Quantifying the effect of user interface design features on cyberstore traffic and sales

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ABSTRACT
Given the resources needed to launch a retail store on the Internet or change an existing online storefront design, it is important to allocate product development resources to interface features that actually improve store traffic and sales. Using a regression model, we predict store traffic and dollar sales as a function of interface design features such as number of links into the store, image sizes, number of products, and store navigation features. By quantifying the benefits of user interface features, we hope to facilitate the process of designing and evaluating alternative storefronts by identifying those features with the greatest impact on traffic and sales.

Keywords
Electronic commerce, Internet retail store design, WWW, economic value, regression analysis, shopping, marketing

CYBERSHOPPING
The promises of on-line shopping touted by the popular press, include convenient access to greater amounts of information that enhances consumer decision making and easy penetration of greater markets for the merchants. Numerous articles equally bemoan these promises. With titles such as "On-line shopping – Virtually Impossible!" critics are quick to point out that expectations are not being met [8]. As one cybershopper stated, "I imagined that buying clothes on-line would be as easy as clicking on a outfit and having it appear on my doorstep. But after the third time I waited more than five minutes for a fuzzy picture to download and then sifted through the information, I realized that the technology has not caught up with my imagination." Regrettably, the number of shoppers and total sales are still marginal, in part, because of poor interfaces and store navigation [3, 7, 9, 16].

Account managers, production staff and merchant partners should not assume customers do not want an item in a retail store if it is not selling. Nor should they conclude that a poor response to a given store design is because of the merchandising mix. It is important to take a harder look at the possible relationship between poorly selling items and screen design and layout. Could customers be having a tough time wading through the screens? Can customers find what they want in the stores? Are customers aware of what products are in the stores? After all, diligence in browsing a store is not a virtue Internet retail marketers should expect from their customers.

While store traffic and sales are adversely influenced by poor interface features, it is important to document and quantify how much sales are impacted as well as to understand the underlying consumer behavior. The number of levels between the store entrance and end product, the number of browsing modes, such as searching by brand or by price, as well as the consistent design of lists and menu bars should influence consumer buying behavior in an on-line marketplace. Using a regression model, we examine the relationship between interface design features and traffic and sales data in order to quantify tradeoffs among different interface redesign alternatives. The model explains variance in store traffic and sales as a function of differences in interface design features. This can be used to assess the existing store and to improve features that are below average. It can also answer questions such as: "What is the value of implementing a search function into a site?" or "What is the value of having a product featured on the home page of a store?". This type of data provides some arguments for redesigning Internet retail stores. Even small improvements in traffic and conversion rates can have a huge influence on sales. This research identifies store and interface features that impact online store traffic and sales.

RESEARCH METHODOLOGY
Survey Sampling
A previous classification of Internet retail stores by Spiller and Lohse [19] identified five distinct types of online retail stores. In the current research, we focus on one of those stores categories that we term **Super Stores**. Super Stores

have a large selection of products. Average information for the customer is extensive, including information about the company, ordering, gift services and "What's new?" sections. The numbers of extra appetizer and customer-care features such as feedback or access to sales representatives are also extensive. Most Super Stores have a product index or a search function. Super Stores also provide the most text information for each product of any store group from our previous study. Number of products on product pages is small with most stores displaying only one product per page. The corresponding page length is one screen page in most cases. Product selection and ordering is supported by a shopping cart metaphor. Some examples of Super Stores noted in the Spiller and Lohse [19] study include: L.L. Bean, Land's End, Spiegel, Online Sports, J.C. Penney, Shoppers Advantage and Service Merchandise. Super Stores are analogous to magalogs [13].

Given the confidential nature of the variables, monthly traffic (number of visits) and monthly sales in dollars, sampling was dependent upon the availability of data from a cybermall. As such, this survey is not a random sample from all Super Stores. It does, however, represent a reasonable cross-section of online retail stores. Service stores offering financial services or information for sale were not considered. Stores that had changed significantly since May 1996 were also excluded from the survey. Thirty-two interface features were measured for the resultant set of 28 online retail stores in August 1996.

Retail Store Attributes

Electronic shopping incorporates many of the same characteristics as "real" shopping. Thus, we examined the marketing literature to identify attributes that shoppers consider when patronizing a retail store. A great amount of research has been done on the evaluation of department stores by consumers. Berry [5] empirically identified a number of attributes using a mail survey. May [12] emphasized the importance of the retail stores' image. Lindquist [10] categorized store components into functional areas such as merchandise selection, price, store policies and store layout. His attribute list is a compilation from 26 researchers in this field.

We adopted the store attributes identified by Lindquist. These attributes are categorized into four groups: merchandise, service, promotion, and convenience. **Merchandise** variables measure product selection, assortment, quality, guarantees, and pricing. **Service** variables examine general service in the store and sales clerk service for merchandise return, credit policies, etc. **Promotion** variables record sales, advertising, and appetizer features that attract customers (e.g., a "What's new" section). **Convenience** variables include store layout and organization features. Arnold et al. [1, 2] extended the convenience attributes to include ease of navigating through the store and a fast checkout. Table 1 summarizes the 32 interface variables

Merchandise:
1 total number of different products
2 levels between home page and shopping home page
3 levels between shopping home page & end product page
4 number of pages of information about ordering, quality, shipping, and guarantees.

Service:
5 gift services
6 FAQ on product related questions
7 number of pages of company reputation information
8 average length of text description about products
9 salesclerk service (email, phone, customer feedback, mailing list)
10 extra product information
11 help on product size selection

Promotion:
12 hours promotion on cybermall entrance
13 hours promotion on other cybermall locations
14 percent price discounts
15 serial position in the cybermall list of stores
16 number of featured products on the home page
17 total number of featured products ("end of aisles")
18 what's new section

Convenience:
19 number of links into the store
20 number and type of different shopping modes
21 average number of items per product menu listing
22 number of lists that have to be scrolled down
23 are products' prices already given in the listings?
24 type of product lists: basic, with pictures, with buttons, with pictures and buttons

Interface Variables
25 menu bars consistent on all pages (every page has search, top of department, top of store, etc.)
26 homogeneity of product listings in each department
27 are shopping modes accessible by button or among other items in a list?
28 background color or pattern
29 help on interface usage
30 image size on the home page
31 number of buttons on the home page
32 product list type (list, list+image,list+button, list+button+image).

Table 1: 32 Online retail store features surveyed.

Regression Diagnostics

Because regression models with too many variables and too few observations lead to potential collinearity problems, we reduced the number of variables in the models. Using stepwise regressions we first identified variables that had no impact in either of the models. Non-significant variables were then deleted and no longer considered in our final models. Table 2 lists 13 predictor variables eventually used in a traffic model that used number of visits per month as the dependent variable, and a sales model that used monthly dollar sales as the dependent variable.

Collinearity among the independent variables causes the model to be very unstable when deleting or adding variables to the model. If two or more variables are completely collinear (i.e., one variable can be written as a linear combination of the others), the model is not full rank and regression coefficients can not be calculated. A measure for collinearity in multiple regression models is the variance inflation factor, VIF_i, which should be smaller than 10 for all variables [11]. This criterion was easily met for all variables. Another measure of collinearity, the condition index, was below the critical value of 30 [4, p. 105]. Plotting residuals versus predicted sales and visits did not reveal any patterns in the residuals. Also, the White Test for heteroskedasticity [20] let us maintain the null hypothesis that errors are homoskedastic and independent from the regressors (prob>chi-square was 0.85 for the traffic model and 0.42 for the sales model).

The quality of our estimates varies across the variables. The standard error, which is a measure for confidence, was relatively high due to the small number of stores in our survey. In order to overcome these limitations, we would need to survey more stores with a greater variance in the interface.

It is also important to note that the statistical model does not detect causalities. The model reveals correlations that might stem from a causal relationship, but correlations might also be completely accidental. We do not know whether advertising promotions *caused* more traffic and higher sales. We can only observe from our specific data that more promotion was associated with more traffic and higher sales. A causal model would require a detailed theory about all different factors influencing these measures.

DISCUSSION OF RESULTS

The summary statistics for both models are highly significant (Table 2). The overall F-test is significant for both models at $\alpha<0.0001$. R^2 values measure the percentage of total variance in the data that can be explained by each independent variable. The variables in the traffic model explain 89.3% of all variance in the store traffic data, the sales model explains 86.8% of the variance in dollar sales data. The usual R^2 value can only improve by adding more variables to the model, even when their contribution is very small or accidental. The adjusted R^2 value takes the number of variables in the model into account. Adding more variables with small contributions will therefore worsen the adjusted R^2 values. Hence adjusted R^2 is a less biased measure for the variance explained by the model and we use it in our interpretations.

Model	DF	F Value	Prob > F	adjusted R^2
Traffic	13	18.260	0.0001	0.8926
Sales	13	14.648	0.0001	0.8679

Table 2 Summary regression statistics for the models

Table 3 summarizes the variables used in the regression analysis. The column titled standardized estimate shows the beta weights calculated for each model. A one standard deviation change in one of the independent variables produces a X_i standard deviation change in the dependent variable. By measuring the relationship of all of the independent variables in standardized units, the relative impact on the dependent variable can be compared directly. Also, the regression estimates in dollars per month or visits per month are not shown to protect the confidentiality of these data. The columns headed Prob>|t| show the significance of individual variables in the regression.

1. Additional products in the store attract more traffic

Each additional product in the store yields additional store traffic. Apparently, shoppers have an idea or some experience of which products they might find in each store. If they are looking for a particular product, they are more likely to find it in a larger store, suggesting that they tend to prefer larger stores to smaller ones. The variable explains 17% of all variance in the number of visits data and is significant ($\alpha<0.0001$). Interestingly, the store size did not have a significant effect on dollar sales. It seems that more products result in more traffic to the store, but the additional traffic did not result in higher sales. Perhaps, consumers can not find what they want once they are in the store. This also implies big stores are no better than small stores at converting traffic into sales.

2. Featuring a FAQ section in the store is associated with more traffic

The second variable records whether the store features a frequently asked question (FAQ) section about the company or it's products. The variable is significant in the traffic model. This suggests that, on average, stores having a FAQ section generate more visits per month, compared to those stores without this section. However, again, it is important to emphasize that we do not talk about causal relationships. A possible explanation for this outcome is that the bigger stores received so many email messages per day that they felt that implementing a FAQ section would be helpful in reducing the cost of this interaction. With this interpretation, the FAQ variable is more of a descriptive indicator for the store's traffic number. In this sense, the FAQ feature is a result of the store’s size, not an independent variable that led to more traffic. The variable had no significant effect on sales.

	Variable	Traffic Model Standardized Estimate	Traffic Model Prob>|t|	Traffic Model R^2	Sales Model Standardized Estimate	Sales Model Prob>|t|	Sales Model R^2
	Intercept	0.0000	0.0066		0.0000	0.4278	
1	Number of products	1.1810	0.0001	0.170	-0.2682	0.1972	n.s.
2	FAQ section available	1.5548	0.0001	0.451	0.1876	0.3785	n.s.
3	Feedback section	-0.7292	0.0001	0.091	0.3674	0.0348	0.011
4	Lists with button + picture	0.4966	0.0044	0.037	0.8369	0.0001	0.579
5	Lists with pictures	0.2872	0.0028	0.039	0.1728	0.0702	n.s.
6	Lists with buttons	-0.0957	0.5910	n.s.	0.5059	0.0201	0.027
7	Store "entrances"	0.3535	0.0025	0.068	0.4122	0.0017	0.095
8	Shopping modes	-0.3435	0.0206	0.013	-0.1390	0.3573	n.s.
9	Appetizers	-0.2548	0.0531	n.s.	-0.0653	0.6327	n.s.
10	Promotion hours	0.1702	0.0339	0.014	0.2235	0.0146	0.038
11	No. featured products	-0.1613	0.1091	n.s.	0.1146	0.2915	n.s.
12	Number of levels	-0.1461	0.1969	n.s.	-0.0321	0.7925	n.s.
13	Consistent menu bars	-0.1978	0.2611	n.s.	-0.3234	0.1062	n.s.

Table 3 Variables used in the regression (n.s. means the variable was not significant)

3. Providing a feedback section for the customers is associated with lower traffic and higher sales

The feedback parameter suggests that having this feature decreased traffic but increased dollar sales. Providing a way for customers to comment on catalog services and interface features is considered to be a method for improving the interface [see, e.g., 6 or 17]. But it is not quite clear how having a feedback section can influence sales to this extent. The results might again be due to the small number of stores that featured this section. Also, assuming that established feedback sections already resulted in improved services and interfaces, higher sales might be explained by this feature to some extent.

4, 5, 6. Improved product lists have a tremendous effect on sales

We expected that any improvement over the cybermall's basic product list window would yield better sales since shoppers could navigate the store much easier and are exposed to more featured products on their way through the store. All product list improvements had a significant impact on either dollars sales or store traffic. Product lists account for 61% of the variance in monthly sales. Product lists also explain over 7% of the variation in store traffic. Thus, improving product lists and store navigation features should have the most impact on sales.

- The basic product list consisted of a scrolling menu listing products (Figure 1).
- An improved version of this list displays either a featured product or a related image adjacent to any product list.
- Another list contains additional buttons to navigate the store, such as a home page or a search button.
- The most sophisticated list windows uses both images and extra navigation buttons.

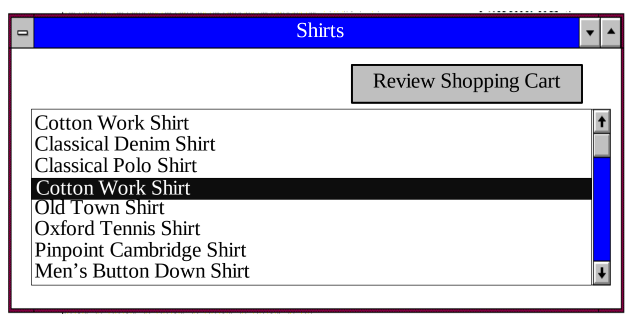

Figure 1: Scrolling menu showing a basic product list.

7. A greater number of "store entrances" yields additional visits and sales

Links from a greater number of cybermall subcategory listings should have a positive impact on visits. These additional links from other locations in the cybermall can be seen as additional “store entrances” or even branches of the store as they offer multiple ways to access a store’s home page. We expected that any additional appearance would facilitate navigation and increase sales. The regression found that each additional listing was associated with additional visits and sales.

Of course, there is probably an upper limit to the number of links into the store. The maximum number of “entrances” in our data was seven. The variable can not be extrapolated beyond this point. The significance of this variable suggests that shoppers frequently used other entrances to locate a particular store. The variable explains 7% of the variance in traffic data and 10% of the variance in dollar sales data.

8. The number of shopping modes has no impact on sales

Additional shopping modes should enhance the navigation capabilities of the interface and also segment customers who, for example, prefer to shop by brand or by price. The variable had no significant effect on dollar sales and a negative effect on the number of visits.

We can only hypothesize the reason for this outcome. It might be due to our data coding. The variable only codes the *number* of different shopping modes, not their quality. A sophisticated search function is considered the same as a very simple list. Many of the smaller cybermall stores feature several simple modes, like lists by price or alphabetically, but none of them offered more advanced shopping modes like a search function. Still, they score higher on this variable due to their many simple shopping modes than a better store with fewer but more sophisticated modes. It might have been more accurate to weigh a search function higher than an alphabetical list. On the other hand, we also defined binary variables coding a search function or a A-Z list and did not find a significant effect of these variables. As mentioned before, the likelihood for type II errors, rejecting true hypothesizes, is relatively high due to the small number of stores in the survey.

9. Appetizer information has no significant effect on traffic or sales

Nearly all the stores provided some information about the company, featured additional information or appetizers, or offered additional services. We hypothesize that the amount of these services would positively impact sales and visits. We coded whether the store provides any additional information over the basic product catalog, like information on the usage of it's products, on health, or other issues customers might be interested in. The variable was not significant in either model. Either consumers do not need and search for this kind of information, or they do but this does not alter the probability of purchasing anything. Whether consumers use appetizer information screens can be determined by analyzing browsers’ navigation paths in server log file data.

10. Promotion on the Cybermall entrance screen generates traffic and sales

Each hour of promotion on the cybermall entrance screen resulted in additional visits and generated additional sales for the store. The variable is significant in both models at the level $\alpha<0.05$. Four percent of the total variance in dollar sales and 1.4% of the total variance in store traffic can be explained by this variable.

While these ads seem to drive sales, the conversion from these ads to *store* traffic is very low. The low conversion to store traffic is probably a function of the end product page design. Promotional ads directed customers directly to an individual product. Often, the remainder of the store was not accessible from these individual screens. There is no navigation path available to navigate from any specific product screen into the store to see some other products or the store’s home page. Figure 2 shows an end product page with navigation buttons to browse other areas of the store. The browse forward and browse back buttons allow customers to navigate from one end product page to another. Without such buttons, the consumer can not look at merchandise adjacent to this promotion item nor can they access information about the company’s reputation, returns policies, etc.

Customers either purchase the promotion product and enter the store afterwards to search for some additional products, or they do not purchase the product and never enter the store. In this sense, these ads provide a reminder or motivate the customer to patronize the store. Promotional activities for particular products in real stores always aim to give shoppers an incentive to patronize the store and to buy some other products as well. The cybermall home screen promotion does not capitalize on these effects very well because there is no direct navigation path available from end product pages to browse other products in the store.

11. The number of featured products along the departmental navigation path has no significant effect

A higher number of featured products along the usual path from the home page to end product pages should have a positive effect on sales. These featured products can be seen as the aisle products in a retail store.

We did not find a significant effect of the number of featured products in the catalogs on sales. The variable also was not significant in the traffic model. We did not study the copy quality of these featured ads. Assuming that on-line shoppers are merely attracted by featured products, it might be concluded that most on-line shoppers are actively searching for particular products in the product lists, no matter how many “advertised products” they see on their way through the store. This, however, is in conflict with findings from a cybermall users focus group survey. Most users in this survey stated that they only dropped into the stores to browse whether or not they found anything

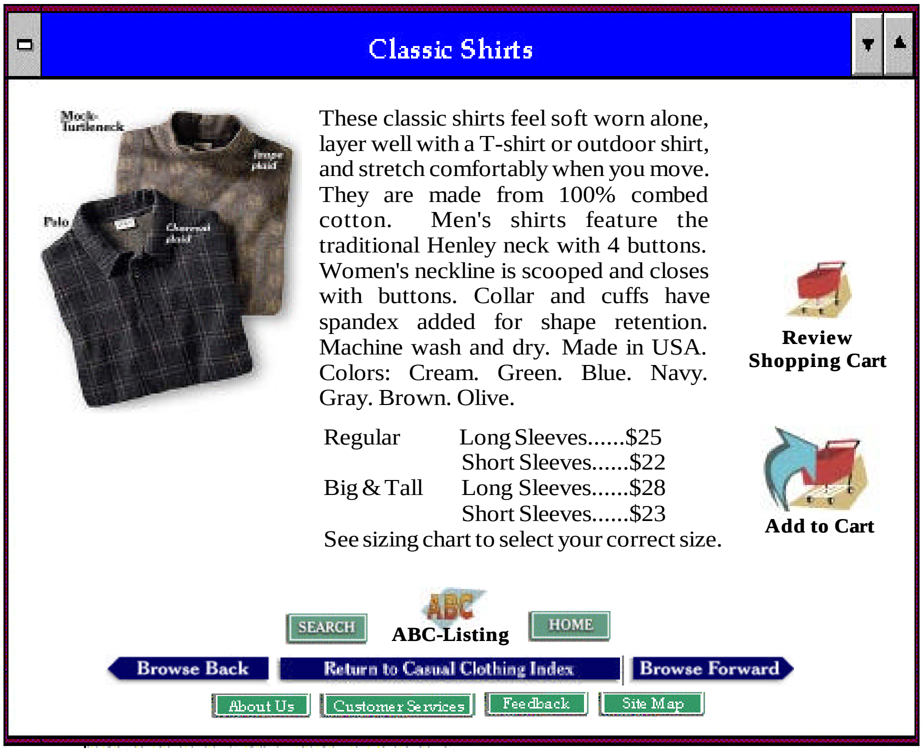

Figure 2: End product page with consistent navigation buttons and icons.

interesting. Very few declared they were looking for something particular. It would be interesting to look at actual purchases in this context. Featured products might have a great impact on customers but at the same time cannibalize on other products in the store, leaving total sales almost unchanged. Unfortunately, we could only look at aggregate sales data in this survey. But this is certainly a promising area for future research.

12. The number of levels between home page and end product pages has no significant effect on visits and sales

The number of levels between the home page and end product pages should have a negative effect on sales because shoppers will have difficulty finding products. We assumed that too many levels between home page and end products would be confusing for shoppers and would reduce buying. This hypothesis must be rejected from our data. The variable was not significant in either model. We tested different level-definitions and eventually used the average number of levels between store entrance and end products in the models. The parameter estimates for the variable are not significant. In order to test this hypothesis more accurately, more similar stores in terms of size (but differing in their level number) should be evaluated.

13. Consistent menu bars have no significant effect in the models

The variable, recording whether the stores featured consistent menu bars on the pages, was not significant in either model. A consistent menu bar meant that every product page in the store had a consistent set of store navigation icons. For example, these might include search the store, move to any other department, top of store, etc. Interface consistency is generally considered to be important from a human-computer interaction perspective [14, 15, 18]. However, it is very hard to code consistency into variables. Studying additional variables describing the concept of consistency, such as the menu organization, wording and consistent use of colors and icons might yield a different result. It may also be the case that in the context of all the other factors influencing traffic and sales, consistent menu bars had a very small non-significant impact.

LIMITATIONS OF THE REGRESSION ANALYSIS

The implications of the small sample size were mentioned a number of times throughout the text. Having only 28 different stores in the sample limits the overall confidence in the parameter estimates as well as increases the

probability for type II errors in the hypothesis testing. A larger number of stores in the sample is necessary to overcome this problem.

Another serious limitation in this study stems from the heterogeneity of shops we surveyed. The regression models do not distinguish between stores on the basis of product types or brands. Implicitly, we assume that the effects we found do not differ for stores selling flowers and stores selling computers, for example.

IMPLICATIONS FOR STORE DESIGN

These preliminary results suggest that improving the browsing and navigation capabilities of stores and especially product lists can generate significantly higher traffic and sales per store. Additional product list information such as price, a thumbnail image, and a longer descriptive product name had the largest impact on sales. We speculate that this facilitated purchase decision making at the point consumers initially view the product.

This is particularly important as we did not find an effect for other storefront variables such as image size, background patterns, or the number of buttons on the storefront screen. It appears that a user interface that facilitates browsing product lists is more important for generating sales than a “fancier” storefront.

The results outlined above can be applied to improve the cybermall in two different ways. First, identify the variables that cause poor performance. Second, concentrate any interface redesign effort on interface features that we identified to have an impact on traffic and sales. The implications of the interface features can be grouped as follows:

Navigation

The cybermall store interface does not enable shoppers to browse products easily. Shoppers have to use product lists, open a particular product, go back to the product list, and open another product screen when they want to compare different products in sequence. Also, if consumers arrive at end product screens via promotion advertisements, there is no navigation path available to navigate from this specific product screen into the store to see some other products. The regression suggests that improving these browsing and navigation capabilities of the stores and especially the product lists will facilitate sales. Featuring products on list screens and providing additional buttons to navigate from these list screens to other store departments or the store entrance facilitates traffic and sales. We would suggest an interface redesign priority on improving these lists with featured products and navigation capabilities.

Promotion

Promotion on the cybermall entrance screen increased sales for stores. Promoting stores in the cybermall entrance increased traffic only by a small amount. Some types of these promotions had no significant effect in the regression. The impact of promotions should be studied in more detail. Is there an effect of the copy text? Are bigger and fewer ads more effective? How can the cybermall customize these promotions to individual users by linking them to demographics or purchase histories? Is there an efficient model for the future allocation of these promotions to stores?

We did not study the impact of advertisements placed in the remaining cybermall content that link to stores. No data about these ads were available. Yet, offering additional store entrances in the form of additional links positively impacts store traffic. Additional ads throughout the cybermall content that represent extra “store entrances” will improve traffic into stores.

Providing additional appetizers or customer services to attract browsers had no effect on traffic or sales in the regression. This research suggests that the provision of this additional information should not be a design priority.

Store Size

Larger stores attract more traffic. But as we have also seen, this traffic does not necessarily translate into higher sales. One reason for this outcome is that consumers may not find the products they are looking for in larger stores. Improved search functions or other shopping modes should overcome this low conversion to sales. However, the regression did not reveal any effect of the shopping modes we surveyed. Since only few stores offered customers multiple modes of shopping, we assume that the sample size was not sufficient to show any effect of these shopping modes. By linking sales data to users’ ZIP codes and demographics, future research could examine whether particular customer segments prefer shops that allow them to shop by, for example, different modes – by price than by product.

Store size is also reflected in the number of hierarchical levels between the store entrance and the product pages. In some stores, the consumer had to pass seven screens before arriving at the final product screen. The statistical analysis of the data did not reveal a negative effect of too many of these levels. Either the sample size was again too small to show an effect, or consumers do not bother to navigate several screens to arrive at the products sought.

Store Presentation

We did not find an effect of "store presentation" variables, such as image sizes, background patterns or the number of buttons on the storefront. Consumers want to find products quickly and effortlessly. It appears that no amount of "sparkle" in the presentation of products can overcome a site design with poor navigation features.

While this research analyzes and quantifies the impact of different the cybermall interface design features on traffic and sales, it does not provide any detail about converting traffic into sales. Analyzing clickstream and browsing navigation data could provide an understanding of how to increase profitability of on-line markets.

CONCLUSIONS

The results suggest that enhancing consumer navigation between product screens and different departments of the store facilitates sales. This type of navigation is currently not very well supported by the interfaces for stores in our cybermall data. This became particularly apparent when we analyzed the effect of cybermall entrance screen promotions for individual products. We quantified a reasonable dollar value of these advertisements but also found them inappropriate for generating store traffic. The reason is simple: these ads only point to individual product screens and there is no navigation path available to navigate from these screens to other products or into the store. In contrast to these navigation issues, we did not find an effect of "store presentation" variables, such as image sizes, background patterns or the number of buttons on the storefront. We would therefore suggest to spend interface development effort on improving the navigation capabilities of the stores rather than on improving the interface display.

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