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Nonuse and Dropout Attrition for a Web-Based Mental Health Intervention Delivered in a Post-Disaster Context

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Abstract

Web-based mental health interventions are an excellent means to provide low cost, easily accessible care to disaster-affected populations shortly after exposure to an event. However, the extent that individuals will access and use such interventions is largely unknown. We examined predictors of nonuse and dropout attrition for a web-based mental health intervention in 1,249 randomly selected adults in two Texas counties—Galveston and Chambers—that were hardest hit by Hurricane Ike in 2008. Participants completed a structured telephone interview to assess demographics, impact of disaster exposure, history of traumatic events, mental health symptoms, and service utilization. Following the interview, participants were oriented and invited to access a web-based intervention and then contacted four months later to evaluate their use of the website and mental health functioning. Separate logistic and Poisson regressions were used to determine baseline predictors of nonuse attrition, predictors of dropout attrition, and predictors of completing intervention modules. Results suggested that the strongest buffer against nonuse attrition and dropout attrition was having considered seeking formal mental health treatment. Results of this study inform the development and dissemination of web-based interventions in future disaster affected areas.

Exposure to a disaster causes significant disruption to daily functioning, the effects of which can persist for weeks and months after the event (Kessler et al., 2008; McLaughlin et al., 2009; Ruggiero et al., 2012; Tracy, Norris, & Galea, 2011). Poorer mental health has been shown to be one of the lingering effects of exposure to a disaster (Norris, Friedman, & Watson, 2002; Norris, Sherrieb, & Galea, 2010; Norris & Wind, 2009), but prevention and treatment services are often limited and difficult to access in the acute post-disaster period.

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Cost and stigma associated with seeking these services may further reduce access. Technology based *e*-health interventions for mental health are a promising means to provide low cost, easily accessible treatment for anxiety and depression to such populations (Amstadter, Broman-Fulks, Zinzow, Ruggiero, & Cercone, 2009). Preliminary reviews of randomized controlled trials (RCTs) of web-delivered treatments addressing anxiety and depression have suggested that these programs have the potential to be efficacious self-help treatments (Amstadter, et al., 2009; Griffiths & Christensen, 2006; Griffiths, Farrer, & Christensen, 2010; Postel, de Haan, & De Jong, 2008). Such interventions allow patients to engage in treatment on a flexible schedule and eliminate many of the barriers associated with other approaches (e.g., travel, expense, privacy, and stigma). However, the extent to which individuals affected by a disaster will access and use such interventions is largely unknown.

Access and use of Internet interventions has been highlighted as an area of concern in the literature. Recent reviews of *e*-health treatments have strongly advocated for research examining causes of attrition in these treatments (Donkin et al., 2011; Kiluk et al., 2011). A recent review examined the methodological rigor of 75 efficacy studies of web-based interventions (Kiluk et al., 2011). Using existing standards for efficacy evaluations of traditional intervention protocols, including the Cochrane Review (Higgins & Green, 2006), Consolidated Standards of Reporting Trials (CONSORT; Schulz, Altman, & Moher, 2010), and APA Division 12 standards for evidence-based practices (Chambless & Ollendick, 2001), the authors developed 14 criteria by which to assess the methodological and analytic strength of Internet-based clinical trials. The findings indicated none met all 14 criteria and that only 3 of the 75 reviewed studies met 13 of the 14 criteria. Further, the average quality rating was 13.6 out of a possible 28 points. An area that was consistently referenced as needing greater attention in the literature was the understanding of rates of attrition and dropout from these interventions. Of the 75 trials reviewed, 30 (40%) failed to report information about dropout, and no study incorporated such information into their analytic strategy. Poor reporting of rates of dropout from web-based treatments have also been found in other reviews of this literature (Donkin et al., 2011). In the few trials that provided such information, there was substantial variability in attrition, with rates ranging from 43% to 99% (Christensen, Griffiths, Korten, Brittliffe, & Groves, 2004; Farvolden, Denisoff, Selby, Bagby, & Rudy, 2005). These high rates of dropout and the overall lack of reporting on dropout limit the conclusions that can be drawn on the efficacy, feasibility, and public health impact of web-based treatments.

Dropout from web-based treatments has been partitioned into two components (Eysenbach, 2005; Melville, Casey, & Kavanagh, 2010). The first component, *nonuse attrition*, is defined as failing to access the intervention. This is similar to participants in a traditional RCT who complete an initial assessment battery, but do not further engage in the intervention. The second component, *dropout attrition*, refers to participants who access the website, but discontinue the treatment process prematurely. Dropout attrition is operationally defined based on the type of website, multi-session *vs.* multi-component. Dropout from multi-session websites, most of which currently address a single health-related domain (e.g., depression), involves discontinued use of the site prior to the final session. This type is similar to prematurely exiting treatment in a traditional RCT. Dropout from multi-component websites, which address multiple health-related domains (e.g., posttraumatic stress, depression, substance use), captures participants who do not complete all of the recommended content. Recommended content is typically guided via screening mechanisms. Identification of predictors of both nonuse attrition and dropout attrition is a necessary first step in improving the usability and efficacy of web-based treatments as well as determining the feasibility that target populations will adopt such approaches.

Two independent teams have reviewed the literature on Internet-based interventions with a focus on overall attrition (Christensen, Griffiths, & Farrer, 2009; Melville et al., 2010). The authors concluded that participants were more likely to prematurely stop treatment if they were older, male, and had increased baseline mental health symptom severity. However, these studies had several limitations that affect their generalization to disaster victims. First, most of the reviewed studies did not report dropout or nonuse attrition rates so distinctions between predictors of these forms of attrition could not be made. Second, few studies assessed participants' reasons for early termination (Carlbring, Westling, Ljungstrand, Ekselius, & Andersson, 2001; Lange et al., 2003; Richards, Klein, & Austin, 2006). Those that did suggest that increased competing responsibilities, lack of resources, and lack of time were commonly endorsed reasons for dropout. These reasons are likely to be amplified in disaster-affected populations, as individuals have numerous competing responsibilities (e.g., contacting insurance agencies, navigating healthcare systems) and may be without basic resources or displaced for extended periods. Indeed, findings from a large outreach program for individuals recently exposed to a trauma indicated that a substantial portion of potential treatment candidates were unable to be reached via telephone or declined services (Shalev et al., 2011).

Third, the majority of these studies included web-based treatments for a single mental health condition. In the wake of a disaster, victims are at high risk for a wide range of mental health difficulties, including symptoms of post-traumatic stress disorder (PTSD), depression, excessive worry, and panic attacks (Norris et al., 2002). Unfortunately, attrition rates for multiple-component websites have not been thoroughly examined in prior work. As such, additional research on nonuse and dropout attrition of *e*-health interventions in disaster-affected populations is particularly important.

The current study examined predictors of nonuse and dropout attrition for a web-based mental health intervention, *Disaster Recovery Web* (DRW). The intervention was made available to a population-based sample that was affected by Hurricane Ike. Hurricane Ike was a strong Category 2 storm that hit Galveston, Texas, in 2008 and is the third costliest hurricane in U.S. history, resulting in 84 American deaths (CDC, 2009). Baseline data were collected from participants prior to their accessing the website a year after the hurricane made landfall. These data served as the source of predictors for nonuse and dropout attrition. Follow-up interviews were conducted via telephone with participants approximately four months after baseline data collection and 16 months after the disaster. The interviews included questions on reasons for nonuse attrition for participants who did not access the website and questions on the usefulness of the site for participants who accessed the website. Based on prior research regarding overall attrition (Christensen et al., 2009; Melville et al., 2010), male gender, older age, and increased baseline mental health symptoms were hypothesized to be associated with increased nonuse and dropout attrition. Further, participants with increased property damage and poorer access to essential services were hypothesized to have increased rates of attrition. These experiences were conceptualized as proximal indicators of increased responsibility and less availability to attend to other tasks. Due to the preliminary state of the literature and the exploratory nature of the current study, no further a priori hypotheses were made.

METHOD

Data Collection

Random-digit-dial methodology was used to survey adults from Galveston and Chambers counties approximately one year after Hurricane Ike's landfall. Data were weighted by age to be consistent with 2008 Census estimates of the populations in these counties. Eligible participants were 18 years or older, had a landline telephone, resided in the area during the hurricane, and reported having Internet access at home. After an eligible household was contacted, interviewers used the most recent birthday method to select a participant. This common and accepted method has been demonstrated to be technically equivalent or superior to other respondent selection techniques and places less burden on the participant (Gaziano, 2005). This approach asks to speak with the person with the most recent birthday, thus avoiding the need to obtain a comprehensive list of all potential respondents in the house and then select one at random. Throughout recruitment, the gender balance in the sample was systemically monitored nightly by supervisors. On evenings where the gender distribution favored one gender, the protocol was adjusted such that interviewers requested to speak with members of the other gender in the household with the most recent birthday. The overall cooperation rate, calculated according to American Association for Public Opinion Research (AAPOR) industry standards (i.e., [completed interviews + screen outs] divided by [completed interviews + screen outs + refusals]), was 66%. A total of 5,536 households were contacted for the interview. A total of 2,403 failed to meet inclusion criteria, 1,768 refused to complete the interview, and 116 were not interviewed because the quota for their area had been met.

Participants

Participants were 1,249 adults who resided in Galveston and Chambers counties in Texas at the time of Hurricane Ike's landfall. The average age for the sample was $M = 45.80$ years ($SD = 17.28$) and was equally distributed across genders due to targeted enrollment. Self-reported ethnicity was 76.1% White, 13.0% Black, 6% Hispanic, 2.4% Asian, 1.1% American Indian/ Alaska Native, 1.1% Native Hawaiian/Pacific Islander, and 0.3% Other. The sample was well educated, with 62% reporting completing some college. Income levels for the sample were normally distributed, with the median annual household income falling between $40,000 and $60,000. All participants reported having regular, good Internet access from their home, as this was an inclusion criterion for the study. The sample was representative of the broader area with regard to income and ethnic background, with the exception of those of Hispanic origin. The reduced proportion of those of Hispanic origin in the study is likely due to the interview and website only being available in English. Further, the mean age of the sample was greater than that of the area and so all subsequent analyses were weighted for age.

Measures

A structured telephone interview assessed demographics (age, gender, and income), impact of exposure to Hurricane Ike, mental health symptoms, and service utilization.

Disaster Exposure—Hurricane exposure questions were modified from prior research with adults affected by Hurricane Hugo (Freedy, Saladin, Kilpatrick, Resnick, & Saunders, 1994) and the 2004 Florida hurricanes (Acierno et al., 2007). Hurricane disaster exposure was assessed with 23 binary items across three primary domains: interpersonal impact, damage to property, and loss of basic services. Domains were created from a review of prior disaster exposure literature, classifications consistent with the Federal Emergency Management Agency (FEMA), and consensus among the authors and other expert consultants on the project. Items assessing interpersonal impact examined the effect of the storm on the participant's personal safety, sense of self, and injury to their broader social network. Items included whether the person feared for their own safety, feared for the safety of loved ones, feared for the safety of pets, was present for the hurricane, and lost their job as a result of the hurricane. The property domain assessed damage caused by the hurricane to the person's home, vehicle, property, and personal items. The loss of basic services domain measured whether the person was without basic services for a period of greater than one week, including water, electricity, clean clothing, food, shelter, transport, and spending money, or was displaced from their home. Responses for each domain were summed and used as predictors. The three domains were entered as individual predictors in the final outcome model.

Mental Health Measures—Mental health was assessed with self-report measures of PTSD, the *PTSD Checklist–Civilian version* (PCL-C; Weathers, Litz, Huska, & Keane, 1994), and depression, the *Center for Epidemiologic Studies–Depressed Mood Scale-10* (CES-D; Radloff, 1987). The PCL-C is a 17-item instrument that assesses DSM-IV criteria B, C, and D for PTSD. Each item consists of five response options (range of possible scores = 17 to 85). The strong psychometric properties of the PCL, including internal consistency, test-retest reliability, convergent validity, discriminant validity, and sensitivity, and specificity have been documented in the literature (Ruggiero, Ben, Scotti, & Rabalais, 2003). Internal consistency for the current sample was excellent (α = 0.92). The CESD-10 is a 10-item instrument that was designed to identify persons at risk for clinical depression (Andresen, Malmgren, Carter, & Patrick, 1994). It was developed from the original 20-item CES-D measure, which has been validated in various populations with high internal consistency, satisfactory test-retest correlations, and strong concurrent validity, discriminant validity, and sensitivity to change (Radloff, 1987; Smarr, 2003). The CESD-10 is widely used and has good predictive accuracy when compared to the full-length CES-D scale. Internal consistency for the current sample was good (α = 0.85). The two scales were entered as individual predictors in the final model.

Mental Health Service Utilization—Mental health service utilization was assessed across two categories. First, participants were asked about their health-seeking behaviors and their use of the Internet for obtaining health-related information. Specifically, participants were asked if (1) they had considered using mental health services in the past, (2) whether they had used the Internet to obtain information about health issues, and (3) whether they had used the Internet to obtain information about mental health issues specifically. Second, participants were asked if they had ever received care for an emotional problem from a (4) doctor, (5) mental health professional, (6) nurse, (7) member of the clergy, or (8) self-help sources. Responses were dichotomous (yes/no). These items were entered as 8 individual predictors in the final models.

Procedures

Computer-assisted structured telephone interviews were conducted by a large survey research firm. Supervisors conducted random checks of data entry accuracy and interviewers' adherence to the assessment procedures. The average interview length was 21 minutes, and respondents were compensated for their participation in the study as well as their access of the website. At the end of the baseline interview, participants were introduced to the web phase of the study and invited to access the DRW website. Specifically, they were told, "The website was designed specifically for people who have experienced a disaster and you might find it to be useful." They were provided with the website address and a unique password, and were told that the password would provide access for the four-month period between the baseline and follow-up telephone interviews. Participants were then contacted four months later to evaluate their use of DRW and mental health functioning as part of a larger study (Ruggiero et al., 2012). Follow-up questions for the non-use sample pertained to reasons for their failure to access the website. Participants were asked to endorse one of five statements that best reflected their lack of use of the website as presented in Table 1. Follow-up questions for those who accessed the website pertained to helpfulness of the website, ease of use, and time spent with the materials.

Web-Based Intervention—The structure of DRW follows that of previously published web interventions (Litz, Engel, Bryant, & Papa, 2007). Briefly, participants were initially provided with an informed consent form and options to consent to the study or decline participation. Consenting participants then completed a brief mental health screen to determine which treatment modules, if any, would be most relevant. The screener was designed to be inclusive, such that participants with sub-clinical symptom levels would screen into the intervention modules. Participants who screened into a module were immediately provided a website dashboard with access to the relevant modules. Those who did not screen into a module were notified that this area did not appear to be problematic for them and that it was not necessary to access the module. However, a link to access the content of the module was still available to these participants, should they choose to review the content. Participants who accessed module content were randomized either to an experimental condition that received full module content or a control condition that received assessment-only content. Content prior to this point was identical for all participants.

Modules were designed to address symptoms of depression, PTSD, generalized anxiety disorder, panic disorder, alcohol abuse, marijuana abuse, and cigarette smoking. Modules were developed with attention to several literatures, including epidemiological research on mental health and health-risk correlates of disasters (Acierno et al., 2007; Acierno, Ruggiero, Kilpatrick, Resnick, & Galea, 2006; Galea et al., 2002, 2003; Norris et al., 2002; Ruggiero et al., 2006, 2009; Vlahov et al., 2002; Vlahov, Galea, Ahern, Resnick, & Kilpatrick, 2004), best practices in behavior therapy and brief interventions (Chambless & Ollendick, 2001; Litz & Gray, 2004), motivational interviewing and enhancement (Burke, Arkowitz, & Menchola, 2003), and sources on self-help, web-based, and distance-learning interventions (Amstadter et al., 2009; Marks, Cavanagh, & Gega, 2007).

Attrition—Nonuse attrition was defined as participants who completed the baseline telephone interview but did not access the website. Dropout attrition was divided into two categories: access attrition and completion attrition. Access attrition was classified as not having accessed a module after completing the website screens. Completion attrition was defined as failing to complete a module after having accessed a module.

Data Analysis

Partial data from the baseline interview was found in 16% of the cases (n = 200). Missing data were addressed with multiple imputation. Missing values were values imputed for 100 data sets according to the guidelines of Little & Rubin (1987), with all available variables in the current analysis serving as auxiliary variables using the NORM software package (Schafer, 1997). Auxiliary variables have been shown to increase the accuracy of final parameter estimates without biasing the results of subsequent analyses (Collins, Schafer, & Kam, 2001). Analyses were then conducted across all 100 data sets and pooled using SPSS 19.

Logistic regressions were used to determine baseline predictors of nonuse attrition and predictors of access attrition for accessing a treatment module. For the access attrition analyses, the sample was divided among those who had screened into at least one module and those who had screened into zero modules. Predictors were grouped into categorically meaningful blocks and entered hierarchically. The first block contained demographic variables; the second block contained disaster exposure variables; the third contained mental health symptoms; and, the final block contained service utilization variables. The dependent variable was dummy coded such that 0 indicated nonuse/dropout and 1 indicated use/adherence. Due to the exploratory nature of the study, variable blocks were entered in a reverse stepwise fashion with removal based on odds ratio (OR). This approach has shown

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to be effective for maintaining error rates when conducting exploratory analyses (Menard, 2002). This process enters all variables within a given block and then removes the variable with the lowest OR. Change in model fit is evaluated with a chi-square difference test such that if model fit improves, the process is repeated for the variable with the next lowest OR. This process is repeated until model fit no longer improves with the removal of a variable. Analyses for the predictors of completion attrition included the number of modules that a person screened into as a covariate.

Predictors for completion attrition within the treatment and control conditions were assessed with separate Poisson regressions. Again, the sample was divided among those who screened into at least one module and those who screened into zero modules. Further, the number of modules for which persons screened positive was included as a covariate in the sample of those who had screened into a least one module.

RESULTS

Descriptive statistics and frequencies for the sample are presented in Table 2 and Figure 1. For the baseline sample (n = 1,249), 48% (n = 597) did not access the website and 0.4% (n = 5) did not consent to the web portion of the study. Those who did not consent were removed from subsequent analyses. All participants who accessed the website and provided consent also completed the module screeners (n = 652). Approximately 30% of the usage sample (n = 192) dropped out after completing the screening assessment. Of those that accessed a treatment module, 9% of the control group (n = 20) and 20% (n = 47) of the intervention group did not complete content for any modules.

A logistic regression was used to determine predictors of nonuse attrition (n_{use} = 652; n_{nonuse} = 597). Variables were grouped into conceptual blocks and entered hierarchically (see Table 3). The final model included significant predictors for age, such that older individuals were less likely to use the website (OR = 0.94, 95% CI 0.90 to 0.99), having considered mental health treatment (OR = 1.44, 95% CI 1.08 to 1.92), and having used the Internet to obtain information about physical health (OR = 1.50, 95% CI 1.14 to 1.97). Nonsignificant predictors that were retained in the model included education (OR = 0.74, 95% CI 0.50 to 1.08) and having received prior emotional support from a member of the clergy (OR = 0.65, 95% CI 0.41 to 1.01). The final model supported the inclusion of an Age X Education interaction (OR = 1.01, 95% CI 1.001 to 1.014; see Table 3). Simple effects analyses were conducted to explicate the interaction terms. Findings suggested that at low levels of education, there was a strong negative relation between age and the likelihood of use ($b = -0.01$, $p < 0.01$). At high levels of education, however, there was no relation between age and the likelihood of using the website ($b < 0.01$, $p = 0.56$).

Logistic regressions were used to determine predictors of access attrition in those that used the study website ($n_{adhered}$ = 460; $n_{dropout}$ = 192). Separate models were used for those who screened into at least one module ($n_{adhered}$ = 324; $n_{dropout}$ = 42) and those who did not screen into any modules ($n_{adhered}$ = 136; $n_{dropout}$ = 150). For those who screened into at least one module, the final model suggested that the number of modules a person screened into was negatively associated with access attrition (OR = 1.66, 95% CI 1.15 to 2.12). However, damage to property was positively related to access attrition (OR = 0.75, 95% CI 0.60 to 0.94). For those who did not screen into any modules, being male was the only significant predictor associated with access attrition (OR = 0.48, 95% CI 0.28 to 0.81).

Finally, separate Poisson regressions were used to evaluate completion attrition among those with a positive module screen and those without a positive module screen (see Table 4). For participants without a positive module screen who were randomized to the control group

($n_{completion}$ = 64; $n_{dropout}$ = 81), being male (b = 0.70, p = 0.01, OR = 2.01, 95% CI 1.16 to 3.48), having used the Internet to search for mental health information (b = 1.10, p = 0.01, OR = 2.99, 95% CI 1.61 to 5.57), increased PTSD symptoms (b = −0.23, p = 0.03, OR = 0.79, 95% CI 0.64 to 0.98), and being younger (b = −0.03, p = 0.01, OR = 0.98, 95% CI 0.96 to 0.99) were associated with reduced completion attrition. For those without a positive module screen and who were randomized to the intervention condition ($n_{completion}$ = 56; $n_{dropout}$ = 85), having searched online for mental health information (b = 1.03, p = 0.01, OR = 2.81, 95% CI 1.46 to 5.42) and increased loss of services (b = 0.51, p = 0.01, OR = 1.67, 95% CI 1.14 to 2.43) were associated with reduced completion attrition. For those with a positive module screen who were randomized to the control condition ($n_{completion}$ = 153; $n_{dropout}$ = 28), the number of positive module screens (b = 0.17, p = 0.01, OR = 1.19, 95% CI 1.06 to 1.34) was associated with reduced completion attrition. For those with a positive module screen and who were randomized to the intervention condition ($n_{completion}$ = 130; $n_{dropout}$ = 55), loss of services was associated with reduced completion attrition (b = 0.09, p = 0.04, OR = 1.09, 95% CI 1.01 to 1.20). Younger age (b = −0.01, p = 0.07, OR = 0.99, 95% CI 0.98 to 1.01) and using the Internet to access health information (b = 0.30, p = 0.08, OR = 1.35, 95% CI 0.96 to 1.92) approached significance.

Follow-up data were obtained from the majority of the nonuse subsample (n = 386, 64%) and the use subsample (n = 491, 76%). For the nonuse subsample, participants were asked to identify reasons for not accessing the website. The most commonly endorsed reason was lack of relevance to their needs (n = 158, 41%; see Table 1). For the access sample, the majority of participants reported using the website between 30 and 60 minutes (n = 275, 56%). The majority rated the website as easy to use (n = 428, 87%) and found it helpful (n = 310, 63%). A large portion of the subsample that used, accessed, and also completed the website endorsed the statement, “The website gave me suggestions to change thoughts, emotions, and behaviors” (n = 216, 44%).

DISCUSSION

The current study provided the first examination of predictors of nonuse and dropout attrition in a web-based intervention for a disaster-affected population-based sample. The main findings suggested that having previously considered seeking mental health treatment and having used the Internet for health-related information reduced nonuse attrition. Further, having used the Internet to obtain health and mental health information was associated with reduced access attrition and completion attrition. Finally, lack of relevance was the most common reason for lack of use of the web-based intervention in those that decided not to use the website. These findings are consistent with prior theoretical and empirical work that has suggested that the relevance of website content reduces attrition and promotes use of Internet-based interventions (Chiu & Eysenbach, 2010). As a result, web-based treatments for disaster-affected populations may be of most relevance and utility to those who have considered or have had some experience with mental health treatments.

The findings of the current study provide preliminary evidence that the relevance of web-based intervention may be malleable. After individuals screened into a module, a notification appeared that the subsequent content was highly relevant and encouraged further participation. Alternatively, those who failed to screen into a module were provided with neutral feedback about the subsequent content, but were also offered an opportunity to continue. As such, those who did not screen into any modules were far more likely to drop out of the intervention (62%) than those who received a positive screen (23%). This finding is consistent with the framework of Chiu and Eysenbach (2010) and further suggests that it may be possible to reduce attrition by emphasizing the relevance of the intervention. However, it may be the case that those with a positive screen had a greater need for care,

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which compelled them to continue. Additional experimental work is needed to further determine the unique effect of providing relevant specific feedback on attrition as opposed to other types of encouragement.

The findings of the current study also provide preliminary information about the reach of a web-based intervention for disaster-affected victims. Reach presents a framework with which to understand the broad effectiveness of an intervention by accounting for the proportion of the population who are candidates for a given approach (Koepsell, Zatzick, & Rivara, 2011). Candidacy is defined as those who are eligible (e.g., have an Internet connection) and can tolerate (e.g., will consent to) the intervention. One strength of web-based trials is the relatively small number of exclusion criteria for participation. Of the 5,536 contacted individuals, 43% were not eligible, whereas 4% refused to participate. Further, 23% of the total number of contacted individuals were invited to treatment. The interpretation of these values is facilitated by a comparison to an alternative strategy of engaging victims of trauma in care—the trauma outreach study (Shalev et al., 2011). Patients in this project were contacted within three weeks of experiencing a traumatic event and assessed for their need for care. Those who displayed distress related to their event, were able to attend traditional psychotherapy, and did not have conflicting medical conditions were invited to treatment. Of the 4,224 individuals who were contacted, 73% were not eligible, 18% refused to participate, and 9% were invited to treatment. The different rates of invitation to treatment highlight the increased inclusivity of web-based approaches. However, additional work is needed to determine if the same segments of the population who would be invited to web-based strategies are also those who would be invited to other approaches. That is, web-based approaches and outreach strategies may provide access to different portions of the population.

The difference in access of interventions across the present study and a large scale outreach study highlight the potential for web-based strategies in stepped care models. Stepped care provides treatment that gradually increases in intensity to best match care with the needs of the patient. Internet-based approaches would be considered a mid-to-low intensity approach. Those needing more treatment would then progress to more intense care, such as face-to-face psychotherapy. Alternatively, the findings suggest that web-based interventions would also serve as an excellent method to help those that have previously received mental health treatment after exposure to a subsequent traumatic event. Prior work has demonstrated the utility of “booster sessions” after treatment to maintain gains (McWhirter, McWhirter, & Bundy, 2011; Raue, Schulberg, Heo, Klimstra, & Bruce, 2009; Schlup, Munsch, Meyer, Margraf, & Wilhelm, 2009). This may be especially true for disaster-affected populations that may be at higher risk for relapse after exposure to a significant event, such as another natural disaster. As shown by the current study, those who have received or considered treatment in the past are more likely to access and use such web-based treatments. Such web-based self-help approaches may provide a fruitful method to provide rapid “booster” sessions to disaster victims after an event to promote their use of previously acquired skills.

Surprisingly, there were relatively few demographic predictors of both types of attrition. Increased age was associated both with nonuse attrition and dropout attrition. However, increased education helped to buffer against the effects of older age with respect to nonuse attrition. It should be noted that the data from the current study were obtained in 2008, and the effect of age in this study was relatively small (OR = 0.99). Recent reports suggest that older adults are increasingly more likely to use the Internet to obtain health-related information (Fox, 2009), especially through mobile devices (Fox, 2010). The association between age and Internet use is likely to diminish as older adults become increasingly familiar with the Internet.

Disaster exposure had an unusual association with attrition rates. Property damage as a result of the disaster was associated with increased dropout attrition. Such an association may be explained by the low relevance of website materials to those that suffered a great deal of property damage. The current website targeted mental health symptoms as opposed to other aspects of disaster recovery (e.g., repairing a home or replacing a vehicle). Those who experienced greater property damage may have completed the screening assessment and felt the content was not relevant to their immediate concerns and elected to drop out. Loss of basic services, however, was related to completion of more treatment modules. This suggests that some elements of disaster exposure may lead to increased use. This pattern of results requires additional work to better understand how specific aspects of a traumatic experience may impact the use of *e*-health interventions.

Interestingly, baseline mental health symptoms were unrelated to nonuse and dropout attrition. This result has implications for the manner in which e-health interventions are disseminated. Targeting those with greater symptom severity may do little to reduce nonuse and dropout attrition. The primary reason for nonuse in the sample was belief that the website was not relevant to their concerns. As such, presenting the website as a means to facilitate all aspects of disaster recovery may improve initial usage rates in future studies and in open access trials. Additionally, the inclusion of a wide array of content for the recovery of others, of lost items, and of self may further increase relevance and reduce attrition.

Consistent with reports from prior reviews of this literature (Christensen et al., 2009; Melville et al., 2010), there were few predictors included in the current study that were highly associated with nonuse and dropout attrition. Further, the odds ratios for those variables that were associated with attrition were modest (1.01 to 1.49). These approaches surprisingly suggest that need, as defined by increased mental health symptoms and disaster exposure, is largely unassociated with usage. Such results strongly advocate the need for work detecting causes of attrition and methods to reduce these rates. Research specifically dedicated to understanding motivational factors for using and completing *e*-health interventions is a critical step in the advancement of this field. Towards this aim, mental health experts are encouraged to partner with collaborators from a broad range of disciplines, including graphic design and marketing, who have greater experience in dissemination, consumer buy-in, and usability. The expertise from such fields is likely to lead to the development of highly engaging content that will promote repeated use. The knowledge gained from such research will directly inform feasibility, efficacy, dissemination, and implementation efforts of *e*-health treatments.

The current study had several limitations. First, measures that would be directly related to attrition, including familiarity with technology, estimated time spent on the Internet, and common tasks completed on the Internet, were not included. Such variables are likely to be strong predictors of nonuse and dropout attrition and should be integrated into future studies. In addition to providing further information about use and nonuse, such variables would improve efficacy research by better informing missing data methods. Experts have recommended that variables likely to predict “missingness” be included in studies, despite their lack of association with the primary research question (Baraldi & Enders, 2010). Such data have been shown to greatly enhance estimates for hypothesized relations when using more advanced methods for handling missing data. Second, the current study had attrition for the follow-up interview, although such rates were observed in similar studies (Postel et al., 2008). This may limit the generalizability of the findings regarding nonuse attrition to the general population. Finally, the intervention in the current study was intended to be used as a secondary prevention treatment that would be accessed and used once. Alternatively, web-based treatments often require participants to access the website multiple times over a period of several days or weeks. Such requirements allow for additional points of dropout that could not be assessed in the current study. Additional work should focus on this critical aspect of dropout within a disaster sample.

Despite these limitations, the current study was the first to present data on non-use and dropout attrition for a web-based intervention in a disaster-affected sample. The findings suggested that such an intervention is most likely to be accessed and used by those who have considered mental health treatment in the past and those with a greater loss of basic services. Nonuse and dropout attrition rates for the current study were 47% and 40%, respectively. These rates are comparable to other web-based interventions. Although these rates are greater than those found in large scale RCTs for traditional face-to-face to treatments (Christensen et al., 2009; Christensen, Reynolds, & Griffiths, 2011), it is notable that this study recruited a population-based sample, whereas RCTs traditionally recruit treatment-seeking samples. Future research should continue to examine predictors of dropout and nonuse across *e*-health interventions. Such work is critical to evaluating the efficacy of these approaches (Donkin et al., 2011) and is necessary to inform dissemination efforts (Christensen et al., 2011).

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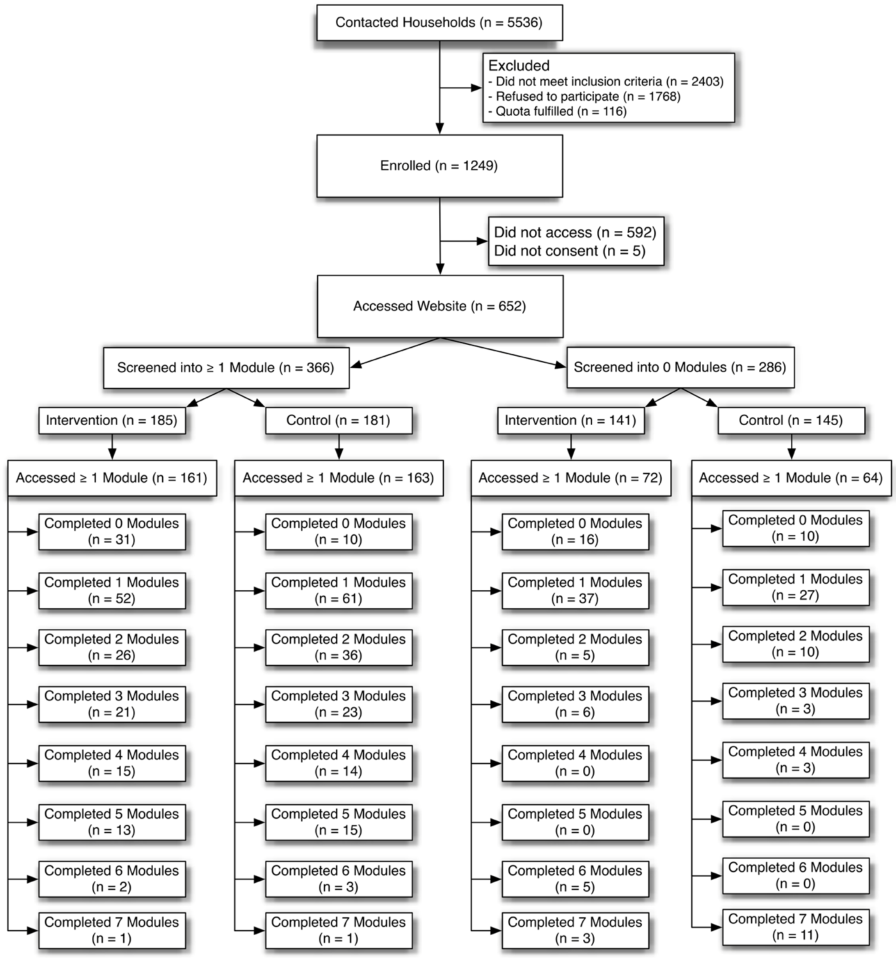

FIGURE 1.
Flowchart of participants lost to nonuse attrition and dropout attrition.

TABLE 1

Statements Endorsed as Reasons for Nonuse from Nonuse Sample That Completed Follow-Up Interview (n = 386)

Reason for not accessing the website	%
You were too busy	18
You did not feel it would be useful to you	15
You were concerned about the security of the website	3
You did not feel it was relevant to your situation	41
You went to the website but had trouble using it	8

TABLE 2

Descriptive Statistics and Frequencies for Sample

Variable	Nonuse Sample (n = 597)		Dropout Sample (n = 259)		Completer Sample (n = 393)	
	n	**%**	***n***	**%**	***n***	**%**
Gender (Male)	321	53.7	159	61.4	161	41.0
Ethnicity:						
Caucasian	445	74.6	202	77.9	297	75.5
African American	81	13.6	18	6.9	63	15.9
Asian American	13	2.2	16	6.1	0	0
Native American	8	1.4	2	0.9	3	0.08
Pacific Islander	4	0.7	4	1.5	6	1.4
Hispanic	38	6.3	15	6.0	21	5.3
Other	8	1.2	2	0.8	3	0.5
Education:						
Completed High School	153	25.7	47	18.3	60	15.4
Some College	180	30.1	96	36.9	170	43.3
Completed College	170	28.4	58	22.5	106	26.9
Graduate Work	94	15.7	58	22.2	57	14.5
Income:						
< $40,000 per year	143	24.0	37	13.9	85	21.7
$40,000–$80,000	145	24.4	74	28.6	115	29.2
> $80,000	206	34.4	116	51.4	141	36.9
Missing	103	17.2	32	12.5	52	13.3
Service Use:						
Sought MH services in past	177	29.7	73	28.2	171	43.5
Searched Online for Health Information	338	56.6	156	60.1	299	76.1
Searched Online for Mental Health Information	142	23.7	54	21.0	156	39.8
Received emotional help from:						
Doctor	118	19.8	37	14.4	109	27.8
Mental Health Provider	116	19.4	45	17.3	113	28.8
Clergy	45	7.5	14	5.5	40	10.3
Nurse	18	3.0	1	0.5	13	3.3

Variable	Nonuse Sample (n = 597)		Dropout Sample (n = 259)		Completer Sample (n = 393)	
	n	**%**	***n***	**%**	***n***	**%**
Self-Help	19	3.2	8	2.9	21	5.4
	M	***SD***	***M***	***SD***	***M***	***SD***
Age	47.51	18.05	45.72	17.38	43.86	15.76
PTSD Symptoms	22.83	9.88	19.70	6.28	24.16	11.54
Depression Symptoms	4.38	5.51	2.87	3.93	5.39	6.16
Interpersonal Impact	1.23	1.04	0.90	0.90	1.29	1.06
Damage to Property	2.50	1.56	2.56	1.36	2.69	1.48
Loss of Basic Services	1.30	1.57	1.00	1.20	1.35	1.56

TABLE 3

Final Model for Logistic Regression Predicting Nonuse Attrition and Logistic Regression

	OR	95% CI
Predictors of Nonuse (n_{use} = 652; n_{nonuse} = 597)		
Education	0.74	0.51–1.09
Age	0.94**	0.90–0.99
Education × Age	1.01**	1.001–1.014
Having Considered Mental Health Treatment	1.44**	1.08–1.92
Having Searched Online for Health Information	1.40**	1.14–1.97
Emotional Support from Clergy	0.65	0.41–1.01
Predictors of Dropout after Completing Screen ($n_{adhered}$ = 393; $n_{dropout}$ = 259)		
Screened into ≥ 1 modules ($n_{adhered}$ = 328; n_{dropou}= 46)		
Number of Positive Modules Screens	1.66**	1.15–2.12
Damage to Property	0.75**	0.60–0.94
Screened into 0 modules ($n_{adhered}$ = 123; $n_{dropout}$ = 145)		
Male	0.48**	0.28–0.81

Note.

* $p < 0.05$.

** $p < 0.01$.

OR = Odds Ratio. 95% CI = 95% Confidence Interval

TABLE 4

Poisson Regression Predicting Dropout Attrition for Module Completion in Intervention and Control Conditions

	Intervention Condition					
	Screened into ≥ 1 module			Screened into 0 modules		
Variable	***b* (*SE*)**	**OR**	**95% CI**	***b* (*SE*)**	**OR**	**95% CI**
Number of Modules with a Positive Screen	0.01 (0.06)	1.01	0.89–1.15	–	–	–
Male	0.10 (0.14)	1.11	0.83–1.46	−0.07 (0.25)	0.94	0.57–1.54
Ethnic Minority	−0.02 (0.19)	0.98	0.96–1.15	−0.16 (0.13)	0.99	0.67–1.32
Education	0.06 (0.06)	1.06	0.94–1.19	0.29 (0.16)	1.33	0.97–1.83
Age	-0.01^{+} (0.01)	0.99^{+}	0.98–1.01	−0.01 (0.01)	0.99	0.98–1.02
Income	−0.04 (0.04)	0.96	0.89–1.05	−0.02 (0.11)	0.82	0.79–1.20
Depression	0.01 (0.02)	1.02	0.97–1.04	0.02 (0.04)	1.02	0.94–1.10
PTSD	0.01 (0.01)	1.01	0.98–1.02	0.01 (0.04)	1.01	0.92–1.09
Interpersonal Impact of the Disaster	−0.09 (0.06)	0.92	0.81–1.04	−0.21 (0.17)	0.81	0.58–1.13
Damage to Property	−0.01 (0.05)	0.99	0.90–1.10	−0.11 (0.12)	0.90	0.71–1.13
Loss of Basic Services	0.09^{*} (0.05)	1.09^{*}	1.01 –1.20	0.51^{**} (0.19)	1.67^{**}	1.14–2.43
Having Considered Mental Health Treatment	−0.13 (0.21)	0.88	0.58–1.32	−0.21 (0.43)	0.81	0.35–1.90
Having Searched Online for Health Information	0.30^{+} (0.18)	1.35^{+}	0.96–1.92	−0.22 (0.27)	0.81	0.47–1.38
Having Searched Online for Mental Health Information	−0.15 (0.16)	0.86	0.63–1.19	1.03^{**} (0.34)	2.81^{**}	1.46–5.42
Having Received Emotional Help From:						
Doctor	0.04 (0.26)	1.04	0.63–1.71	−0.73 (0.89)	0.48	0.08–2.77
Mental Health Provider	0.17 (0.25)	1.19	0.73–1.94	0.20 (0.92)	1.22	0.20–5.21
Clergy	−0.08 (0.22)	0.92	0.60–1.42	0.59 (0.71)	1.80	0.45–2.32
Nurse	−0.47 (0.42)	0.62	0.27–1.42	1.17 (0.93)	1.47	0.52–1.98
Self Help	0.03 (0.07)	1.02	0.32–1.15	0.20 (0.74)	1.04	0.67–1.87

	Control Condition					
	Screened into ≥ 1 module			Screened into 0 modules		
Variable	***b* (*SE*)**	**OR**	**95% CI**	***b* (*SE*)**	**OR**	**95% CI**
Number of Modules with a Positive Screen	0.17^{**} (0.06)	1.106^{**}	1.06–1.34	-	-	-
Male	−0.01 (0.13)	0.993	0.47–2.62	0.70^{**} (0.25)	2.01^{**}	1.16–3.48

	Control Condition					
	Screened into ≥ 1 module			Screened into 0 modules		
Variable	***b* (*SE*)**	**OR**	**95% CI**	***b* (*SE*)**	**OR**	**95% CI**
Ethnic Minority	−0.11 (0.16)	1.263	0.79–1.12	−0.03 (0.07)	0.98	0.68–1.12
Education	−0.04 (0.05)	1.071	0.87–1.07	0.29 (0.16)	1.33	0.97–1.83
Age	< 0.01 (0.01)	0.84	0.99–1.01	−0.03* (0.01)	0.98*	0.96–0.99
Income	0.05 (0.04)	0.918	0.97–1.14	−0.12 (0.08)	0.89	0.77–1.04
Depression	< 0.01 (0.01)	1.184	0.97–1.02	0.02 (0.04)	1.02	0.94–1.10
PTSD	0.01 (0.01)	1.006	0.99–1.02	0.18* (0.07)	1.20*	1.04–1.38
Interpersonal Impact of the Disaster	0.08 (0.06)	0.827	0.96–1.22	−0.18 (0.17)	0.84	0.61–1.16
Damage to Property	−0.01 (0.05)	0.966	0.89–1.09	−0.23 (0.11)	0.79	0.64–0.98
Loss of Basic Services	0.02 (0.06)	0.998	0.92–1.14	0.12 (0.14)	1.13	0.86–1.49
Having Considered Mental Health Treatment	0.23 (0.21)	1.054	0.84–1.90	0.49 (0.39)	1.63	0.75–3.52
Having Searched Online for Health Information	0.07 (0.15)	1.189	0.79–1.45	−0.62 (0.31)	0.54	0.29–0.99
Having Search Online for Mental Health Information	−0.17 (0.14)	1.083	0.64–1.10	1.10** (0.32)	2.99**	1.61–5.57
Having Received Emotional Help From:						
Doctor	−0.09 (0.22)	1.023	0.60–1.42	−0.22 (0.46)	0.80	0.33–1.96
Mental Health Provider	0.17 (0.22)	0.992	0.78–1.81	−0.15 (0.59)	0.86	0.27–2.75
Clergy	0.01 (0.19)	1.006	0.69–1.48	−0.93 (1.13)	0.40	0.04–3.63
Nurse	−0.19 (0.31)	1.106	0.45–1.53	2.03 (1.24)	1.23	0.43–2.67
Self Help	−0.12 (0.31)	0.993	0.87–1.25	0.05 (0.09)	1.10	0.89–1.22

Note.

* $p < 0.05$.

** $p < 0.01$.

+ $p < 0.06$.

OR = Odds Ratio. 95% CI = 95% Confidence Interval.

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