Testing Web Site Design and

Promotional Content

Xavier Drèze and Fred Zufryden*

August 18, 1998

**Xavier Drèze is Assistant Professor of Marketing at the University of Southern California, Fred Zufryden is the Ernest W. Hahn Professor of Marketing at the University of Southern California.* *The authors would like to express their gratitude to Kurt Eto for allowing them to use his Web site in the name of science.*

Abstract

The World Wide Web has grown at a spectacular rate as a medium for promoting and marketing products and services. At the same time, little is known about the effectiveness of advertising on the Internet. Yet, the Web offers unique, but so far largely unexplored, research opportunities for measuring and analyzing the effectiveness of promotional content. In this paper, we develop and apply a conjoint analysis-based methodology to evaluate the design and the effectiveness of promotional content on the Web. This methodology is shown to be ideally suited for this purpose by virtue of its unobtrusiveness, external validity, large sample sizes, timeliness, as well as its low implementation cost.

Introduction

It has recently been suggested (Ducoffe, 1996; and Ducoffe et al., 1996) that "continuing developments in the area of new media technology represent *the* most important influence on the future of the advertising industry over the next 10 to 15 years." This view is supported by the tremendous growth of the Internet and the World Wide Web that has been witnessed in recent years. This growth is of particular significance to the advertising industry as "advertiser-supported" Web sites have proliferated on the Internet (Hoffman, Novak and Chatterjee 1995). In particular, Novak and Hoffman (1996) describe three major types of advertiser-supported sites: 1) sponsored content sites (e.g., Los Angeles Times), 2) sponsored search agents and directories (e.g., Yahoo) and 3) entry portal sites (e.g., Netscape). Here, advertisers, such as company sponsors, may insert "banner ads" in the latter publisher sites that provide links to company Web sites which may include advertising and sales information about company products. This advertising sponsorship model is gaining significant attention as a means of advertising and selling products and services on the Web. Moreover, various related business models are currently emerging for Web-based advertising, including single-sponsored sites as well as various fee arrangements (e.g., finder's fees, and microfee payment per unit content), that suggest future changes and growth in advertising revenue generation on the Web (Zilber, 1997).

Nevertheless, advertising expenditures on the Web are currently small relative to those of standard media. For example, 1995 Web expenditures have been estimated at 312 millions of dollars for the Web versus 38.1 billions for the television medium (Jupiter Communications, 1996). However, the astonishing growth of Web users in recent years, the rapidly increasing commitments by numerous companies to establish a presence on the Web (*The Economist*, 1995), as well as the growing proportion of overall company advertising budgets dedicated to Web advertising, all suggest a formidable potential for Web-based advertising in the years to come that cannot be overlooked. In 1995, the number of advertiser sites on the Web was *fifty times* greater than it was two years before (CASIE report, 1995).

Concurrently to sponsoring Web sites through advertising, many companies are also setting up their own Web sites as an alternative way to reach consumers. The costs associated with hosting a Web site vary greatly depending on the scope of the project. The operating costs of internally managed Web sites range from $200,000 to $3 millions (Forrester Research, 1995). In addition to the running cost of the Web sites, the cost of designing the Web site content can be steep. According to a recent report from Forrester Research (1997), the expenditure on third party Web site designer is expected to reach $10 billion in 2000, from $582 in 1996. The same report states that the average cost of developing the content of a Web site is currently $267,000.

Given the promise of the Web as a medium for electronic commerce and advertising, third party companies, such as Netcount and I/Pro, have emerged that are now focusing on developing relevant census-based measures of advertising effectiveness for Web-based advertising. By tracking visitor flows as well as advertising exposure patterns, measures are currently being developed that not only provide a means of measuring advertising effectiveness but also suggest a pricing structure for Web-based advertising in relation to standard media. However, the measurement of advertising effectiveness on the Web is a complex problem. In particular, the impact of promotional content on the Web is not accurately known because of difficulties associated with measurement (Murphy, 1996). Aside from the technical problems associated with measuring Web traffic and exposure patterns, measurement is further complicated by the fact that the Web environment for advertising has characteristics that distinguish it from those of standard advertising media. In particular, Web advertising has hybrid characteristics that combine those of the print, broadcast, outdoor, and direct response media. Moreover, continuing enhancements in graphic technology which is giving rise to growing advertising creativity on the Web, with developments such as animated ads on screen, (e.g., see Zilber, 1997 and Word at http://www.word.com for illustrations) may make advertising effectiveness measurement on the Web even more challenging in the future.

In this paper, we describe the development and application of a new Web-based methodology for evaluating the effectiveness of "promotional content" on the Web. The promotional content may be defined at two levels: 1) at the level of a Web *page*, which may include specific product information or other promotional content, or 2) at the level of a Web *site* that consists of a collection of Web pages which may include specific product and promotional content as well as potential purchase transaction information. In subsequent sections, we describe the features of the proposed methodology, the steps for its implementation, and illustrate its application to a problem that involves the analysis and the design of the promotional content characteristics of an actual Web site.

Features of the Proposed Methodology

In a recent report based on a joint project of the Association of National

Advertisers, Inc., and the American Association of Advertising Agencies, with the support of the Advertising Research Foundation (CASIE, 1995), guiding principles have been described for interactive media audience measurement that motivate the present study. This report strongly stresses the need for *non-intrusiveness* in advertising audience measurement. However, such a requirement is seldom achieved in standard advertising testing methodologies. For example, various commercial advertising and copy testing services rely on self-reported measures of advertising effectiveness from respondents that may include advertising recall, recognition, comprehension, attitudinal, and persuasion information (Stewart and Furse, 1986). Aside from the fact that these measures may not be valid measures of effectiveness, they do not meet the criterion of non-intrusiveness as the data are collected through survey-based methods that may be subject to social desirability, or reactive biases. In-theater testing methods suffer from similar drawbacks as well. These are not only based on intrusive measurement methods (e.g., survey or electronic dial), applied to individual respondents, but they also lack in *external validity*. For example, off-air pre- and post-advertising tests that are administered within an in-theater setting are artificial, in the sense that they take place in a controlled environment that does not resemble the home surroundings in which individuals usually view TV commercials. In contrast, on-air tests do not suffer from externally validity bias as they place ads within the home setting. However, they are subject to response or experimental biases since respondents are typically subsequently asked about their reactions through surveys.

Here, we propose a Web-based methodology that eliminates biases of current advertising testing methods and offers significant advantages over the latter in a number distinctive and important ways:

- **Unobtrusive** - The methodology is based on an experimental method that is totally transparent and unobtrusive to each respondent. In particular, respondents go about their normal "surfing" activities on the Web and have no way of knowing that they are being manipulated (i.e., exposed to particular advertising stimuli that are part of a well defined experimental design). Additionally, the methodology develops measures of effectiveness that are based exclusively on the mouse-click streams which reflect respondents' flow and viewing behavior on a given Web site as they go about their normal surfing activities on the Web. Hence, measurements are based on *actual respondent behavior* and do not suffer from any experimental effects or any of the self-report biases.
- **Experimentally-based** - The methodology is based on a rigorous experimental design that draws on methods of *conjoint analysis*, a widely applied market research technique, (Green and Rao, 1971; Wittink and Cattin, 1981; Cattin and Wittink, 1982). Our experimental methodology permits 1) the randomization of test groups as well as respondent matching, 2) an unobtrusive manipulation of test stimuli as well as an unobtrusive data collection from Web users.
- **Externally valid** - The methodology is designed to test the effectiveness of content on the Web and is implemented on the Web itself. The subjects that are being monitored are actual Web surfers engaged in their own Web surfing activities, and not a random sample of individuals who might or might not be involved with the product tested. Thus, the method does not suffer from any biases due to lack of external validity as content is viewed in its actual form, by actual viewers, and within

its actual viewing environment (i.e., within the Web site environment for which it is intended). Although the methodology, at this time, does not attempt to project beyond this environment, ways to extend the methodology to test content of other media vehicles, such as print, radio or TV on the Web, are being investigated by the researchers.

- **Based on large sample sizes** - Because Web traffic is very large, this Web-based methodology permits the collection of large sample sizes. While traditional concept testing methodologies, such as conjoint analysis, are frequently being used with only a few hundred respondents, this Web-based methodology can draw on tens of thousand of respondents in a short amount of time and at a low cost. In fact, as applied to a given Web site, the methodology collects complete *census* data in the sense that it permits the collection of behavioral data (i.e., *mouse-click streams*) from *all* visitors that have accessed the given site over a defined study period. Thus, the methodology is free of random sampling error and expected to have high reliability.
- **Instantaneous -** The electronic data is collected from respondents instantaneously as their behavior occurs, in real time. Thus, the methodology potentially provides instantaneous measures of advertising and site content effectiveness.
- **Low cost** - Because of the relatively high traffic on the Internet and World Wide Web, the methodology is extremely easy and inexpensive to implement. All that is required is access to the publisher's Web site - that is the Web site that contains the pages whose content will be evaluated and the implementation of a relevant experimental design to evaluate the promotional situation at hand.

Development and Application of the Methodology

In this paper we illustrate the application of the proposed Web-based methodology to the problem of analyzing and measuring the effectiveness of a Web site's promotional contents. Because it involves a set of Web pages and their related contents, this problem is potentially more complex than one which would merely involve the evaluation of advertising content within one particular Web page within a Web site. However, it should be emphasized that our methodology can be applied to both of these situations as well as to the problem of Web-based product design in general (Drèze and Zufryden, 1997).

In this section, we describe the general framework of the proposed methodology within the context of an actual case application to Web site content analysis and effectiveness measurement. Our methodology was used in conjunction with a Web site that promotes and markets music CDs directly on the Internet. The Web site owner wanted assistance in appropriately designing his Web site so as to provide appropriate descriptive information as well as purchase-related information about its CD products. The potential information to be delivered at the Web site consisted of factors such as description of CD products and titles, sample sound clips, placement of endorsements from critics, as well as CD product ordering information. A basic objective of our study was to evaluate Web site content configuration characteristics that would most effectively communicate the promotional information within the Web site. The methodology was implemented according to the following nine basic steps (see Figure 1 for a flow chart):

Define Potential Web Site Attributes and Levels

The first step of the methodology involves the definition of the alternative Web site attributes and corresponding levels that will be investigated. For example, in this illustration, based upon discussions between the researchers and the Web site owner, *four* essential Web site descriptor attributes were defined: *Background*, *Image Size*, *Sound File Display* and *Celebrity Endorsement*.

There are a wide variety of possibilities in terms of background colors. Historically, all Web sites had the same gray background. Then, Web site designers became bored with gray and started using other colors, ranging from “traditional” colors such as paper white to more exotic colors such as bright pink. The latest trend is to use backgrounds with multicolored patterns. This increased flexibility in terms of background colors does come at a price however. First, using complex backgrounds may slow down both transmission and display time as more information needs to be exchanged between the Web server and the Web browser. Second, one can never be sure of how the color will be displayed on an unknown PC system. Not all computers are setup to display the same number of distinct colors (256 colors is now the norm, but many systems still can only display 16 colors at one time while other can display 16 million). When there is not sufficient room in a computer’s color palette to display the requested color, it will either substitute it for a different color, or it will use dithering to produce a color that closely matches the requested color (the actual technique used can be defined in the “Web browser’s” settings).

With this in mind, we decided to test three different types of backgrounds (see

Table 1). The first possible background is the simplest one: *Free*. That is, the background color is left undefined and no background information is specified within the HTML (hypertext markup language) page description. This causes the browser to use whichever color the user has defined as the default background color. The advantages of this background setting are that it does not slow down the Web surfing process, since no information is transferred, and that one can hope that the user has defined default colors that he/she finds pleasing. The second possible background was *Green*. Green was chosen because it mixes well with the various graphical images used throughout the test site. The last possible background was *Tiled*, a gray and white tile-like patterned background. This background is more elaborate than the two other ones, it is more aesthetically pleasing, but it also trades-off aesthetics for potentially longer download times. Of course, once a background is specified for a given visit, the surfer will see the same background on every page of the site. The surfer will also see the same background in the event of a repeat visit to the test Web site.

Our second attribute is the *Image Size* of the graphical items used throughout the test Web site. When using pictures, one makes a simple trade-off: the larger the picture, the better it looks, but also the longer it takes to download. Long download times can sometimes upset net surfers, as they may become impatient, causing them to leave a site despite its overall attractiveness. Hence, we decided to test two different sizes (*Large* and *Small*) for each of the graphical images. The *Large* images were vertically and horizontally twice as big as the *Small* ones (i.e., four times larger in terms of number of pixels).

There are several formats under which sound can be encoded into files. The formats currently used most are AIFF (in use on Macintoshes and Amigas), WAV (for IBM PCs and compatibles), and AU (for UNIX based machines). Traditionally, Web sites offer either one of these three formats, or all of them. Offering all of them can sometimes be overwhelming for a surfer who is confronted with a large choice of songs under different file formats. For this purpose, we decided to test two alternative levels of the *Sound File Display* attribute. One level was defined as *Generic*. This corresponded to a display table where all the available songs under the three file formats were displayed (see Figure 2 for an example of a page that incorporates this feature along with a *Free* background and *Small* images). Under the second scenario, called *Computer-Specific*, the Web server determined the type of machine used by the Web surfer, and only offered him/her a table containing the type of sound file that is appropriate for his/her computer. For instance, if the surfer had a Sun workstation, only AU files would be presented on the Web pages (see Figure 3 for an illustration of such a page which also incorporates a *Tiled* background and *Small* graphical images). Similarly, if the surfer had a Macintosh, only AIFF files would be displayed.

Our last experimental attribute was the location of *Celebrity Endorsements*. The main CD title sold on the Web site, “Straight to the jugulæ,” has received a fair amount of positive press. Originally, all the critic quotes related to this album were displayed on a separate page that only contained quotes from critics. We tested this setup against one in which a specific endorsement (by the “Angryman,” a popular DJ in Northern California) was chosen and additionally displayed on one of the central pages. It was placed within the main body of the site, right below the image representing the cover picture of the “Straight to the jugulæ” CD. Clicking on the critic endorsement also provided a short cut to the page containing the various other critic quotes. Thus, as noted in Table 1, the *Celebrity Endorsement* attribute could take on the values *No* or *Yes*, depending on whether or not the “Angryman’s” endorsement was included within the main text body of the test Web site.

Develop Web Site Fractional Factorial Design Matrix

In conjoint analysis, because of the difficulty of developing and testing concepts corresponding to a full factorial design, particularly as the number of attributes and levels becomes large, it is common practice to develop and apply an orthogonal fractional factorial design. The fractional design consists of an appropriately chosen subset of all possible designs that may be formed with the defined attributes and levels (Green and Rao, 1971). For example, in our situation, we have four different attributes. One of these attributes has 3 levels, the other ones have 2 levels each. Consequently, there is a total of $3x2^3 = 24$ different Web sites that could be designed from the defined attributes and levels. The smallest fractional factorial design for this configuration is a design matrix consisting of a total of *eight* Web site test concepts, with configurations and corresponding dummy variable codes (x_i, i=1,...,5), as described in Table 2. This fractional design was generated by using CI2, a commercial conjoint analysis package.

Develop Test Site Design Concepts on the Web

At the next step, test stimuli corresponding to *each* of the test concepts of the design matrix are developed. In this case, in accordance with the design of Table 2, *eight* test concept stimuli, including the current Web site configuration, defined as a reference case, were developed and installed on the Web site's server. We defined site indices $j=0$ to 7, with site $j=0$, the "reference" design, corresponding to the current Web site configuration.

Note that in standard conjoint analysis, test concept stimuli are typically designed by use of *concept cards*, which merely provide verbal descriptions of each test concept, or other visual stimuli (Green and Rao, 1961). In contrast, our proposed methodology does not suffer from external validity biases since it is based on *actual* products (i.e., Web sites). That is, according to the design of Table 2, eight *actual* alternative Web site versions, including their corresponding Web pages and design contents, were developed and installed on the site's server by means of specifically designed software.

Randomize Respondents to Test Web Site Design Concepts

At the next stage, it is necessary to assign surfers to alternative test Web site design concepts. In order to implement this assignment process, a randomization method was developed and used which was based on the distinct Internet Protocol addresses (IP addresses) of each visitor. Thus, based on his/her IP address, each visitor was assigned one of the eight sites configuration. This insured that a particular visitor saw the same site configuration during each repeat visit. This assignment is totally transparent to the user. There is nothing in the site configuration or content of pages that may lead the user to suspect that what he/she received was actually processed by our software. The user is unaware that had he/she requested the same pages from a computer with a different IP address, he/she might have received a different set of pages. Moreover, we went to great length to develop a technique that did not require visible page content manipulation techniques such as cgi-scripts (Drèze and Eto, 1997). This was necessary to ensure that the technique used to test the different profiles was unobtrusive and transparent to the user.

One potential problem with this method is that repeat visitors might have different IP addresses each time they visit our Web site. Indeed, this could occur if they access the Web through a service provider that gives them a different IP address each time they connect, or if they use different computers (e.g., computers from a computer lab at a University, using a different computer for each of their visits). To ensure that such visitors see the same Web site configuration at each of their visits, we only used the first half of the IP address for our randomization. This guaranties that every computer from the same organization accesses the same Web configuration (e.g., all users accessing our test site from the University of Southern California will see the same Web pages, but they will see different ones than visitors using AOL or other Internet providers).

Collect Site Effectiveness Measurement Data From Respondent Click Streams

The next step involves the collection of relevant data on the basis of which site effectiveness measures can subsequently be developed. Here, based on the randomization procedure described above, data were collected corresponding to the eight matched Web site visitor groups. The data were developed primarily by tracking the mouse click streams of visitors that accessed each one of the defined alternative Web test sites. Thus, each time visitors would request a Web page, the following information was recorded in a special log file:

- IP address of the visitor
- Web site configuration seen by the visitor

- Date and time of the page request
- Name of the page requested
- Name of the previous page requested
- Name and version number of the visitor's Web browser software

From this basic information, numerous measures can be extracted (Drèze and Zufryden, 1997), including the following:

- Visitor's operating system (Windows, Macintosh, UNIX, etc.)
- Ability of visitor to handle Frames
- Ability of visitor to handle JAVA scripts
- Total number of pages accessed during the site visit
- Total time spent on the visit
- Time spent per page

In this study, because the specialized study site that was chosen generated moderate traffic, the data collection phase ran for a period of several months to permit the collection of a sufficiently large data sample. On this basis, a total sample size of N=788, was collected over a three month period which provided ample subsample sizes for each of the test Web site cells. Moreover, the overall sample was split into test (n_1=540) and holdout (n_2=248) subsamples, gathered over two consecutive time periods, to permit both descriptive and predictive model testing. We emphasize at this point that the data collection takes place as the surfer visits our test site. It is done automatically by the software we installed on the server, and does not affect the surfer's interaction with the Web site. That is, the impact of a particular site's content design characteristics, and site effectiveness, are inferred by tracking the normal behavioral patterns (i.e., click streams) of the visitors rather than obtained from obtrusive measurement procedures that are commonly used in standard conjoint analysis (e.g., measuring expressed subject preferences by some rating or ranking instruments, see Wittink and Cattin, 1981).

Develop Site Effectiveness Functions of Web Site Attributes and Levels

One of the relevant issues at this stage is the development of content effectiveness measures and related effectiveness functions. Unfortunately, to date, no industry standards have yet emerged for measuring the effectiveness of content, such as advertising, on the Web (Novak and Hoffman, 1996; Murphy, 1996). In this study, we focused on measures that would reflect site attractiveness and visitor interest in the site contents, and thus could serve to compare the overall effectiveness of alternative Web sites as well as that of their component characteristics (e.g., of explanatory variables corresponding to levels of attributes of *Background*, *Image Size*, *Sound File Display,* and *Celebrity Endorsement*).

From a methodological standpoint, we found that standard response modeling techniques, such as the use of linear additive regression models (OLS), were inappropriate. This is because, among other reasons, the data did not conform to the requirements of normally distributed random errors. Thus, given their flexibility in dealing with alternative error distributions, procedures for “limited dependent variables” (Hauseman et al., 1984) were considered to formulate appropriate response functions instead. There are numerous potential effectiveness measures that may be defined to characterize Web site effectiveness (Drèze and Zufryden, 1997). In this section, we develop models for two effectiveness measures that we found most relevant in our study: the *Number of Pages Accessed* and *Time Spent* during a site visit.

a) <u>The Poisson Regression Model of Number of Pages Accessed</u>

The Poisson regression model has been shown to be useful in situations involving *count* data (Maddala, 1984). We use the Poisson to model the *Number of Pages Accessed* by a visitor during a site visit. To implement the Poisson over the range *k ³ 0*, we define a random variable *k* as the *Number of Pages Accessed - 1*. Thus, the probability that a visitor will access *k* pages of a given site is stated as:

$$P(k) = e^{-l}\, l^{k} \,/\, k! \quad \text{, for } k \text{ ³ } 0 \tag{1}$$

with l , the mean of the Poisson, given by the relationship:

$$\ln\ l = b_o + b_1 X_1 + b_2\, X_2 + ... + b_I\, X_I, + e \tag{2}$$

where X_i , $i=1,....,\ I$ are explanatory variables (e.g., characteristics of site visited, as well as browser and operating system descriptor characteristics), $b_i\,(i=0,1,...,\ I\ )$ are constant coefficients, and e is an error term.

b) <u>The Exponential Regression Model of Time Spent on a Site</u>

The *Time Spent* during a site visit is best modeled as a random variable *t* using *survival* analysis techniques (Kalbfleisch and Prentice, 1980). In this paper, we restrict our attention to Exponential regression, which is one of the most tractable of the limited dependent variable approaches for modeling time intervals. However, we note that this approach may readily be extended to consider more complex model formulations as well as distributional assumptions of unobserved heterogeneity (Jain and Vilcassim, 1991). The probability of spending an amount of time *t* at a site is stated as the Exponential model:

$$\ln(t) = a_0 + a_1 X_1 + a_2\, X_2 + ... + a_I\, X_I, + e^*, \tag{3}$$

with a_i *(i=1,...., I)* constant coefficients, and $e^* = -e$ and error term, with e given by the *extreme value* distribution.

Assess Site Attributes and Levels Part-Worth Effectiveness Values

The parameters of the effectiveness models described above may be used to assess site attributes and levels *part-worth* effectiveness values. To do this, the parameters of the Poisson and Exponential models were estimated by *maximum likelihood estimator* techniques (Gourieroux, 1984; Cameron, and Trivedi, 1986).

When designing the study, we had a-priori hypotheses about the impact of each of the attribute levels. We now review these hypotheses as we discuss the results of our empirical analyses for the *Number of Pages Accessed* and *Time Spent* models (see Table 3 for a summary of our hypothesed versus empirical results):

a) Background

Relative to background, we hypothesized that the *Tiled* background would have a beneficial impact, as compared to the *Free* background, yielding a greater number of pages accessed during a visit as well as a greater time spent on as site. Conversely, we hypothesized that the *Green* background would appear relatively unattractive, and lead to a lesser number of pages accessed, as well as a smaller amount of time spent per site visits.

These hypotheses regarding the impact of the *Green* background were supported by our empirical results. The negative coefficients obtained for the *Green* background in both the Poisson (see Table 4) and the Exponential (see Table 5) models supported our a-priori beliefs as they show that that *Green* does have a negative impact on *Number of*

Pages Accessed as well as on *Time Spent*. While this impact was statistically significant (*p-level*<0.05) for the Exponential, it was, however, not statistically significant in the case of the Poisson model.

With respect to the *Tiled* background, we found that it had a positive effect on *Number of Pages Accessed* (see Table 4), but had a negative effect on *Time Spent* (see Table 5). These results were marginally statistically significant (*p-level*<0.1) for the Poisson model and statistically significant (*p-level*<0.05) for the Exponential regression model. In particular, *Tiled*, by virtue of its relatively large positive coefficient, in the Poisson model, suggests that it is the most impactful explanatory variable affecting *Number of Pages Accessed*.

b) <u>Image Size</u>

The overall impact of the size of the graphical image files was hypothesized to be more complex. We thought that since *Small* images load faster, they would induce the visitor to see more pages, but allow him/her to do so in less time. Hence, *Small* (*Large*) images would have a positive (negative) impact on *Number of Pages Accessed*, but a negative (positive) impact on *Time Spent* on a site.

Our empirical results only partially supported our a-priori notions. Indeed, *Large* images were shown to negatively impact the *Number of Pages Accessed*. This was clearly shown in Table 4, where the coefficient of *Image* is not only negative but statistically significant (*p-level*<0.05). However, we were unable to support our prior hypothesis that a *Large Image* would have a positive impact on *Time Spent*. As shown in Table 5, the corresponding coefficient was not significant in this case.

c) <u>Sound File Display</u>

In relation to the *Sound File Display* formats, we thought that the *Generic* table would be more cumbersome, causing the visitors to be less interested in the Web site, and leave prematurely. This would yield less page requests, and less time spent on the visit than for the *Computer-Specific* table. Here, as expected, we found that the coefficients for *Sound File Display* were indeed negative in both models for *Number of Pages Accessed* (Table 4) and *Time Spent* (Table 5). However, this result was only found to be statistically significant (*p-level*<0.05) in explaining *Time Spent*.

d) <u>Celebrity Endorsement</u>

We postulated that adding one major celebrity's endorsement within the main text body of the site would spark visitor interest, yielding more page requests and more time spent on the site. This hypothesis was largely supported by our empirical results. As shown in Tables 4 and 5, the coefficients for *Celebrity Endorsement* were found to be positive for both the *Number of Pages Accessed* and *Time Spent*. While the coefficient was statistically significant (*p-level*<0.05) for *Time Spent*, it was only marginally significant for the model of *Number of Pages Accessed* (*p-level*=0.147).

e) <u>Java Scripts and Frames</u>

Other attributes were analyzed that were not entirely under our control: *Use of Java Scripts* and *Use of Frames* (see Table 3). These attributes were defined by dummy variables (1=*Yes*, 0=*No*) to indicate whether the visitor's browser could handle Frames and JAVA scripts, respectively. We were able to monitor these capabilities when visitors came in, but we could not impose them (i.e., if a visitor comes in with a browser that does not handle JAVA, we could not force him/her to see the JAVA applets contained in our site). Thus, we treated the use of JAVA and Frames as a natural experiment. Our expectation for these two attributes was that *Use of JAVA Scripts*, and *Use of Frames*, being much touted features of the latest batch of browsers, would result in visitors who have JAVA and/or Frames enabled Web browsers spending more time visiting the site, and requesting more pages.

In the case of *Use of JAVA Scripts*, (see Tables 4 and 5) we found that both its impact on the *Number of Pages Accessed* and *Time Spent on a Site* were highly statistically significant (*p-level*<0.001), relatively large, in comparison with those of the controllable independent variables that were discussed above, and also *negative*. Contrary to our initial beliefs, these empirical results suggested that the use of JAVA significantly adversely affects the effectiveness of our site. Upon reflection, we suggest that this result may due to the fact that, although potentially more attractive, it takes longer to load pages which contain JAVA Scripts. The longer downloading time appears to be an irritant to Web surfers which not only lessens the number of pages viewed but also the length of time they will spend at the Web site. Indeed, a recent study that focuses on the value of advertising on the Web (Ducoffe, 1996) postulates "irritation" as a measure of advertising value and suggests that long waiting times, while loading a screen, may contribute to the impatience and irritation of Web surfers.

In the case of *Use of Frames* (see Table 4), there is mixed support of our prior hypotheses. *Use of Frames* contributes positively to the explanation of *Number of Pages Accessed*, as we had posited, although the corresponding coefficient has only marginal statistical significance (*p-level*= 0.116). This result, nevertheless, coincides with our prior belief that Frames should promote the viewing of more pages by more effectively providing links to them.

In contrast to our prior hypothesis, we found that *Use of Frames* adversely affects the *Time Spent on a Site* (see Table 5). The corresponding coefficient is not only found to be negative but is also highly significant (*p-level*=0.001). One possible explanation for this is that Frames may provide too much ease in navigating through a site and hence a visitor may tend to spend less time on a site to satisfy his information or curiosity needs.

f) <u>Operating Systems</u>

Another attribute that was beyond our control was the PC *Operating System* used by individual surfers. We defined four additional dummy variables to code alternative levels including *Windows 95, Windows 3.1, Macintosh, UNIX,* and *Other* systems. In this case, we found that the corresponding coefficients for these explanatory variables were all highly statistically significant, as well as all positive, for both the *Number of Pages Accessed* and *Time Spent* models (see Tables 4 and 5). Interestingly, the UNIX system, by virtue of its relatively large coefficients, was the most impactful of the four popular operating systems considered in the effectiveness models. In addition, in conformance with prior expectations, operating systems in the *Other* category, were found to be less impactful than the four popular operating system types.

The larger coefficients for the UNIX operating system may be explained by the fact that most UNIX based computers are directly connected to the Internet using fast Ethernet connections while most PCs and Macintoshes use slower dial-up connections.

The mixed results we obtained in validating our hypotheses do not detract from the validity of our methodology. Quite the opposite! Eleven of the twelve parameters of the Exponential regression and eight of the Poisson regression parameters were significant at the *p*=0.1 level (with two others significant at the *p*=0.15 level). Our analysis shows that the impact of the various components available to advertisers and Web designers may not be obvious and that our methodology will be helpful in measuring this impact. Among other results, it allowed us to discover that although developers consider the use of JAVA scripts to be a selling point for their sites, Web users may actually become irritated when they encounter them.

Validate Effectiveness Response Models

In our study, we first concentrated on model validation on the basis of the *descriptive fit* of the effectiveness models. As noted above, by referring to *p-levels*, we identified a number of statistically significant variables that explained the Web site effectiveness measures. Moreover, in terms of overall descriptive goodness of fit, the chi-square statistics, shown in Tables 4 and 5 also provide support of our models in view of the very close compatibility that is indicated between our proposed effectiveness models of *Number of Pages Accessed* and *Time Spent* with our empirical data. Here, the *Prob.* > χ^2 are negligible, suggesting a very high overall descriptive goodness of fit for both models.

In addition, we also conducted tests of *predictive fit* of our proposed effectiveness models. We utilized the estimated models from Tables 4 and 5 (based on the analysis sample of size 540) and then used these models to predict both the average *Number of Pages Accessed* and *Time Spent*, by setting the models' independent variables with corresponding data values from the holdout sample (consisting of the subsequent 248 site visits). We then compared the predicted values of both average *Number of Pages*

Accessed and *Time Spent*, respectively, with their observed empirical counterparts. The results of this test indicated very good predictive validity of the models as we found that the mean absolute percent error (MAPE) between actual and predicted average *Number of Pages Accessed* was 2.81%, while the MAPE for *Time Spent* was only 1.57%.

Another test of the Poisson model's overall predictive goodness of fit, involved the evaluation of the theoretical Poisson distribution in (1) by using values of the independent variables, from the holdout sample period, in the model estimated from the test data sample shown in Table 4. Hence, we predicted and then aggregated the Poisson probabilities over each of the 248 visitors in the holdout sample. Thus, as illustrated in Figure 4, we found a relatively good compatibility between the predicted and observed frequencies of the random variable *k*, (*Number of Pages Accessed - 1*) over the entire holdout sample. We further performed a chi-square test to examine the coincidence between the observed and predicted distributions shown in Figure 4. Here, we found a *p-level*=0.999 which suggested the rejection of a null hypothesis of independence between the predicted and observed distributions. This test provides yet additional support for the model's predictive ability. Moreover, it suggests the potential use of a *distribution of pages accessed* for a Web site (Drèze and Zufryden, 1997) as an effectiveness measure in a manner similar to the use of a *distribution of advertising exposures* in media analysis (Hulk and Thomas, 1973; Zufryden, 1987; and Pedrick and Zufryden, 1991).

Simulate Web Site Alternatives

An essential purpose of our proposed methodology is to permit the evaluation of Web site content characteristics so as to arrive at an improved design for our study Web site. As noted above, the analysis provides information concerning those explanatory variables (including Web site content design features) that are expected to most enhance overall Web site effectiveness. Moreover, based on the proposed methodology, a decision-maker can easily evaluate alternative Web site configurations, by specifying specific levels of a proposed Web site's attributes (e.g., *Background*, *Image Size, Sound File Display*, *Celebrity Endorsements*, etc.) in equations (2) and (3). This provides corresponding effectiveness value measures for both *Number of Pages Accessed* and*Time Spent*, as well as information about potential trade-offs between the measures.

Here, we illustrate how trade-offs among alternative Web site configurations may be analyzed by means of an *efficient frontier* method (Hauser and Shugan, 1983). Our approach was to simulate the "full factorial" Web site profiles that could be generated from the attributes that were studied (both from our controlled and natural experimental conditions). Thus, given that there are three *Backgrounds* and two of each of *Image Size, Sound File Display*, *Celebrity Endorsement*, *Java* and *Frame* levels, respectively, a total of $3*2^4 = 96$ Web site configurations were defined. We then evaluated the characteristics of each of these sites (by appropriately setting the dummy variables) in each of the effectiveness model equations (2) and (3) to estimate the corresponding values of average *Number of Pages Accessed* and average *Time Spent* (in seconds), respectively. We then plotted the corresponding coordinates for each of the 96 possible Web site designs (see Figure 5).

Obviously, subject to certain Web site capacity constraints, site configurations that can achieve higher values with respect to both *Time Spend* and *Number of Pages Accessed* by site visitors are more desirable from a Web site owner's point of view. This is because a site owner should desire to maximize both the breadth and depth of exposure to a Web site's promotional contents. These configurations should suggest greater attractiveness from the viewpoint of Web surfers as well. Thus, as we move in a northeast direction in Figure 5, we can find more attractive site configurations. In particular, the most desirable Web configurations are those whose coordinates lie on the outermost portions of the graph.

For example, in Figure 5, it is noted that one of the configurations for which *Celebrity Endorsement* was also placed, within the main text body of the site, provides one of the more desirable site configurations in terms of our two effectiveness dimensions. However, it is observed that there may be trade-offs involved with further variations in site design characteristics. Thus, by also providing a *Tiled* background, the *Number of Pages Accessed* tends to increase further. However, this is at the cost of some reduction in the amount of *Time Spent*. By subsequently adding *Frame* capabilities, the average *Number of Pages Accessed* is seen to further increase. However, this too further decreases the amount of *Time Spent*. Thus, efficient frontier analysis suggests that there are three Web site configurations which dominate other configurations. Therefore, the choice of the *best* Web site configuration depends on how a decision-maker (e.g., Web site owner) trades off one effectiveness dimension for the other (i.e., *Number of Pages Accessed* vs. *Time Spent*). Hence, it is clear that our model provides a potentially useful approach for evaluating and designing Web site contents and configurations. Moreover, it provides a useful approach for evaluating the potential effectiveness trade-offs that may result from variations in Web site features.

Conclusion

In this paper we described a conjoint-based methodology for evaluating the effectiveness of content on the Web. The methodology is based on an experimental procedure that permits the testing and measurement of alternative attribute designs in a manner that is unobtrusive, timely, cost-effective, as well as free of random sampling error, directly on the Web.

We illustrated the application of the methodology to the design of a Web site that promoted and marketed CD music products on the Web. In this illustrative case, our methodology permitted us to develop effectiveness measures as functions of explanatory variables. In particular, we found that *Number of Pages Accessed* and the *Time Spent* were potentially useful and relevant effectiveness measures which could be explained by independent variables for attributes that included *Background*, *Image Size, Sound File Display*, *Celebrity Endorsement*, *Use of Java* and *Frames,* as well as *Operating System*.

However, our methodology has some limitations that should be noted. As has been described, our approach assigns a unique Web test site to each visitor on the basis of a visitor's distinct Internet Protocol Address (IP address). However, it was noted that repeat visitors might have a different IP address when they access a site from a given provider, or if they use different computers to access a site. To mitigate this problem, we only used the first half of the IP address for our randomization to insure that every computer from the same organization accesses the same Web configuration (e.g., all users accessing the test site from AOL will see the same Web site).

Another limitation of our study is that data on site visitor characteristics were not available for this study. At present, with the exception of panel data samples, such as those from the NPD Group which is limited to demographics of PC users (Novak and Hoffman, 1996), individual surfer data corresponding to unique visitors on the Web (e.g., demographics) are not generally available. One way of obtaining such data is through (obtrusive) survey methods such as on-site registrations on the Web. Unfortunately, visitor registrations can only be done on a voluntary basis and therefore are inherently biased, as they are neither census-based nor representative, from a statistical standpoint, because of their inherent self-selection biases. Third party companies, such as Netcount, are currently exploring the issue of tracking individual surfer characteristics on the Web in less obtrusive ways.

A final limitation of our study involves the effectiveness measures used to evaluate the various test sites. It might be argued that although *Time Spent* on a Web site and *Number of Pages* accessed during a site visit should be expected to relate to visitors' purchase behavior, it would be desirable to use an objective function expressed directly in terms of sales or profitability. This can be accomplished if one tracks individual purchases in addition to data such as that gathered in our study. In fact, we attempted to track individual visitor purchases. Unfortunately, the relatively low traffic to the Web site and the sparseness of the purchase data precluded a meaningful analysis of sales or profitability in this case.

Despite these limitations, our methodology suggests a great deal of promise as a useful tool for studying Web site promotional content effectiveness and designing Web site content. As tracking measures on the Web become more refined in the future, it is expected that accurate individual measurements will ultimately be available that will provide not only unique individual user behavior patterns (e.g., the specific click streams of unique site visitors) but also the specific characteristics of the site visitors (e.g., demographics). Thus, it is expected that the Web will eventually come closer to fulfilling its potential and promise as the ultimate medium for market segmentation at the individual consumer level - that is, for targeting unique individual surfers with individually-designed promotions, content, products and services on the Web.

References

CASIE, "CASIE Guiding Principles of Interactive Media Audience Measurement," *Coalition for Advertising Supported Information and Entertainment*, 1995. http://www.commercepark.com/AAAA/bc/casie/guide.html.

Cameron, A. and P. Trivedi, "Econometric Models Based on Count Data: Comparisons and Applications of Some Estimators, *"Journal of Applied Econometrics***,** 1, 1, January 1986.

Cattin, P. and D. R. Wittink, "Commercial Use of Conjoint Analysis: A Survey," *Journal of Marketing*, 46, pp. 44-53, 1982.

Drèze, Xavier and Kurt Eto, "Creating Dynamic Web Pages to Better Appeal to Your Audience," University of Southern California, Graduate School of Business, Working paper, 1997.

____________ and Fred Zufryden, "A Conjoint Analysis Approach for Web-Based Product Design Evaluation," University of Southern California, Graduate School of Business, Working paper, 1997.

Ducoffe, Robert, H., "Advertising Value and Advertising on the Web," *Journal of Advertising Research*, Vol. 36, No. 5, pp. 21-35, September/October 1996.

_________________, Dennis Sandler, and Eugene Secunda., "A Survey of Senior Agency, Advertiser, and Media Executives on the Future of Advertising," *Journal of Current Issues and Research in Advertising*, 1996.

The Economist, September 16, 1995.

Forrester Research, 1995, "People and Technology Strategies," Vol. 2, No. 5, http://www.forrester.com.

Forrester Research, 1997 , "Web Outsourcing to Reach $10 Billion by 2000," News Release, http://www.forrester.com.

Gourieroux, C., A. Monfort, and A. Trognon, "Pseudo Maximum Likelihood Methods: Applications to Poisson Models," *Econometrica*, Vol. 52, No. 3, pp. 701-719, May 1984.

Green, P. E. and V. Rao, "Conjoint Measurement for Quantifying Judgmental Data," *Journal of Marketing* Research, 8, pp. 355-63, August 1971.

Hauseman, Jerry, Bronwyn H. Hall, and Zvi Griliches, "Econometric Models for Count Data With an Application to the Patents-R&D relationship," *Econometrica*, Vol. 52, 4, pp. 909-38, July 1984.

Hauser, John R., and Steven M. Shugan, "Defensive Marketing Strategies," *Marketing Science*, Vol. 3, pp. 327-351, Fall 1983.

Hoffman, Donna L., Thomas P. Novak, and Patrali Chatterjee, "Commercial Scenarios for the Web: Opportunities and Challenges," *Journal of Computer-Mediated Communication*, Vol. 1, No. 3, 1995.

Hulks, B. and S. G. Thomas, "Preface - A Simple Model for the Prediction of Television Coverage and Frequency Distribution, *Admap*, December 1973.

Jain, D. C. and N. J. Vilcassim, "Investigating Household Purchase Timing Decisions: A Conditional Hazard Function Approach," *Marketing Science*, Vol. 10, No. 1, pp. 1-23, Winter 1991.

Jupiter Communication, "Web As Revenue Jumps 83 Percent in Second Quarter, According to Jupiter AdSpend Data," *Press Release*, September 3, 1996.

Management Science, Vol. 33, No. 10, pp. 1253-1266, October 1987.

Figure 1

Methodology for Web Site Content Effectiveness Analysis

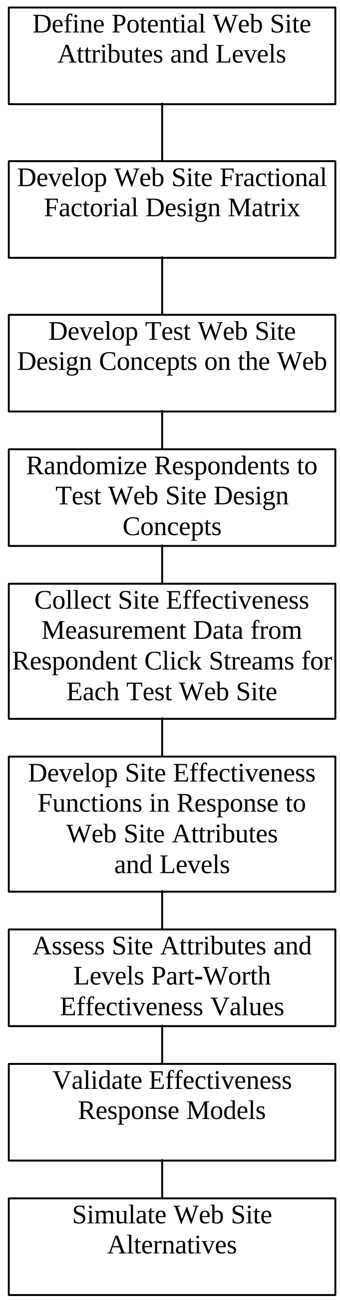


Figure 2

Sample Page With Generic Sound File Display

Figure 3

Sample Web Page With Computer-Specific Sound File Display

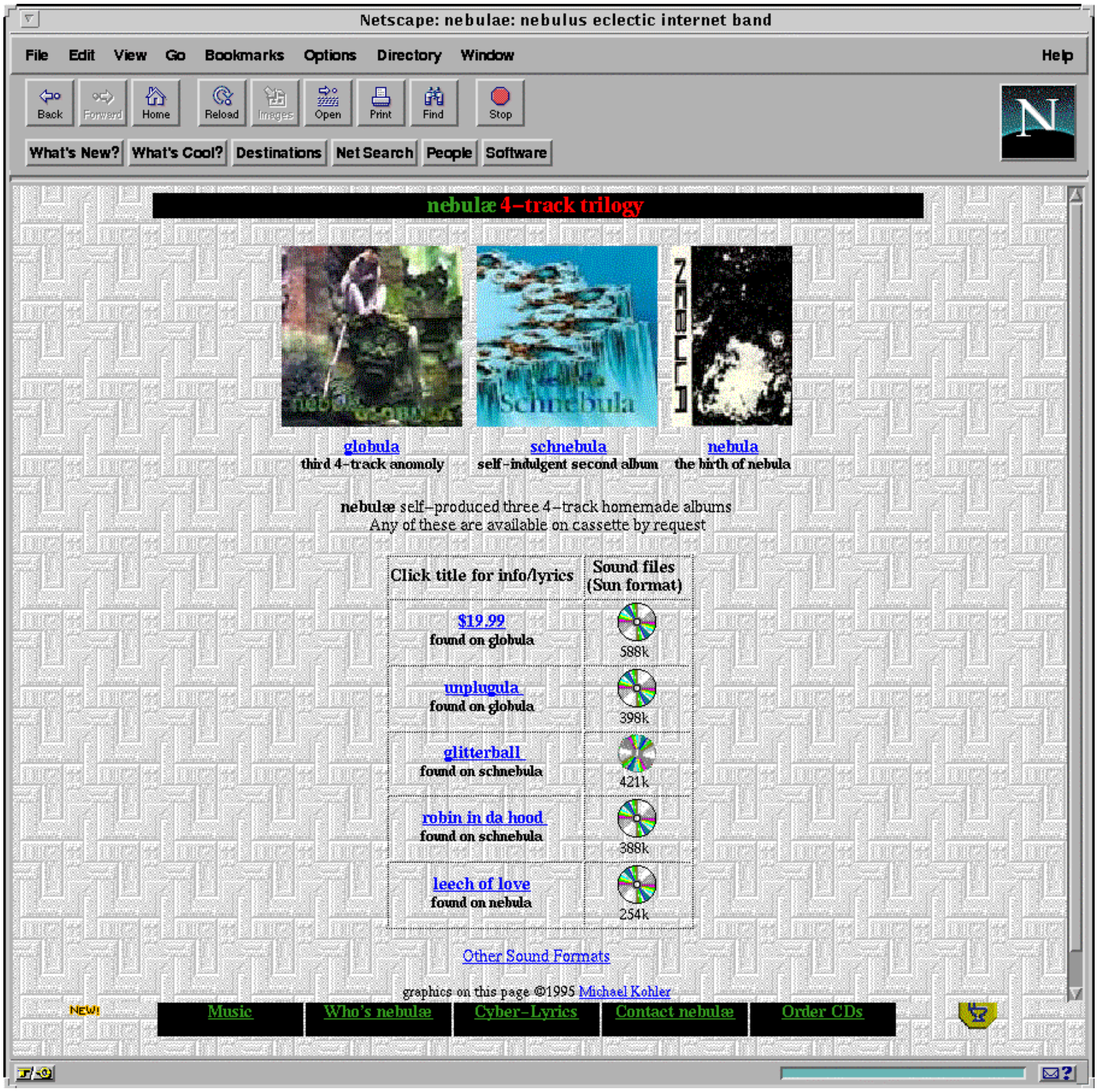


Table 1

Web Site Descriptor Attributes and Levels

Attributes:	Levels:
Background	i) Free ii) Green iii) Tiled
Image Size	i) Small ii) Large
Sound File Display	i) Generic ii) Computer-Specific
Celebrity Endorsement	i) No ii) Yes

Table 2
Design Matrix for Test Web Site Concepts*

Test Site	Background x_1	x_2	Image x_3	Sound x_4	Endorse x_5
0	**0**	**0**	**0**	**0**	**0**
1	**0**	**0**	**1**	**1**	**1**
2	**1**	**0**	**0**	**1**	**0**
3	**1**	**0**	**1**	**0**	**1**
4	**0**	**1**	**0**	**1**	**1**
5	**0**	**1**	**1**	**0**	**0**
6	**1**	**0**	**0**	**0**	**1**
7	**1**	**0**	**1**	**1**	**0**

*** Dummy Variable Coding of Attribute Levels:**

Background	x_1	x_2
Free:	**0**	**0**
Green:	**1**	**0**
Tiled:	**0**	**1**

Image Size	x_3
Small:	**0**
Large:	**1**

Sound File Display	x_4
Generic:	**0**
Computer:	**1**

Celebrity Endorsement	x_5
No:	**0**
Yes:	**1**

Table 3
Expected impact of Web Site Attributes vs. Empirical Results

		Expected vs. Empirical Results:	
Attribute	Level	Impact on Number of Pages Accessed*	Impact on Time Spent on Site*
Background	i) Free	0	0
	ii) Green	- (-NS)	- (-S)
	iii) Tiled	+ (+MS)	+ (-S)
Image Size	i) Small	0	0
	ii) Large	- (-S)	+ (-NS)
Sound File Display	i) Generic	0	0
	ii) Computer-Specific	+ (-NS)	+ (-S)
Celebrity Endorsement	i) No	0	0
	ii) Yes	+ (+MS)	+ (+S)
Use of Java Scripts	i) No	0	0
	ii) Yes	+ (-S)	+ (-S)
Use of Frames	i) No	0	0
	ii) Yes	+ (+MS)	+ (-S)

*** Hypothesized Results:**
- **+ Coefficient expected positive**
- **- Coefficient expected negative**

*** Empirical Results:**
- **(+) Coefficient positive**
- **(-) Coefficient negative**
- **(S) Coefficient statistically significant (*p-level* $\leq$0.05)**
- **(MS) Coefficient marginally statistically significant (0.05<*p-level*$\leq$0.15)**
- **(NS) Coefficient not statistically significant (*p-level*>0.15)**

Table 4

Poisson Regression Model of Number of Pages Accessed*

	Coef.	Std. Err.	*p-level*
Green	-0.039	0.085	0.648
Tiled	0.117	0.070	0.096
Image	-0.160	0.054	0.003
Sound	-0.046	0.055	0.408
Endorse	0.080	0.055	0.147
Java	-0.751	0.059	0.000
Frame	0.103	0.065	0.116
Win95	0.961	0.194	0.000
Win3.1	0.424	0.203	0.037
Unix	1.530	0.205	0.000
Mac	0.875	0.201	0.000
Constant	0.519	0.208	0.012

*** Model c^2 = 343.77 (11 *df*)**
***Prob.* > c^2 = 0.0000**

Table 5

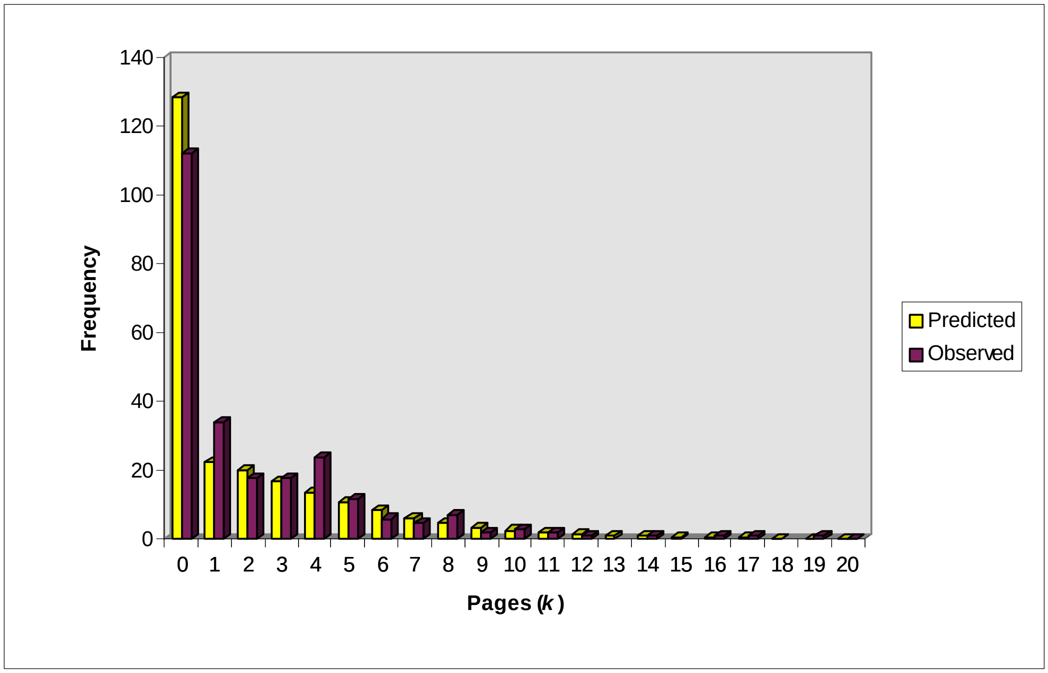
Exponential Regression Model of Time Spent on a Site*

	Coef.	Std. Err.	*p-level*
Green	-0.297	0.133	0.026
Tiled	-0.353	0.115	0.002
Image	-0.013	0.090	0.889
Sound	-0.198	0.089	0.027
Endorse	0.293	0.090	0.001
Java	-0.867	0.104	0.000
Frame	-0.363	0.110	0.001
Win95	1.037	0.236	0.000
Win3.1	0.476	0.243	0.050
Unix	1.806	0.287	0.000
Mac	0.913	0.245	0.000
Constant	4.236	0.256	0.000

*** Model c^2 = 183.40 (11 *df*)**
***Prob.* $>c^2$ = 0.0000**

Figure 4

Predicted vs. Observed Distributions of Pages Accessed*



* **Pages (*k*) is defined as *Number of Pages Accessed -1***
Chi-square = 1.246 (9 *df*)
***p-level*=0.999**

Figure 5

Efficient Frontier Analysis of Alternative Web Site Simulations