Health Services Research 4, 187–197.

Calhoun, P.S., Bosworth, H.B., Grambow, S.C., Dudley, T.K., Beckham, J.C., 2002. Medical service utilization by veterans seeking help for posttraumatic stress disorder. American Journal of Psychiatry 159, 2081–2086.

Cameron, A.C., Trivedi, P.K., 1998. Regression Analysis of Count Data. Cambridge University Press.

Econometric Software, 2002. LIMDEP. Author, Plainview, NY.

Elhai, J.D., Ford, J.D., 2007. Correlates of mental health service use intensity in the National Comorbidity Survey and National Comorbidity Survey Replication. Psychiatric Services 58, 1108–1115.

Elhai, J.D., North, T.C., Frueh, B.C., 2005. Health service use predictors among trauma survivors: a critical review. Psychological Services 2, 3–19.

Elhai, J.D., Jacobs, G.A., Kashdan, T.B., DeJong, G.L., Meyer, D.L., Frueh, B.C., 2006a. Mental health service use among American Red Cross disaster workers responding to the September 11, 2001 U.S. terrorist attacks. Psychiatry Research 143, 29–34.

Elhai, J.D., Patrick, S.L., Anderson, S., Simons, J.S., Frueh, B.C., 2006b. Gender- and trauma-related predictors of use of mental health treatment services among primary care patients. Psychiatric Services 57, 1505–1509.

Gardner, W., Mulvey, E.P., Shaw, E.C., 1995. Regression analyses of counts and rates: Poisson, overdispersed Poisson, and negative binomial models. Psychological Bulletin 118, 392–404.

Gurmu, S., Trivedi, P.K., 1992. Overdispersion tests for truncated Poisson regression models. Journal of Econometrics 54, 347–370.

Hall, D.B., Zhengang, Z., 2004. Marginal models for zero inflated clustered data. Statistical Modelling 4, 161–180.

Heilbron, D.C., 1994. Zero-altered and other regression models for count data with added zeros. Biometrical Journal 5, 531–547.

Insightful Corporation, 2005. S-Plus. Author, Seattle, WA.

Kessler, R.C., Olfson, M., Berglund, P.A., 1998. Patterns and predictors of treatment contact after first onset of psychiatric disorders. American Journal of Psychiatry 155, 62–69.

Lambert, D., 1992. Zero-inflated Poisson regression with an application to defects in manufacturing. Technometrics 34, 1–14.

Lewis, S.F., Resnick, H.S., Ruggiero, K.J., Smith, D.W., Kilpatrick, D.G., Best, C.L., Saunders, B.E., 2005. Assault, psychiatric diagnoses, and sociodemographic variables in relation to help-seeking behavior in a national sample of women. Journal of Traumatic Stress 18, 97–105.

Lin, E., Parikh, S.V., 1999. Sociodemographic, clinical, and attitudinal characteristics of the untreated depressed in Ontario. Journal of Affective Disorders 53, 153–162.

Long, J.S., 1997. Regression Models for Categorical and Limited Dependent Variables. Sage Publications.

MacCallum, R.C., Zhang, S., Preacher, K.J., Rucker, D.D., 2002. On the practice of dichotomization of quantitative variables. Psychological Methods 7, 19–40.

Mathworks, 2006. Matlab. Author, Natick, MA.

McCullagh, P., Nelder, J.A., 1989. Generalized Linear Models, 2nd edn. Chapman and Hall.

Muthén & Muthén, 2008. Mplus. Author, Los Angeles, CA.

Oliver, M.I., Pearson, N., Coe, N., Gunnell, D., 2005. Help-seeking behaviour in men and women with common mental health problems: cross-sectional study. British Journal of Psychiatry 186, 297–301.

Parslow, R.A., Jorm, A.F., 2000. Who uses mental health services in Australia? An analysis of data from the National Survey of Mental Health and Wellbeing. Australian and New Zealand Journal of Psychiatry 34, 997–1008.

Powers, R.H., Kniesner, T.J., Croghan, T.W., 2002. Psychotherapy and pharmacotherapy in depression. Journal of Mental Health Policy and Economics 5, 153–161.

Roberts, R.O., Bergstralh, E.J., Schmidt, L., Jacobsen, S.J., 1996. Comparison of self-reported and medical record health care utilization measures. Journal of Clinical Epidemiology 49, 989–995.

SAS, 2006. SAS. Author, Cary, NC.

Scientific Software International, 2005. HLM. Author, Lincolnwood, IL.

SPSS Inc., 2006. SPSS For Windows. Author, Chicago, IL.

Statacorp, 2006. Stata. Author, College Station, TX.

StatSoft, 2006. Statistica. Author. Tulsa, Oklahoma.

Tabachnick, B.G., Fidell, L.S., 2001. Using Multivariate Statistics, 4th edn. Allyn and Bacon.

TSP International, 2005. TSP. Author, Palo Alto, CA.

Walker, E.A., Newman, E., Koss, M.P., 2004. Costs and health care utilization associated with traumatic experiences. In: Schnurr, P.P., Green, B.L. (Eds.), Trauma and Health: Physical Health Consequences of Exposure to Extreme Stress. American Psychological Association, Washington, DC, pp. 43–69.

Wang, P.S., Lane, M., Olfson, M., Pincus, H.A., Wells, K.B., Kessler, R.C., 2005. Twelve-month use of mental health services in the United States. Archives of General Psychiatry 62, 629–640.