PETER J. DANAHER, GUY W. MULLARKEY, and SKANDER ESSEGAIER*

In this study, the authors examine factors that affect Web site visit duration, including user demographics, text and graphics content, type of site, presence of functionality features, advertising content, and the number of previous visits. The authors use a random effects model to determine the impact of these factors on site duration and the number of pages viewed. The proposed method accounts for three distinct sources of heterogeneity that arise from differences among people, Web sites, and visit occasions to the same Web site by the same person. The model is fit using one month of user-centric panel data, and it encompasses the 50 most popular sites in a market. The results show that, in general, older people and women visit Web sites for a longer period. Some surprising results are revealed in an examination of interactions between these demographic and site characteristic variables. For example, sites with higher levels of advertising usually result in lower visit duration, but this is not the case for older people. The model also yields insights into the relative importance of different sources of heterogeneity in visit duration; heterogeneity in visit occasions dominates over individual-level and Web site–specific heterogeneity.

# Factors Affecting Web Site Visit Duration: A Cross-Domain Analysis

Having a large number of visitors is crucial for many Web sites because a major part of their revenue is derived from advertising (East 2003, p. 85). An almost equally important performance measure that is unique to Web sites is visit duration, which is sometimes referred to as "stickiness" (Bhat, Bevans, and Sengupta 2002). Visit duration is defined as the amount of time a user is on a Web site and is now a standard industry measure that is routinely reported by Internet audience-measurement agencies, such as comScore Media Metrix, Hitwise, and Nielsen/NetRatings. A related Web site measure is the depth of visit, which is measured by the number of pages viewed (Dreze and Zufryden 1997).

Web site visit duration is important for several reasons. First, although click-through rates for banner advertisements have declined in the past five years, there is still value derived from mere exposure to the advertisements (Briggs and Hollis 1997; Flores 2001). Bucklin and Sismeiro (2003) and Danaher and Mullarkey (2003) find that exposure to Web advertising is more likely for longer page durations; this phenomenon is analogous to longer exposure times to television advertisements (Rossiter et al. 2001). For example, Danaher and Mullarkey (2003) report that as page-exposure duration increases from 20 to 40 to 60 seconds, unaided recall for a banner advertisement increases from 26% to 43% to 50% of visitors, respectively. Second, longer page duration also helps maintain user interest in a site (Bucklin and Sismeiro 2003; Hanson 2000) and gives users more time to consider and complete purchase transactions (Bucklin and Sismeiro 2003). Moe and Fader (2004b) show that enhanced user interest helps generate repeat visits, which leads to greater long-term sales. Third, from a business investment point of view, Demers and Lev (2001) show that sites with longer visit duration also have higher monthly stock returns. Although visit duration may not drive stock prices in a causal sense, some investors use Web site duration as an indicator of future earnings. This finding persisted even after the Internet stock market crash in the spring of 2000 (Demers and Lev 2001).

The motivation for the current study is the recognition of Web site visit duration as a key performance metric and the relative paucity of research on factors that affect visit duration. Given that many Web sites derive revenue from advertising (East 2003) and the everyday use of personal demographics as a way to target advertising, the first group of possible factors is Web site visitor demographics. Other fac-

*Peter J. Danaher is a professor, Department of Marketing, Faculty of Business and Economics, University of Auckland (e-mail: p.danaher@auckland.ac.nz). Guy W. Mullarkey is Key Account Manager, Shell New Zealand Ltd. (e-mail: guy.mullarkey@shell.com). (He conducted this research while at University of Auckland.) Skander Essegaier is Associate Professor of Marketing, LAREQUAD Research Center, University of Tunes, Tunisia (e-mail: skander.tunes@gmail.com).


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tors that have been shown to be related to Web site likeability and length and depth of visit include the usability, text, graphics, and advertising content, that is, characteristics of the sites themselves (Dreze and Zufryden 1997; Ghose and Dou 1998; Grenfell 1998; Hofacker and Murphy 2000). Another factor that potentially affects visit duration is the number of previous visits to a Web site (Bucklin and Sismeiro 2003). Thus, the factors we examine herein include demographic characteristics of visitors, the type of site (e.g., entertainment, news), the site content (e.g., text, graphics, navigation features), and the number of previous visits. Our study is the first to examine how the characteristics of users, sites, and their interaction affect visit behavior. Moreover, rather than restricting ourselves to just one or two sites, we broaden the scope to 50 major Web sites in a market.

Our proposed random effects model generalizes a model that Ansari, Essegaier, and Kohli (2000) developed for movie ratings by taking into account three possible sources of heterogeneity: individual level, product level (i.e., Web site), and visit-occasion level. This "triple-heterogeneity" model enables us to identify the most important sources of heterogeneity with a decomposition of the total variation in visit duration and depth. This examination of variance decomposition is somewhat analogous to Van Heerde, Gupta, and Wittink's (2003) recent work, which decomposes sales elasticity into category, brand, and quantity components.

Our data come from a Nielsen/NetRatings panel of more than 3000 Web-enabled people, all of whom provide personal demographic information. We obtained measures of Web site characteristics from a separate group of judges, who assessed each of the top 50 sites in terms of their text, graphics, and advertising content, as well as site features, such as the ability to customize pages, feedback provision, navigation aids, and availability of chat rooms.

## *RELEVANT LITERATURE*

Previous research into Web site browsing behavior is limited. To date, some studies have investigated repeat visits (Chatterjee, Hoffman, and Novak 2003; Moe and Fader 2004a) and purchase conversion rates (Moe and Fader 2004b), whereas others have examined the depth of search (Johnson et al. 2004). Some interesting findings have emerged from these studies, such as Web users engaging in only a limited amount of search across sites (Johnson et al. 2004; Zauberman 2003), despite the ease with which a wide search is possible on the Internet. Moe and Fader (2004b) find that though aggregate figures for customer loyalty (measured as visits per visitor) show an increase over time for Amazon.com and CDNow.com, the individual-level data reveal that someone making more frequent visits to these sites does so at a decreasing rate. This finding affects downstream sales. Moe and Fader (2004b) subsequently show that more frequent shoppers have a higher probability of eventual purchase.

Whereas the preceding studies examine Internet browsing, banner ad exposure, and purchasing behavior, only Bucklin and Sismeiro's (2003) study has direct relevance to our study. They develop a model for analyzing Internet clickstream data for visitors to an automotive Web site. Their study takes into account a user's decision to select another page within a site or to exit the site, and it also models page duration when another page is selected. Their page visit duration covariates are largely technical measures of the site. For example, their results show that longer page duration is associated with higher bytes transferred, greater cumulative pages viewed before the current page (i.e., visit depth), a reload request for a page, an error in a page transfer, and longer server response time. Shorter page views are associated with having dynamic content (e.g., requiring a call to a site's database). Although these measures are of technical interest to a webmaster, they are somewhat inaccessible to everyday Web designers, Web advertisers, and e-commerce investors. For this reason, we use Web site characteristics that are more user-friendly, such as graphics, text, and advertising content. Our model of Web site duration differs from that of Bucklin and Sismeiro (2003) in several additional ways. Because they have the browsing behavior for just one site collected by that site's server, there is no demographic information about their visitors. Indeed, one of the frustrations for webmasters is that they often know very little about their visitors because data are limited to just the browsing behavior for their own site. Potential demographic factors that affect Web site duration include gender, age, education, and occupation (Dreze and Hussherr 2003). In contrast, our data come from a panel of Web-enabled people who are monitored unobtrusively for a month, and demographic data are collected at recruitment. Moreover, we have the site duration and number of pages viewed for all sites visited that month, not just detailed clickstream data for a single site. This enables us to broaden our study to the top 50 Web sites in a market and to develop a cross–Web site analysis, in contrast to previous studies that examine only one or two sites in detail.

## *THE MODEL*

### *Data Preview*

Our data come from a panel of homes recruited and maintained by ACNielsen's NetRatings service.[1] The panel comprises more than 3000 people and is based on a user-centric methodology similar to that which comScore Media Metrix (Coffey 2001) uses. We provide more details on the data subsequently. Although ACNielsen's user-centric method monitors a panelist's entire browsing behavior, several quality-control checks and aggregations were applied before we received the data. The key aggregation is that all URLs visited within the same domain are aggregated up to the domain name.[2] The period for our data is November 2000.

An initial inspection of the data revealed several features that must be accounted for in a model of Web site duration. These include the following:

- Different panelists do not visit the same repertoire of Web sites. For example, in our data, the average number of different sites a person visits from the top 50 sites is just 4.3.
- The same person may visit the same site more than once in a month.

[1]Note that only the panel's home-based browsing is monitored. Workplace Web activity was not monitored at the time we obtained these data.

[2]For example, a person might visit AOL.com, drill down several pages, and then leave to visit Weather.com. The data provided to us include only the total time spent on the AOL.com domain (not separate URLs within AOL.com) and the total number of pages viewed.

- There is heterogeneity in visit duration among people, such that some users tend to have consistently shorter or longer visits to all sites.
- Sites that are similar in purpose often have similar duration times across different people. For example, we observe this with Google.com, which usually has short one-page visits.

An additional modeling consideration that is not evident from the data is that Web sites may not appear the same at each visit because of dynamically created pages or because of a different path being tracked by a visitor. This gives rise to product heterogeneity, something that is not often considered in the marketing literature. However, Ansari, Essegaier, and Kohli (2000) recently identified product heterogeneity as an important issue when modeling a person's evaluation of a movie, and Ansari and Mela (2003) found that it is germane to e-mail marketing. As with movies and e-mail, Web sites have several intangible features beyond observed attributes.

Because our measured variable is duration time, it is natural to consider a survival model initially, which has previously been applied in the marketing literature (e.g., Jain and Vilcassim 1991). Cox's (1972) proportional hazard model seems like a reasonable starting model because it incorporates covariates. However, to accommodate the anticipated individual-level heterogeneity, which we noted previously in our third bulleted point, Cox's model must be stratified by each person, which precludes the estimation of demographic effects because they are constant within a person-based stratum (Allison 1995). This makes Cox's model unsuitable for our application. An alternative method for accommodating individual-level heterogeneity is a random effects survival model known as the gamma frailty model (Hougaard 2000). Although this model is suitable for person-level heterogeneity, it cannot be extended to incorporate product-level heterogeneity, a requirement that we identified previously as potentially important in this application.

Rather than restricting ourselves to survival models simply because the dependent variable is time, a much more flexible class of models becomes available if we model the log of duration. Because we are working with duration data that are right skewed, it is natural to log-transform the duration time (Mosteller and Tukey 1977). Indeed, a plot of log(duration) for the 23,264 Web site visits in our database appears like a normal distribution. Using the log-transformation on duration enables us to employ a lognormal model (Allison 1995) that accommodates heterogeneity, unequal personal Web site repertoires, and multiple visits by the same person to the same Web site, all of which characterize our data. Bucklin and Sismeiro's (2003) model also uses a lognormal formulation for page duration.

*Notation*

Let $y_{ijk}$ be the log of the time that person i spends on Web site j for the kth visit. Because person i does not visit each Web site, we denote the index set of the sites visited as $W_i$, where $W_i = \{j_1, j_2, \ldots, j_{n_i}\}$. Each Web site $j \in W_i$, where $n_i$ is the total number of different Web sites visited by person i, i = 1, 2, …, n. Because there are potentially multiple visits to Web site j by person i, k ranges from 1 to $n_{ij}$, where $n_{ij}$ is the number of visits that person i makes to site j. Thus, the total number of observations is

$$N = \sum_{i=1}^{n} \sum_{j=1}^{n_i} n_{ij}.$$

*Model Development*

As we mentioned previously, and similar to the case of movies and music, Web sites cannot be completely described in terms of a few observable attributes. Visit duration at a Web site is shaped by a multitude of complex site attributes that affect its attractiveness, but unfortunately, these attributes are often difficult to observe and measure. A Web site's unobserved attributes contribute to its "feel and touch" and lead to differences in appeal across domains. Therefore, in our modeling approach, we account for not only individual-level heterogeneity but also Web site–level heterogeneity to allow for differences in Web site appeal and the downstream effect on Web site visit duration. In doing so, we build on the methodology that Ansari, Essegaier, and Kohli (2000) first proposed.

Our model has three components: In the first component, we model the dependent variable (log-duration) as a function of observed Web site attributes (denoted as $Z_j$, which is a $w \times 1$ vector of Web site j's characteristics). These Web site attributes have different regression weights for each person (denoted as $\beta_i^Z$), reflecting individual-level heterogeneity, and result in a linear model, written as $\beta_i^Z Z_j$. The second component arises from considering the dependent variable a function of observed personal characteristics (denoted as $X_i$, which is a $d \times 1$ vector of person i's demographic characteristics), which have different regression weights for each Web site (denoted as $\beta_j^X$), reflecting site-level heterogeneity. The resultant linear model for this component is $\beta_j^X X_i$.

Unlike Ansari, Essegaier, and Kohli's (2000) case, in which respondents rated each movie only once, Web sites in our data set are often visited multiple times by the same person. Indeed, approximately 47% of initial visits to one of the top 50 Web sites in our data are followed by another visit to the same site later in the month, with an average of 2.2 return visits in a month. As a result, in our application, we need to capture not only the unobserved person-level and Web site–level heterogeneity but also the observed and unobserved differences across multiple visit occasions to the same Web site by the same person.

Thus, a third component arises from viewing the dependent variable as a function of observed characteristics of a particular visit occasion to the same Web site by the same person (denoted as $M_k$, which is a $m \times 1$ vector of the characteristics of the kth observed visit, such as the day of the week or the number of previous visits to the site). To reflect occasion-level heterogeneity across multiple visits, we assign different regression weights for each person–Web site pair (denoted as $\beta_{ij}^M$). The resultant linear model for this component is $\beta_{ij}^M M_k$.[3] Thus, our model is a triple-heterogeneity model that captures person-level, product-

[3]Strictly speaking, $M_k$ should be written as $M_{(ij)k}$ to reflect that the kth visit is nested within the (ij)th person–Web site pair, but we use the $M_k$ notation for simplicity.

level, and visit-occasion-level heterogeneity, whereas Ansari, Essegaier, and Kohli's (2000) model is a double-heterogeneity model that captures only person-level and product-level heterogeneity.

A combination of the three components yields the full model,

$$(1) \qquad y_{ijk} = \beta_j^X X_i + \beta_i^Z Z_j + \beta_{ij}^M M_k + \varepsilon_{ijk},$$

where $\varepsilon_{ijk}$ is a random error that is i.i.d. normal with a mean of zero and a variance of $\sigma^2$, which we used to capture any remaining unexplained variation.

In the spirit of the hierarchical Bayes method, we can decompose the random effect regression coefficients in Equation 1 into fixed and random parts as follows:

$$(2) \qquad \begin{aligned} \beta_j^X &= \beta^X + \gamma_j, \quad \gamma_j \sim N(0, \Omega), \\ \beta_i^Z &= \beta^Z + \lambda_i, \quad \lambda_i \sim N(0, \Phi), \text{ and} \\ \beta_{ij}^M &= \beta^M + \mu_{ij}, \quad \mu_{ij} \sim N(0, \Psi). \end{aligned}$$

Substituting Equation 2 into Equation 1 yields

$$(3) \qquad \begin{aligned} y_{ijk} = {} & \beta^X X_i + \beta^Z Z_j + \beta^M M_k + \lambda_i Z_j \\ & + \gamma_j X_i + \mu_{ij} M_k + \varepsilon_{ijk}. \end{aligned}$$

For the three random effect terms in Equation 3, we can write

$$(4) \qquad \begin{aligned} \lambda_i Z_j &\sim N(0, Z_j' \Phi Z_j), \\ \gamma_j X_i &\sim N(0, X_i' \Omega X_i), \text{ and} \\ \mu_{ij} M_k &\sim N(0, M_k' \Psi M_k). \end{aligned}$$

By setting the first element of $X_i$, $Z_j$, and $M_k$ to be 1 to permit an intercept term and by partitioning $\Phi$, $\Omega$, and $\psi$ into

$$\Phi = \begin{bmatrix} \phi_1 & \phi_2' \\ \phi_2 & \Phi^* \end{bmatrix}, \ \Omega = \begin{bmatrix} \omega_1 & \omega_2' \\ \omega_2 & \Omega^* \end{bmatrix}, \text{ and } \Psi = \begin{bmatrix} \psi_1 & \psi_2' \\ \psi_2 & \Psi^* \end{bmatrix},$$

we can rewrite the random effect linear combinations in Equation 4 as

$$(5) \qquad \begin{aligned} \lambda_i Z_j &\sim N(0, \phi_1 + 2\phi_2 Z_j^* + Z_j^* \Phi^* Z_j^*), \\ \gamma_j X_i &\sim N(0, \omega_1 + 2\omega_2 X_i^* + X_i^* \Omega^* X_i^*), \text{ and} \\ \mu_{ij} M_k &\sim N(0, \psi_1 + 2\psi_2 M_k^* + M_k^* \Psi^* M_k^*), \end{aligned}$$

where $X_i^*$, $Z_j^*$, and $M_k^*$ are the demographic profile for person i, the vector of descriptors for Web site j, and the vector of visit-occasion descriptors for the kth visit of person i to Web site j, respectively (each vector excluding the intercept term). We denote the left-hand side of the respective terms in Equation 5 as $\tau_i = \lambda_i Z_j$, $\delta_j = \gamma_j X_i$, and $\eta_{ij} = \mu_{ij} M_k$. Thus, an alternative way to write Equation 3 is[4]

$$(6) \qquad y_{ijk} = \beta^X X_i + \beta^Z Z_j + \beta^M M_k + \tau_i + \delta_j + \eta_{ij} + \varepsilon_{ijk},$$

where $\tau_i \sim N(0, \sigma_\tau^2[Z_j])$, $\delta_j \sim N(0, \sigma_\delta^2[X_i])$, and $\eta_{ij} \sim N(0, \sigma_\eta^2[M_k])$; note that the three variances are functions of $Z_j$, $X_i$, and $M_k$, respectively. If the demographic, Web site, and visit-occasion information is ignored in the variances of these random effects distributions (i.e., only the first term in the variances of Equation 5 is taken into account), we simply have $\tau_i \sim N(0, \phi_1)$, $\delta_j \sim N(0, \omega_1)$, and $\eta_{ij} \sim N(0, \psi_1)$, which results in a standard mixed effects model with homoskedastic variances (Laird and Ware 1982). Therefore, the difference between Ansari, Essegaier, and Kohli's (2000) model and a standard mixed effects model is that their model has heteroskedastic random effects (which are functions of $X_i$, $Z_j$, and, in our case, $M_k$), whereas the usual mixed effects model has homoskedastic random effects. Subsequently, we empirically examine the fit of Model 6 under some alternative variance specifications in the random effect terms.

*Models for Average Page Duration and Pages Viewed*

Because our data include the number of pages viewed within a domain, we also model the average page duration, which is the ratio of the total domain duration to the total pages viewed for each separate visit. Furthermore, we model the number of pages viewed. We estimate all three models with the "Mixed" procedure in SAS, which has the ability to accommodate the three sources of heterogeneity.[5]

## *EMPIRICAL ANALYSIS*

*Data in Detail*

As we mentioned previously, the data we used to fit our models come from ACNielsen's NetRatings service in New Zealand, which employs a user-centric methodology. This panel comprises 3284 people recruited to represent people ages 2 and older with Internet access. We obtained data for November 2000, during which 1852 panelists (56%) used the Internet at least once. Demographic information about age, gender, occupation, and education, as well as the education and occupation of the main income earner in the home, is obtained at recruitment for each panelist. Table 1 shows the demographic profile of the panel. Compared with the general population, this panel of Internet users tends to be slightly younger and is better educated, with a corresponding skew toward students and professional employment. Such "upscale" demographic skews have also been observed for Internet users in the United States (Degeratu, Rangaswamy, and Wu 2000) and the United Kingdom (Emmanouilides and Hammond 2000).

ACNielsen's software captures each URL and visit duration for that URL as panelists proceed through their Internet session. However, as we mentioned previously, the data supplied to us are aggregated to the domain level, and they report the total domain visit duration and the total number of pages visited.[6]

[4]We can also write Equation 6 with an explicit fixed effect intercept term as $y_{ijk} = \alpha + \beta^{X*}X_i^* + \beta^{Z*}Z_j^* + \beta^{M*}M_k^* + \tau_i + \delta_j + \eta_{ij} + \varepsilon_{ijk}$, where $\alpha = \beta_0^X + \beta_0^Z + \beta_0^M$.

[5]As for the domain duration data, the log-transformation is taken of the page duration. Note also that the number of pages viewed begins at 1 and is discrete, so we apply Cameron and Trivedi's (1998) transformation of count data, log(pages – .9), which has near-zero skewness and low kurtosis.

[6]Our data also have the number of hits, which is distinct from the number of pages viewed.

Table 1
DEMOGRAPHIC PROFILE OF PANELISTS

| | | *Panel Percentage* | *Population Percentage* |
|---|---|---|---|
| Gender | Male | 54 | 49 |
| | Female | 46 | 51 |
| Age | 2–19 | 25 | 24 |
| | 20–29 | 12 | 14 |
| | 30–39 | 20 | 17 |
| | 40–49 | 19 | 16 |
| | 50–59 | 17 | 12 |
| | 60+ | 7 | 17 |
| Education | Grammar school or some high school only | 34 | 54 |
| | High school graduate or some college | 46 | 34 |
| | Bachelor's or postgraduate degree | 21 | 12 |
| Occupation | Blue collar | 7 | 20 |
| | Administration/sales | 10 | 10 |
| | Homemaker | 6 | 9 |
| | Student | 21 | 20 |
| | Self-employed | 12 | 8 |
| | Professional | 32 | 16 |
| | Retired/unemployed/other | 12 | 17 |

Notes: Sample base is the 1665 people who accessed at least one of the top 50 sites in November 2000.

More than 23,000 different sites were visited in November 2000, totaling 292,790 visits, but two-thirds of these sites are visited just once. Because of this low visit incidence for the majority of sites and because we subsequently content-analyze each site, we selected just the top 50 Web sites.[7] Moreover, because of the importance of advertising revenue for most Web sites, we considered only sites that carry advertising. This eliminated several bank and government Web sites, for example. Our final sample size, based on visitors to at least one of these 50 sites, was 1665 people, who had a total of 23,264 visits over the course of the month.

Table 2 lists the top 50 Web sites in order of frequency of usage. It is not surprising that the high-usage sites tend to be portals, Internet service providers (ISPs), and search engines. Other frequently visited sites are Web-hosting services, entertainment, and software products. Table 2 also gives the median site duration (measured in seconds) and the median number of pages viewed. There is much variation in visit duration and depth across the sites. For example, the portal GoHip.com has a median duration time of only 43 seconds, whereas the median duration time for games/entertainment sites, such Imperialconflict.com, Neopets.com, and Swirve.com, all exceed 1000 seconds (approximately 16 minutes). Likewise, for the number of pages viewed, search engines such as AltaVista.com and Google.com average between one and two pages viewed, whereas many of the entertainment sites average more than ten pages viewed.

*Content Analysis of the Top 50 Web Sites*

In addition to characteristics of Internet users, we also study Web site features to determine whether they affect visit duration. Understanding the effect of Web site design and content on a user's visit duration might help webmasters tailor their sites to retain visitors for longer periods, resulting in the downstream benefits we mentioned previously.

Some potential Web site design features that have been examined previously in the context of visit duration include the text and graphics content and background complexity (Dreze and Zufryden 1997), advertising content (Dreze and Zufryden 1997; Hofacker and Murphy 2000), and functionality (e.g., content customization, search functions, discussion boards; Ghose and Dou 1998). All these features are easy for a Web user to assess and are similarly easy for a webmaster to manipulate. For example, if a Web user notes that there is a lot of advertising on a site's home page, resulting in unappealing ad clutter (Kent 1993) that lowers visit duration, the webmaster can attempt to reduce the clutter without markedly sacrificing advertising revenue.

Three judges, who were instructed to visit each domain and examine the site for five minutes by clicking across pages, assessed each of the top 50 Web sites. During this surfing period, judges rated the site's text and graphics content, background complexity, advertising content, and functionality items. This made the content analysis more detailed than merely using the home page (e.g., Ha and James 1998) but not so time consuming as to make the evaluation too arduous.

We based the coding instructions and coding forms on Grenfell's (1998) work. The instructions (which are available on request) specified how the analyses should be conducted and defined all of the technical terms used in the coding sheet. We measured text and graphics content and background complexity on a five-point scale, anchored by "simple" (1) and "complex" (5). We coded advertising content so that Codes 1 through 5 denoted 1, 2–3, 4–5, 6–7, and 8 or more advertisements, respectively, on a typical page.[8] We measured functionality with 19 items, which we based largely on Grenfell's (1998), Ghose and Dou's (1998), and Ha and James's (1998) measures; these items included features such as online help, search functions, site maps, user

[7]These 50 sites had the highest total count of the number of pages viewed over the course of the month.

[8]There are different numbers of advertisements per page, so judges later reported that they used the home page as an initial indication of ad quantity and then modified their assessment (if necessary) after the five-minute browsing period.

Table 2
LIST OF THE TOP 50 WEB SITES WITH AVERAGE VISIT DURATION AND SITE ATTRIBUTES

| *Site Name* | *Site Type* | *Text Content* | *Graphics Content* | *Background Complexity* | *Advertising Content* | *Functionality Score* | *Median Visit Duration* | *Median Pages Viewed* | *Average CVisit* |
|---|---|---|---|---|---|---|---|---|---|
| about.com | Portal | 4 | 1 | 1 | 2 | .42 | 110 | 3 | .5 |
| altavista.com | Search | 3 | 1 | 2 | 1 | .68 | 106 | 1 | 1.3 |
| amazon.com | Retail | 4 | 3 | 2 | 1 | .53 | 156 | 3 | .3 |
| aol.com | Portal | 3 | 3 | 1 | 3 | .53 | 84 | 2 | .4 |
| ask.com | Search | 1 | 1 | 1 | 1 | .47 | 87 | 2 | .4 |
| bluemountain.com | Greetings | 4 | 4 | 3 | 1 | .53 | 288 | 5 | .6 |
| bolt.com | Entertainment | 4 | 3 | 4 | 3 | .58 | 318 | 10 | 2.9 |
| bonzi.com | Portal | 4 | 1 | 1 | 1 | .32 | 53 | 1 | .4 |
| cartoonnetwork.com. | Entertainment | 1 | 4 | 1 | 2 | .37 | 280 | 7 | .7 |
| clear.net.nz | ISP | 3 | 3 | 2 | 2 | .53 | 101 | 2 | 1.8 |
| cnet.com | Service | 3 | 3 | 2 | 2 | .42 | 114 | 2 | .7 |
| cnn.com | News | 4 | 4 | 2 | 2 | .68 | 164 | 2 | 2.4 |
| ebay.com | Auction | 2 | 1 | 1 | 1 | .79 | 224 | 3 | 2.3 |
| egreetings.com | Greetings | 2 | 3 | 3 | 2 | .42 | 440 | 4 | .6 |
| excite.com | Portal | 4 | 2 | 3 | 2 | .74 | 91 | 2 | 1.8 |
| ezboard.com | Messaging | 2 | 4 | 3 | 1 | .42 | 1188 | 8 | 2.2 |
| flybuys.co.nz | Service | 2 | 3 | 2 | 1 | .32 | 307 | 6 | .4 |
| foxkids.com | Games | 1 | 4 | 1 | 2 | .26 | 570 | 8 | .4 |
| go.com | Portal | 4 | 2 | 2 | 2 | .37 | 118 | 2 | .7 |
| gohip.com | Portal | 3 | 2 | 1 | 2 | .32 | 43 | 2 | 1.9 |
| google.com | Search | 1 | 1 | 1 | 1 | .53 | 98 | 2 | 2.1 |
| homestead.com | Hosting | 1 | 3 | 2 | 1 | .42 | 110 | 4 | .6 |
| hotbar.com | Software | 1 | 3 | 2 | 1 | .26 | 107 | 7 | 5.5 |
| icq.com | Messaging | 4 | 3 | 3 | 1 | .74 | 51 | 1 | 1.6 |
| ihug.co.nz | ISP | 3 | 3 | 3 | 4 | .47 | 66 | 1 | 2.5 |
| imperialconflict.com | Games | 2 | 2 | 3 | 1 | .53 | 1473 | 22 | 10.0 |
| lycos.com | Portal | 3 | 2 | 2 | 1 | .84 | 74 | 1 | .9 |
| microsoft.com | Software | 3 | 2 | 2 | 1 | .47 | 60 | 2 | 1.1 |
| msn.com | Portal | 4 | 3 | 2 | 1 | .68 | 176 | 3 | 3.7 |
| mtnsms.com | Messaging | 1 | 2 | 2 | 1 | .26 | 275 | 4 | 2.5 |
| nbci.com | Portal | 4 | 2 | 2 | 3 | .47 | 71 | 2 | .7 |
| neopets.com | Entertainment | 3 | 3 | 3 | 1 | .42 | 1185 | 16 | 2.8 |
| netscape.com | Portal | 4 | 3 | 2 | 3 | .79 | 82 | 1 | 2.5 |
| nzcity.co.nz | Portal | 4 | 3 | 2 | 3 | .53 | 65 | 2 | 3.7 |
| nzherald.co.nz | News | 4 | 3 | 3 | 2 | .47 | 241 | 2 | 2.3 |
| nzoom.com | Portal | 4 | 4 | 3 | 2 | .47 | 101 | 2 | 1.7 |
| paradise.net.nz | ISP | 1 | 3 | 3 | 1 | .32 | 66 | 2 | 3.1 |
| passport.com | Portal | 2 | 1 | 1 | 1 | .37 | 66 | 2 | 4.4 |
| shockwave.com | Entertainment | 2 | 3 | 1 | 3 | .37 | 174 | 3 | .5 |
| stuff.co.nz | News | 4 | 3 | 2 | 2 | .32 | 151 | 3 | 2.4 |
| swirve.com | Entertainment | 4 | 3 | 2 | 1 | .47 | 5089 | 22 | 6.5 |
| trademe.co.nz | Auction | 3 | 2 | 2 | 1 | .63 | 222 | 7 | 2.4 |
| tripod.com | Hosting | 4 | 2 | 2 | 1 | .53 | 76 | 2 | .5 |
| webshots.com | Software | 3 | 3 | 2 | 1 | .47 | 90 | 3 | 1.2 |
| xtra.co.nz | Portal | 4 | 2 | 2 | 1 | .42 | 69 | 1 | 2.3 |
| xtramail.co.nz | Service | 2 | 3 | 2 | 1 | .37 | 171 | 3 | 2.5 |
| yahoo.com | Portal | 4 | 2 | 1 | 1 | .58 | 163 | 4 | 3.0 |
| zdnet.com | Service | 4 | 2 | 3 | 2 | .63 | 145 | 3 | 1.5 |
| zfree.co.nz | ISP | 3 | 4 | 2 | 2 | .37 | 127 | 2 | 3.6 |
| zone.com | Games | 3 | 4 | 4 | 4 | .53 | 259 | 3 | 5.9 |

registration, e-mail contact availability, chat rooms, and message boards. Table 3 provides the complete list. We coded each of these items on a two-point scale (yes = 1, no = 0). We obtained an overall functionality score between 0 and 1 for each Web site by averaging the 19 items.

We assessed interjudge reliability using Rust and Cooil's (1994) proportional reduction in loss (PRL) index, which is a generalization of Cronbach's alpha that takes into account the number of judges and the number of scale categories for each item. Rust and Cooil recommend that PRL values should be greater than .7 for adequate interjudge reliability. In general, the PRL values we obtained in our study were very high (.79 for text content, .65 for graphics content, .75 for background complexity, and .91 for advertising content), and the average PRL across the 19 functionality items was .89. Therefore, we can reasonably conclude that the assessment of the content of the top 50 sites is reliable.

The middle columns of Table 2 display the ratings for the top 50 sites on text, graphics, background, and advertising attributes, as well as the average functionality score, and Table 3 shows the percentage of sites that were rated as a 4 or 5 (i.e., high) on these attributes for the entire group of 50 sites we used in the analysis. More than 40% of the sites were judged to have high text content, whereas few were judged to have high background complexity and advertising content. The overall average functionality score is 49%.

*Model Variables*

Our model for Web site duration in Equation 6 contains three broad groups of variables: demographic characteris-

Table 3
PROFILE OF SITES AND DESCRIPTION OF THE FUNCTIONALITY ITEMS: TOP 50 WEB SITES

| | | *Percentage* |
|---|---|---|
| Site type | Auction | 4 |
| | Entertainment | 20 |
| | ISP | 8 |
| | News | 6 |
| | Portal | 30 |
| | Service[a] | 26 |
| | Software | 6 |
| Site features | High text content[b] | 42 |
| | High graphics content | 16 |
| | High background complexity | 4 |
| | High advertising content | 4 |

| *Functionality Item* | *Description* | *Percentage with Item* |
|---|---|---|
| 1 | A button or function that enables a user to change the site's language. | 24 |
| 2 | A button or function that enables a user to change the site's graphic or text content mix. | 12 |
| 3 | A button or function that enables a user to change the site's page layout. | 16 |
| 4 | A button or function that enables a user to customize the site's content. | 32 |
| 5 | Are there any e-mail contact addresses on the site? | 74 |
| 6 | Can users view product/service information on the site? | 98 |
| 7 | Is there any form of online help available? | 84 |
| 8 | Does the site have a basic search function? | 80 |
| 9 | Does the site have a detailed site map available? | 30 |
| 10 | Does the site have links related to other relevant parts of the site present? | 94 |
| 11 | Can the user download site paraphernalia (e.g., wallpaper) on this Web site? | 36 |
| 12 | Does this site have user registration as an option? | 84 |
| 13 | Does the site encourage feedback with online survey forms? | 30 |
| 14 | Does the site encourage feedback with e-mail? | 76 |
| 15 | Does the site have online problem diagnostics tools? | 2 |
| 16 | Does the site have a clear section that features recent updates? | 58 |
| 17 | Does the site have any chat rooms available? | 32 |
| 18 | Does the site have topic-specific discussion forums? | 34 |
| 19 | Does the site have message boards available? | 32 |
| | Average functionality score (on a 0 to 1 scale) | 48.8 |

[a]Service sites include Web-hosting messaging, search and retail sites, and sites initially classified as providing a service.
[b]"High" means that the site feature was rated a 4 or 5 on a five-point scale.

tics of users, Web site characteristics, and variables related to visit occasions. We now give more details on the actual variables used in our empirical application of the model in Equation 6.

*Demographic descriptors*. Table 1 gives the four demographic variables that are measured for each panelist. In the model, gender is binary coded (1 = male, 2 = female). We use panelists' exact ages (ranging from ages 2 to 83) rather than code the ages into categories. Table 1 lists three education categories, which we code as dummy variables: Those with "grammar school or some high school" (low education), which was the baseline, those with "high school or some college" (medium education), and those with a "college degree" (high education). We similarly code the occupation categories that appear Table 1 as dummy variables; "retired/unemployed" is the baseline.

*Web site descriptors*. We list the observed Web site characteristics in Table 3. We coded site type as the dummy variable, with portals as the baseline. We use the site attribute scores for text, graphics, background complexity, and advertising content that appear in Table 2 directly in the model. Because some of the 19 functionality items are either highly correlated among themselves (e.g., items 2–4 and 17–19) or correlated with particular site types, we use just the average functionality score for each Web site (see Table 2).

*Visit occasion descriptors*. These variables pertain to the conditions under which a particular visit takes place. The first variable is "weekend visit," which indicates whether a particular visit occurs on a weekday or weekend; we code this as 1 if the observed visit occurs on a Saturday or a Sunday. In line with the work of Bucklin and Sismeiro (2003), the second variable measures the cumulative number of previous visits to a given Web site by a given person.[9] We operationalize this by creating a variable called "CVisit,"

[9]Because our data are restricted to just the month of November, we have no way of knowing when a panelist first visits a particular Web site (i.e., the data are left censored). Therefore, it is difficult to claim that such a variable captures any potential learning or fatigue effects due to multiple visits by the same person to the same Web site.

which is the cumulative number of previous visits to a particular site by a panelist before the occurrence of the present visit, but only from November 1, 2000, which is the beginning of our observation window. For example, if a person visited Google.com on November 2, 7, 11, and 20, CVisit has a value of 0 on November 2 but increases to 1, 2, and 3, respectively, on November 7, 11, and 20.[10] In the last column of Table 2, we provide average values of CVisit for a person's final visit to a site in November for the top 50 Web sites.

*Interactions*. It might be expected that interactions of all or some of the demographic, Web site, and visit-occasion descriptors also affect visit duration and pages viewed. Therefore, we include all possible pairwise interactions of the fixed effects in the model of Equation 6.

## *RESULTS*

### *Model Comparison*

We previously discussed several alternative models, which we now compare. The first is a model with fixed effects only (Equation 6 without the $\tau_i$, $\delta_j$, and $\eta_{ij}$ terms), which is equivalent to an ordinary least squares regression model. The second model is Ansari, Essegaier, and Kohli's (2000) random effects model, in which the random effects are, in turn, linear functions of demographic and Web site covariates.[11] The third model is a simplification of Ansari, Essegaier, and Kohli's model, which has homoskedastic random effects; this is essentially Equation 6 without the $\beta^M_{ij}M_k$ and $n_{ij}$ terms. The remaining model is the one we proposed in Equation 6, in which the random effects are homoskedastic but allowance is made for repeat visits.

We compare these models on the basis of their log-likelihood and Bayes information criterion (BIC), which takes into account the number of estimated parameters and does not require alternative models to be nested within one another. The model with the highest BIC value is deemed to be the best. As an additional model comparison, we split our data into calibration and validation data sets. In our case, we use the first 1000 people (corresponding to 13,544 site visits) for calibration, which leaves 665 people (with 9720 visits) in the validation data set. We compare across the four models using three criteria: relative absolute deviation (RAD), which is the average of the absolute value of the difference between the estimated and the actual log-duration divided by the estimated log-duration; the mean absolute deviation (MAD), which is the absolute value of the difference between the estimated and the actual log-duration; and the root mean square error (RMSE), which is the square root of the averaged squared differences between the estimated and the actual log-duration. For the validation data, we also compare the bias and variance.

Table 4 shows that the highest log-likelihood and BIC occur for the model that we propose in Equation 6, that is, the mixed effects model with homoskedastic random effects. Note that the mixed effects model is a significant improvement over both forms of Ansari, Essegaier, and Kohli's (2000) model, showing the benefit of including fixed and random effects for visit occasions to the same site by the same person. The RAD, MAD, and RMSE criteria for the calibration data show that the proposed model performs better than all other models. All the models do worse for the validation data than for the calibration data, but they perform similarly; however, the mixed effects model does slightly better than the other models. All models have small bias in the validation data, showing that the mean squared error is largely composed of variance, not bias. Thus, on balance, the mixed effects model with homoskedastic random effects performs as well as or better than the alternative models. Therefore, hereinafter, we report results only for this model.

### *Parameter Estimates for the Domain Duration Model*

Table 5 gives the parameter estimates for the mixed effects model with homoskedastic random effects. This time

[10]Because CVisit ranges from 0 to 30 and is heavily skewed to the right, we follow the work of Bucklin and Sismeiro (2003) by taking a log transformation and using log(1 + CVisit) in the model.

[11]Note that Ansari, Essegaier, and Kohli's (2000) model does not have the $\beta^M_{ij}M_k$ term in Equation 1.

Table 4
MODEL COMPARISON

| | *Fixed Effects Only*[a] | *AEK*[b] | *AEK–Homoskedastic Effects* | *Mixed Effects–Homoskedastic Effects* |
|---|---|---|---|---|
| Log-likelihood | –24,908[c] | –24,307 | –24,496 | –23,834 |
| Parameters | 42 | 61 | 42 | 45 |
| BIC | –25,108 | –24,597 | –24,296 | –24,048 |
| *Calibration Data (13,544 Observations)* | | | | |
| RAD (%) | 26.0 | 23.3 | 24.1 | 20.8 |
| MAD | 1.20 | 1.05 | 1.10 | .92 |
| RMSE | 1.52 | 1.35 | 1.40 | 1.18 |
| *Validation Data (9720 Observations)* | | | | |
| RAD (%) | 26.7 | 27.1 | 27.2 | 27.1 |
| MAD | 1.23 | 1.23 | 1.23 | 1.22 |
| RMSE | 1.55 | 1.55 | 1.55 | 1.54 |
| Bias | –.03 | .06 | .06 | .08 |
| Variance | 2.41 | 2.40 | 2.40 | 2.37 |

[a]Equivalent to ordinary least squares regression model.
[b]AEK = Ansari, Essegaier, and Kohli's (2000) original model.
[c]Log-likelihood for the null model with an intercept only is –25,624.

Table 5

PARAMETER ESTIMATES FOR THE DOMAIN AND PAGE DURATION AND PAGES-VIEWED MODELS

| | *Domain Duration Model* | | *Page Duration Model* | | *Pages-Viewed Model* | |
|---|---|---|---|---|---|---|
| | *Estimate* | *t-Statistic* | *Estimate* | *t-Statistic* | *Estimate* | *t-Statistic* |
| Intercept | **3.87** | 11.2 | **3.09** | 12.2 | –.57 | –1.3 |
| Gender (female) | **.23** | 2.8 | .08 | 1.1 | **.48** | 4.2 |
| Age | **.02** | 3.0 | **.01** | 2.4 | **.02** | 2.4 |
| Software | –.46 | –1.6 | **–.41** | –2.0 | .08 | .2 |
| Auction | **.78** | 2.6 | .24 | 1.2 | 1.45 | 1.8 |
| Entertainment | **1.21** | 6.0 | **.47** | 3.3 | **1.63** | 3.7 |
| Services | .03 | .2 | .00 | .1 | .37 | 1.3 |
| ISP | **–.54** | –2.0 | –.08 | –.4 | –.78 | –1.8 |
| News | **.43** | 2.0 | **.42** | 2.8 | –.33 | –.7 |
| Portal[a] | — | — | — | — | — | — |
| Text content | **–.17** | –2.2 | **–.15** | –2.8 | –.07 | –.7 |
| Graphics content | **.23** | 2.8 | .05 | .8 | **.36** | 3.3 |
| Background complexity | .04 | .5 | .03 | .4 | .04 | .4 |
| Advertising content | **–.32** | –3.7 | –.11 | –1.8 | **–.28** | –2.1 |
| Functionality | **.96** | 2.0 | **1.59** | 4.6 | –1.19 | –1.8 |
| Weekend visit | –.01 | –.5 | –.03 | –1.6 | .04 | 1.8 |
| Log(1 + CVisit) | .01 | 1.0 | –.00 | –.4 | **.06** | 2.1 |
| Gender × age | **–.005** | –2.1 | –.00 | –.5 | **–.007** | –2.8 |
| Age × software | .007 | 1.7 | .001 | .3 | **.012** | 2.7 |
| Age × services | **.006** | 2.0 | .003 | 1.4 | .003 | .8 |
| Age × ISP | **.010** | 2.2 | .004 | 1.2 | **.013** | 2.3 |
| Age × text content | **.003** | 2.5 | **.003** | 2.6 | .001 | .9 |
| Age × graphics content | **–.003** | –2.2 | –.001 | –.8 | **–.005** | –3.1 |
| Age × advertising content | **.005** | 3.4 | **.002** | 2.4 | **.005** | 3.3 |
| Age × functionality | **–.036** | –4.8 | **–.028** | –5.0 | **–.017** | –2.0 |
| $\sigma^2_\tau$ | .05 | | .08 | | .04 | |
| $\sigma^2_\delta$ | .09 | | .04 | | .17 | |
| $\sigma^2_\eta$ | .60 | | .26 | | .93 | |
| $\sigma^2$ | 1.58 | | 1.05 | | 1.56 | |

[a]Baseline dummy variable.

Notes: Because none of the education and occupation variables are significant, they are not reported here. Note also that for brevity, only interactions that are significant for at least one of the models are reported. Statistically significant terms appear in bold.

we use the entire sample of 1665 people. Only two demographic variables are statistically significant: gender and age. The positive estimated coefficients for these two variables show that, in general, women visit Web sites for longer periods and that visit duration increases with age. However, there is a significant, negative coefficient for the gender × age interaction, showing that older women have shorter visits than older men. Education and occupation do not have a significant impact on the length of a site visit. This finding on the age of Web users is supported by Dreze and Hussherr's (2003) study, in which eye fixation times on Web pages are longer for older people. However, they do not find a significant gender effect or an interaction between gender and age, as we do.

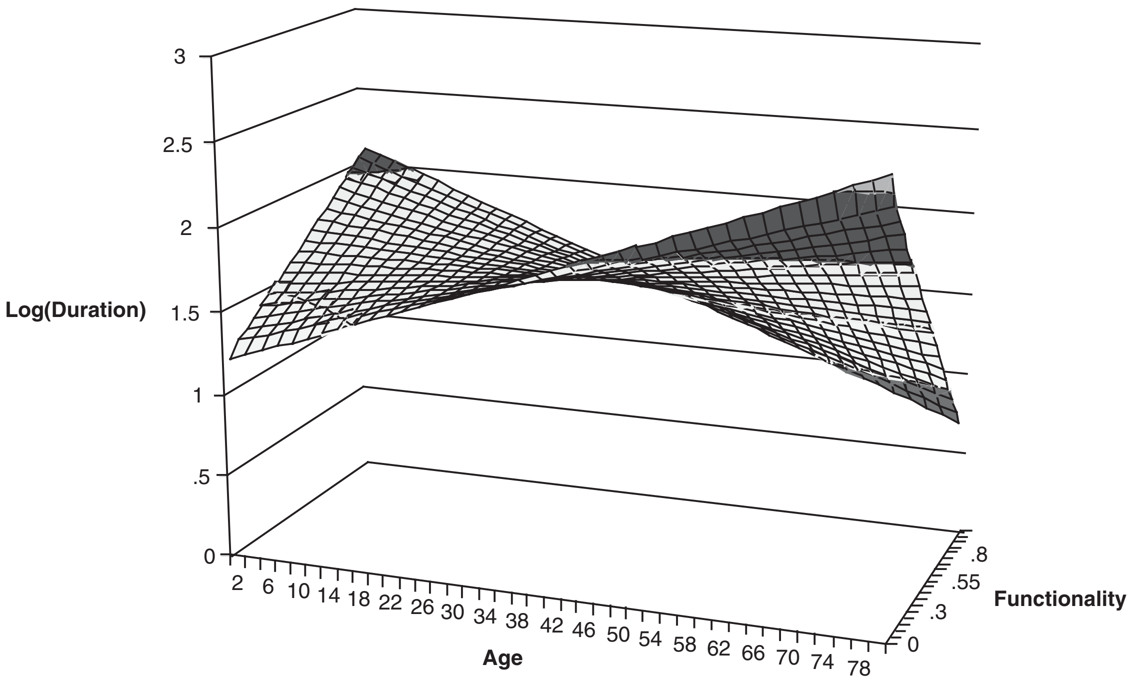
In addition, entertainment sites have significantly longer visit durations ($p < .0002$) than portals (the baseline site type). Auction and news sites have longer visit durations than portals ($p < .05$), and ISPs have shorter durations.

Of the Web site characteristics, text, graphics, and advertising content, as well as Web site functionality, are all significant at the 5% level. However, each of these variables also interacts with user age. We provide a more complete discussion subsequently, but for now, we comment only on graphics and advertising content. The longer duration for sites with high graphics content is likely due to the combined effect of many entertainment sites' high graphics content and the longer download times for graphics for people with a phone modem (only 2% of the panelists had broadband at the time of the study). The negative coefficient for advertising shows that a higher level of advertising on a site is associated with shorter site visits. Dreze and Hussherr (2003) find that many Web users actively avoid banner advertisements (even though they may be peripherally exposed to the advertisement). Moreover, Schlosser, Shavitt, and Kanfer (1999) find that Web advertisements are disliked more than those in conventional media. This is consistent with our finding that sites with six or more advertisements per page may be driving away visitors, but this depends on a user's age, as we now discuss.

### *Interactions*

We examined all possible pairwise interactions among the demographic, Web site characteristic, and visit-occasion fixed effects. After we found significant two-way interactions, we also looked for possible three-way interactions, but none were significant. We report only significant interactions in Table 5, but they illustrate several interesting relationships between age, in particular, and Web site types and features. One of the most intriguing interactions is that between age and functionality. The positive main effect coefficient for functionality demonstrates that enhancing a site's interactive and customization features increases visit duration. However, the coefficient for the age × functionality interaction is negative. Figure 1 illustrates how these two variables interact by plotting the estimated log-duration (with all other variables held constant) for varying age and

Figure 1
ESTIMATED DURATION AS A FUNCTION OF AGE AND WEB SITE FUNCTIONALITY




functionality. For younger visitors, duration increases with increasing functionality, whereas the reverse is true for older Web users. Indeed, a point of inflexion occurs in Figure 1 at age 27 and functionality .49. Thus, enhanced Web site functionality increases duration for users less than approximately age 30, but the site must have a functionality score of at least .49 to achieve above-average duration. For example, Foxkids.com currently has a functionality value of .26 and clearly appeals to younger Web users. It needs to enhance its functionality to greater than .49 to secure longer visits from its users.

The interaction between age and advertising content also warrants further investigation. Figure 2 illustrates this and shows that increasing advertising levels reduces duration for younger people, which is consistent with the negative main effect for advertising. However, somewhat surprisingly, for older Web users, the reverse occurs; visit duration increases as advertising levels increase. The inflexion point occurs at age 67. Thus, although Web advertising is often perceived negatively by most age groups, it does not negatively affect older Web users. Therefore, advertisers aiming to reach an older target audience may find the Web to be a fruitful medium.

*Variance Component Decomposition*

Estimates of the variance components in Equation 6 also appear in Table 5. The largest component corresponds to the visit-occasion effects by the same person to the same Web site ($\eta_{ij}$), followed by Web site effects ($\delta_j$) and then individual-specific effects ($\tau_i$). Table 6 gives the variance decomposition for random effects models with increasing capacity to capture heterogeneity. Note that the total of the variance terms is nearly the same across the three models, so that the four terms, $\sigma^2_\tau$, $\sigma^2_\delta$, $\sigma^2_\eta$, and $\sigma^2$, are essentially a decomposition of the mean squared error of actual versus predicted values.

The first model has fixed effects only, with no attempt to capture heterogeneity. The second model, which has separate random effects for people and Web sites, shows that there is heterogeneity at the person and Web site levels, but a substantial amount is still unexplained because the estimate of $\sigma^2$ remains large relative to both $\sigma^2_\tau$ and $\sigma^2_\delta$. It also indicates that person and Web site heterogeneity levels are about the same in magnitude, which is somewhat surprising. The final model shows the dramatic effect of capturing visit-occasion heterogeneity, which is derived from repeat visits to the same site by the same person. Models that ignore this visit-occasion heterogeneity are likely to understate the size of overall heterogeneity effects and also misplace heterogeneity sources exclusively on people and Web sites when the bulk of assignable heterogeneity resides in the variability across people within specific Web sites. Based on the variance decomposition of the heterogeneity, the percentages attributable to individual-level, Web site–specific, and visit-occasion heterogeneity are 7%, 12%, and 81%, respectively. This enables us to identify the major source of heterogeneity as attributable to visit-occasion effects that are unobserved in our data, such as the time of day a site is visited, the content of the Web pages at the time of the visit, and the link/path taken to arrive at a Web site. Thus, a webmaster who wants to enhance the duration of a visitor will be comforted to know that much of the heterogeneity in visit duration is due to unobserved factors that are specific to the actual visit occasion rather than to the

Figure 2
ESTIMATED DURATION AS A FUNCTION OF AGE AND ADVERTISING CONTENT

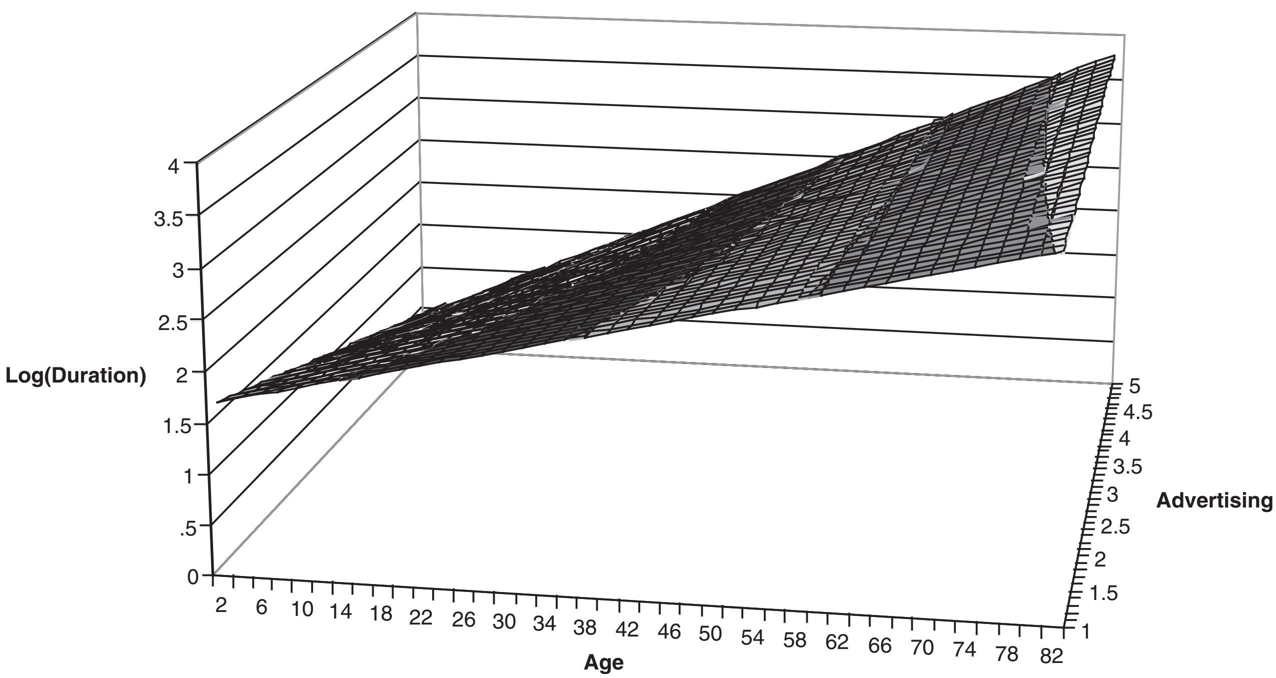



Table 6
DECOMPOSITION OF RANDOM EFFECTS

| | Estimates | | | | |
|---|---|---|---|---|---|
| *Random Effects in Model* | $\sigma^2_\tau$ | $\sigma^2_\delta$ | $\sigma^2_\eta$ | $\sigma^2$ | *Total* |
| None | — | — | — | 2.34 | 2.34 |
| Person, site | .23 | .19 | — | 2.03 | 2.45 |
| Person, site, visit occasions | .05 | .09 | .60 | 1.58 | 2.32 |

type of visitor or intrinsic unobserved attributes of the site. Knowing this, webmasters can endeavor to find ways to capture user interest at the time of the visit. Our fixed effects results in Table 5 give some indication of how this might be done, such as increasing the functionality of a site.

The estimated value of $\sigma^2$ relative to the other variance components is indicative of the remaining variability in duration times when explanatory factors and heterogeneity are accounted for. Note the decline in the estimate of $\sigma^2$ from the first to the second and third models. The percentage reduction between the first and the second models is 13%, but this increases markedly to 32% when we compare the first and third models. This also indicates that the addition of visit-occasion heterogeneity causes a significant improvement in the explanatory power of our proposed model.

*Parameter Estimates for the Page Duration and Visit Depth Models*

Table 5 also gives the parameter estimates for models of the average page duration and the number of pages viewed. The average page duration model has fewer significant fixed effect terms than the domain duration model, but age, text, functionality, and their interactions emerge as significant and in the same direction as those of the domain duration model. Software sites have less time per page, but news sites have more time than portals.

The pages-viewed model shares many similarities to the domain duration model in terms of which main effects and interactions are significant. In addition, the pages-viewed model has a statistically significant effect for the cumulative number of repeat visits ($p < .04$). Previously, we noted that a high number of previous visits has no influence on domain duration but is positively associated with more pages viewed. Together, this suggests that frequent visitors are viewing more pages within the same time span. That is, they are becoming more efficient in their browsing as they gain experience with a site. This is consistent with learning effects across repeat Web site visits, as Bucklin and Sismeiro (2003) and Johnson, Bellman, and Lohse (2003) also find.

## CONCLUSION

The purpose of this research is to sharpen our understanding of the key drivers of Web site visit duration and depth, such as personal, Web site, and visit-occasion factors. Our findings make a contribution in three areas: managerial, substantive, and methodological.

From a managerial perspective, our results are of value to practitioners who are interested in developing traditional targeting strategies using standard segmentation instruments, namely, demographic and Web site design specifications. Specifically, our results can be used by (1) webmasters to tailor their sites' features and functionality to particular age groups to sustain longer visits and (2) advertisers to target certain age groups through the Web. The discovery of significant interactions between age and Web site features, such as text, graphics, and advertising content, reinforces the importance of customizing Web pages and being restrained with advertising content. For example, we observe that, in general, increasing levels of text and advertising content result in shorter visit times, but this is not the case for older Web users, who stay longer on sites with more ad content (six or more advertisements per page). Danaher and Mullarkey (2003) show that longer visits result in higher banner advertising recall, which implies that, in general, Web advertising is more suited to older people than to younger people. For example, our model predicts that the expected duration time for an 18-year-old male visiting a portal with just a basic level of functionality features is 72 seconds, but this increases by 55% to 112 seconds for 60-year-old men. The appeal of Web advertising to older people might come as a surprise to Web advertisers, who often target younger males because of their high Internet use (Gershberg 2004). Conversely, older people are less inclined to stay for longer periods if a site has too many graphics and overdoes the functionality features, such as the ability to customize pages and the provision of online chat rooms. Older Web users seem to prefer a "keep-it-simple" Web site format and functionality, but the opposite is true of younger visitors; this seems intuitively reasonable.

From a substantive perspective, we show that most of the unobserved heterogeneity in duration times can be assigned to the "situation" of the visit occasion. We find that situation variance explains approximately 80% of the assignable heterogeneity. In contrast, trait variance (both person-specific and Web site–specific traits) accounts for only 20% of the assignable heterogeneity. Compared with our previous finding, the current finding suggests that no matter how optimized they are, traditional segmentation strategies driven by personal demographic characteristics have a limited impact. Similarly, strategies that involve repositioning the product (in terms of redesigning a Web site's attributes to make it more appealing to a target audience) also have limited effectiveness. Managers should use the insights from our first finding to optimize their traditional segmentation strategies if all that is available to them are demographics and Web site design variables. However, the greatest potential for increased effectiveness lies in the development of new segmentation strategies that are dynamically based on the situation at the time of the visit, that is, after a user enters a Web site. For example, Montgomery and colleagues (2004) use a method called "path analysis" to predict purchase likelihood after six pages are viewed. Monitoring a visitor's sequence of pages viewed can be used to create customized Web pages on the basis of the path taken. Our findings confirm that it is preferable to customize pages on the basis of the immediate history of the current visit rather than a visitor's personal characteristics or a Web site's attributes.

On the methodological front, we show how to account for unobserved visit-occasion heterogeneity across multiple visits by the same person to the same Web site. In addition to person-specific and product-specific heterogeneity, visit-occasion heterogeneity is another source of heterogeneity that arises when customers have multiple experiences with a product. In such situations, we show how a triple-heterogeneity model can be developed to accommodate these three sources of heterogeneity simultaneously. Visit-occasion heterogeneity is the most important source in our application. Previous heterogeneity models (Ansari, Essegaier, and Kohli 2000; Ansari and Mela 2003) capture the heterogeneity that arises only from person-specific and product-specific sources. We also show that these heterogeneity models (including ours) are members of a larger class of random effects models with heteroskedastic variances.

An area for further research is the use of person-specific parameter estimates to help customize a site for a particular user, the aim of which is to maximize visit duration. This is analogous to the approach taken by Ansari and Mela (2003), who customize e-mail content to maximize click-through rates. Empirical Bayes estimates of all three random effects in our model are obtainable with SAS (Verbeke and Molenberghs 1997) and can be used for such customization.

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