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Horst Treiblmaier
Vienna University of Economics and Business, horst.treiblmaier@fh-steyr.at

Andreas Pinterits
Deloitte, apinterits@deloitte.at

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Using Log-Linear Models to Analyze the Use of Hedonic Information Technologies on Corporate Websites

Horst Treiblmaier
Vienna University of Economics and Business
Horst.Treiblmaier@wu.ac.at

Andreas Pinterits
Deloitte
apinterits@deloitte.at

ABSTRACT

The Internet allows combining various multimedia applications in order to create a holistic online experience. Companies integrate utilitarian and hedonic elements in their Websites in order to improve their overall effectiveness and efficiency. In this exploratory research paper we present the results of a longitudinal study, in which we analyze the use of four different hedonic information technologies (wallpapers/screensavers, e-cards, sweepstakes, online games) on corporate websites. We differentiate between sites which offer high and low involvement products. We use log-linear models to visualize our results and to show which combinations of hedonic instruments are most popular over time. Our results show that in general companies have reduced the application of hedonic instruments over time while simultaneously specific combinations of instruments have become quite popular.

Keywords

Hedonism, Website, Involvement, Log-Linear Model, Mosaic-Plot.

INTRODUCTION

The idea of segmenting consumers according to their predisposition to seek experiences is not new in scholarly literature. While most consumer behavior literature perceives shoppers as rational beings, who actively process large amounts of information before making purchasing decisions (Venkatraman and MacInnis, 1985), other researchers highlight the symbolic, hedonic and esthetic nature of consumption (Hirschman and Holbrook, 1982) and the importance of emotion and affect (Brave and Nass, 2003).

The differentiation between utilitarianism and hedonism can be traced back to the distinction between extrinsic and intrinsic motivation. The former can be defined as being "… perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself", while the latter "refers to the performance of an activity for no apparent reinforcement other than the process of performing the activity per se" (Teo, Lai et Lim, 1999 , p. 26). For the remainder of this paper, hedonic systems denote those that provide "self-fulfilling value to the user", i.e. are intrinsically motivated, while utilitarian systems aim to provide "instrumental value to the user" (van der Heijden 2004, p. 696). In information systems research, this difference is reflected in the frequently used Technology Acceptance Model (TAM) (Davis, 1989), in which perceived usefulness (in the "core" TAM model) reflects extrinsic motivation, and perceived enjoyment (in several extensions of the TAM) reflects intrinsic motivation (Teo et al. 1999).

The Internet makes it possible to combine hedonic and utilitarian elements on a single website, which has the potential to make the interaction for the consumer more engaging and enjoyable (Hoffman and Novak, 1996). In the online world, the borders between gaming and business sometimes even become blurred, as is exemplified by the virtual community "Second Life" (cf. The Age, 2007). The combination of virtual games and real business appeals to both online users with a hedonic predisposition and companies striving to make real money in the online world. This development is seen by some authors as a trend that frees playing games from being regarded as childish and a waste of time for adults rather than as a way to unleash one's creative potentials and bring fun back to the workplace (de Chenecey, 2005).

Previous research has highlighted the importance of intrinsic motivation on behavioral intention to use and actual system use (Venkatesh, 1999). Consequently, many researchers have chosen users' hedonic motives as their focus of research. As far as the World Wide Web is concerned, we found several constructs which have been used to measure users' hedonic predispositions. In the following section, we first look at recent scholarly literature to introduce the most important hedonic constructs and highlight their relevance for current information systems research. Subsequently, we analyze the usage of four popular hedonic instruments. In order to assess how frequently companies utilize these instruments or combinations of them and how usage has changed over time, we present the results of a longitudinal study. These results may help researchers and practitioners to find out which hedonic instruments are most suitable for improving a website's appearance. Finally, conclusions and managerial implications are presented.

THEORETICAL BACKGROUND

In scholarly literature a multitude of constructs, such as entertainment, playfulness, enjoyment, cognitive absorption, affective quality and fun, are used to measure the perceived impact of hedonic elements. Several of them can be traced back to the more general construct of "Flow", which was introduced by Csikszentmihalyi (1990, p. 4) and describes "the state in which people are so involved in an activity that nothing else seems to matter". Many of these constructs exhibit a high level of conceptual similarity and will therefore defined and shortly discussed below.

Figure 1 contextualizes constructs such as playfulness, perceived affective quality, cognitive absorption, perceived enjoyment and perceived playfulness and illustrates how they are hypothesized to impact the "core constructs" of the Technology Acceptance Model, viz. "perceived usefulness", "perceived ease of use" and "intention to use" (some authors focus on actual behavior instead). It has to be noted that only those extensions of the original model are depicted, which include hedonic constructs. Some of the authors use more elaborate models that include additional elements. However, since the purpose of this paper is to highlight the importance of hedonism for companies' websites rather than to evaluate a theory, we confine our analysis only to those aspects of the models, which are relevant in the context of this research. As can be seen in Figure 1, hedonic constructs can be either seen as antecedents of perceived ease of use and/or perceived usefulness or as mediating variables between "ease of use" and the "intention to use"/"actual behavior". All of the studies cited found a significant influence of hedonic constructs on either usefulness or ease of use or directly on the intention to use, therefore indicating a need for websites to appeal to users' hedonic motives. Additionally, there exist many related papers which incorporate hedonic constructs in similar models, e.g. the impact of perceived enjoyment on attitude (Lin and Bhattacherjee, 2010) or the overall value of hedonic digital artifacts on behavioral intentions (Turel, Serenko and Bontis, 2010).

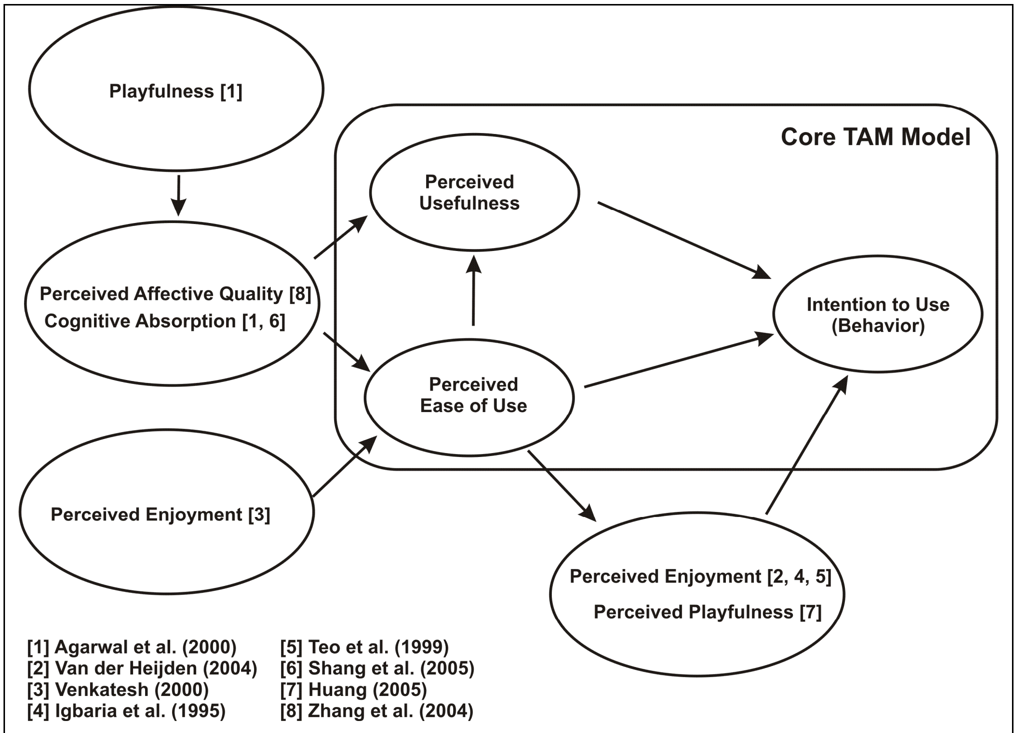
Playfulness [1]
Core TAM Model
Perceived Usefulness
Perceived Affective Quality [8]
Cognitive Absorption [1, 6]
Intention to Use (Behavior)
Perceived Ease of Use
Perceived Enjoyment [3]
Perceived Enjoyment [2, 4, 5]
Perceived Playfulness [7]
[1] Agarwal et al. (2000)
[2] Van der Heijden (2004)
[3] Venkatesh (2000)
[4] Igbaria et al. (1995)
[5] Teo et al. (1999)
[6] Shang et al. (2005)
[7] Huang (2005)
[8] Zhang et al. (2004)

Figure 1. Hedonic Extensions of the Technology Acceptance Model (Agarwal and Karahanna, 2000; Huang, 2005; Igbaria, Iivari and Maragahh, 1995; Shang, Chen and Shen, 2005; Teo, Lai and Lim, 1999; van der Heijden 2004; Venkatesh 2000; Zhang and Li, 2004)

In all of the papers cited above, hedonism represents an important antecedent for raising consumers' awareness, increasing the intention to use a system and inducing a certain behavior. Since this importance has been frequently validated by scholarly research, we conduct an exploratory research to find out how companies actually make their websites “fun”, “pleasant”, “exciting”, “enjoyable”, “pretty”, “beautiful”, “interesting” …, as is proposed in the literature.

RESEARCH QUESTIONS

In view of the vital importance of entertaining websites and the lack of scholarly research on the actual usage of hedonic instruments on the Web (as opposed to numerous studies which confirm their general theoretical importance from a user’s point of view), we conduct an exploratory study, focusing on four major research questions. In a first step, it is essential to measure the actual usage of various hedonic instruments. Therefore, we analyze the occurrence of four instruments over time.

- Which instruments are frequently used on company websites and how does usage change over time?

Various hedonic instruments can be used to achieve particular goals. We analyze whether certain combinations turn out to be more frequently used than others.

- Which combinations of instruments are preferably used?

Several of the companies manufacture or trade goods that can be classified as low involvement (e.g. crude oil or washing powder), while others deal in high involvement goods (e.g. articles of fashion or cars). Involvement can be seen as the importance or personal relevance users attach to a certain artifact (Barki and Hartwick, 1989). We categorized a company as low involvement, if the majority of its product portfolio could be classified as low involvement. In our exploratory research, we seek to detect whether these two groups exhibit significant differences according to their use of hedonic instruments.

- How do combinations of hedonic instruments differ between low and high involvement companies?

Our research presents one of the few longitudinal studies in Web analysis. Analyzing the same websites at three different points in time enables us to see whether the instruments or combinations thereof have increased or decreased in popularity over time. This information informs researchers and practitioners in E-Marketing about current website trends.

- How do combinations of hedonic instruments change over time?

RESEARCH METHOD

We analyzed all consumer-goods companies from the Austrian Top 500 for the use of different hedonic instruments, which resulted in a total of 187 websites from 155 organizations in 2002. The analysis was done by using a checklist which was used to check for the existence of various hedonic instruments. Only the two options ‘Yes’ and ‘No’ were given.

Since some companies operate different websites in order to promote various brands, the number of sites exceeds the number of organizations. The survey was conducted three times, starting at the end of 2002. The second survey was performed in the third quarter of 2004, and the third survey took place in the fourth quarter of 2006. During that period nine websites were shut down due to changes of company structures. The resulting sample therefore contains 534 data points from 178 websites. Since three of the companies could not be clearly classified as high or low involvement, a total of 175 companies (525 data points) were used for all involvement analyses.

A complete list of different instruments would exceed the scope of this paper. Frequently found instruments include e-cards, guest-books, music and ring-tones for download, online games, product configurators, different kinds of recipes, sweepstakes, wallpapers/screensavers, and web cams. For all further analyses we focus on the four most popular hedonic instruments, which exceeded 25% usage in 2002: e-cards, sweepstakes, wallpapers/screensavers, and online games. In order to answer research question (a), we analyzed the data with descriptive methods. In order to answer questions (b) to (d) we use mosaic plots, which are area-proportional representations of frequencies, to visualize the resulting multi-dimensional contingency tables (Meyer, Hornik and Zeileis, 2006a).

We first aggregate our data into contingency-tables and analyze them by fitting log-linear models (Bishop and Fienberg, 1969; Goodman, 1970; Goodman, 1972; Knoke and Burke, 1991; Mosteller, 1968). The models are used to examine relationships between nominal variables (Agresti and Finlay, 1986), thus representing odds rather than the values of the nominal variables. Odds are ratios between occurrences belonging and occurrences not belonging to a certain category, i.e. they express the chance that a randomly selected occurrence belongs to a certain category. General log-linear models do not distinguish between independent and dependent variables (Knoke and Burke, 1991).

Fitting log-linear models represents an explorative approach. We start with a saturated model, which allows for interactions between all variables (Agresti and Finlay, 1986), and subsequently fit models with decreasing numbers of interactions. The fit of the models gives insights into the dependencies between the website instruments. We used the statistical software R for the analysis (R Development Core Team, 2006), which is an open source system for statistical computing and graphics (Hornik, 2006). A huge repository of extensions (packages) provides functions for a wide number of statistical methods. The package “vcd” visualizes contingency tables as mosaic plots (Meyer et al. 2006a), and the package “MASS” is used to fit the log-linear models to the data.

RESULTS

The left part of Figure 2 illustrates how the overall usage of hedonic instruments declines over time. In 2002, a total of 114 companies used at least one hedonic instrument, as opposed to 105 in 2004 and 90 in 2006. A Chi-square test of independence reveals that the drop in numbers is significant ($\chi 2$: 6.77, d.f.: 2, p: 0.034). The right-hand side of Figure 2 shows the number of companies using at least one instrument in the period 2002-2006, split by involvement (i.e. each company is included three times). 52% of the high involvement companies use at least one of the hedonic instruments on their websites, as opposed to 67% of the low involvement companies ($\chi 2$: 10.97, d.f.: 1, p: .0009).

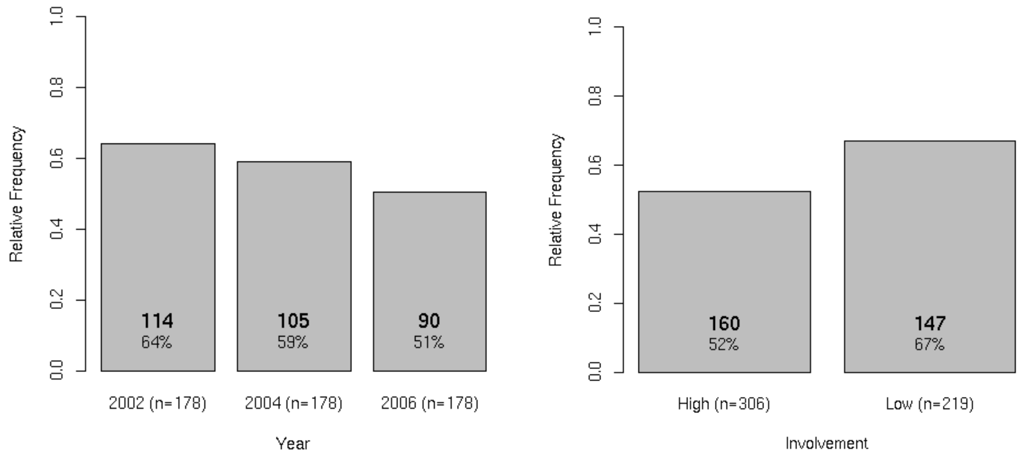

Figure 2. Total Usage by Year and Involvement

In Figure 3 we include the different types of hedonic instruments. The left part of the figure illustrates how usage has changed over time, with only e-cards exhibiting a significant change ($\chi 2$: 11.24, d.f.: 2, p: 0.004). In 2002 and 2006, sweepstakes were the most frequently used instrument, whereas in 2004 wallpapers/screensavers were the most popular hedonic instrument. Splitting our total sample by involvement shows that low involvement companies use online games ($\chi 2$: 11.02, d.f.: 1, p: 0.001), sweepstakes ($\chi 2$: 18.68, d.f.: 1, p: 0.000) and e-cards ($\chi 2$: 4.73, d.f.: 1, p: 0.030) significantly more often than high involvement companies.

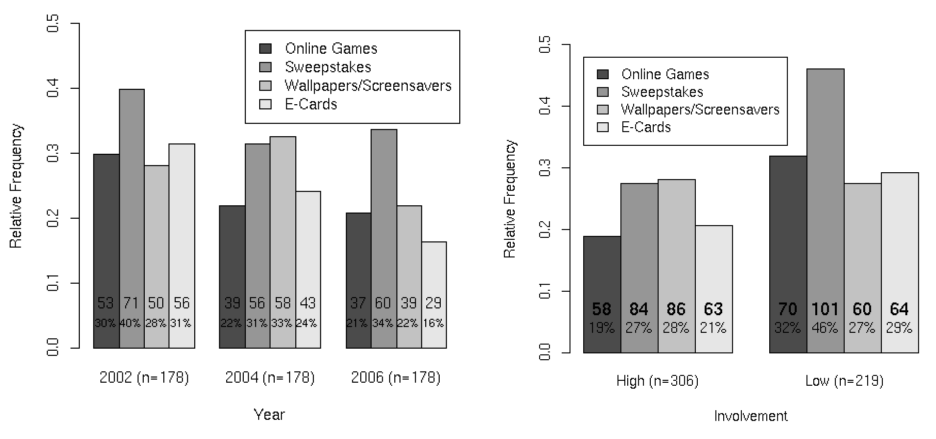

Figure 3. Instrument Usage by Year and Involvement

Up to this point we have treated the instruments as being used independently of each other. However, since different instruments may appeal to varying customer segments or hedonic predispositions, we now analyze whether some combinations of instruments (i.e. the simultaneous usage of two or more instruments) are more popular than others.

Figure 4 shows a mosaic plot visualizing all possible combinations of online games, sweepstakes, wallpapers/screensavers and e-cards in the period from 2002 to 2006. The size of the boxes, which is area-proportional, represents the number of companies using this combination (Meyer, Hornik and Zeileis, 2006b). Thus, doubling the number of companies in a single category also doubles the space the box takes up in the plot. The area in the upper left (n = 225) represents the number of cases where companies have used neither of the instruments, whereas in the lower right (n = 24) all instruments are used simultaneously. A comparison of the size of the different boxes illustrates the popularity of the various combinations of instruments.

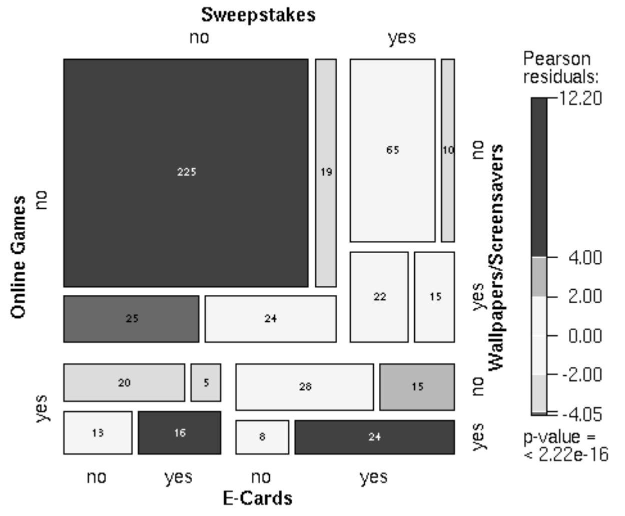

Figure 4. Mosaic Plot of the Overall Instrument Usage

The shadings of the boxes represent the deviation of the observed values (residues) from the expected values of a log-linear model with no interactions between the single instruments (Meyer et al. 2006b). The boxes with darker shadings differ significantly from the expected occurrences, indicating that certain combinations of instruments are preferred. We therefore conclude that there are relations between the usage of different instruments. Figure 4 illustrates that the combination "no instruments at all (n = 225)", "online game, wallpaper/screensaver, e-card and no sweepstakes (n = 16)" and "all four instruments (n = 24)" are used significantly more often than could be expected from the independence model. Wallpapers/screensavers (n = 25) without any other instrument are used significantly less frequently than expected. The p value for the overall model is highly significant (p < .001), indicating that relationships between the single instruments exist. In the following sections we investigate which combinations turn out to be the most popular and study the influence of involvement and time lapse.

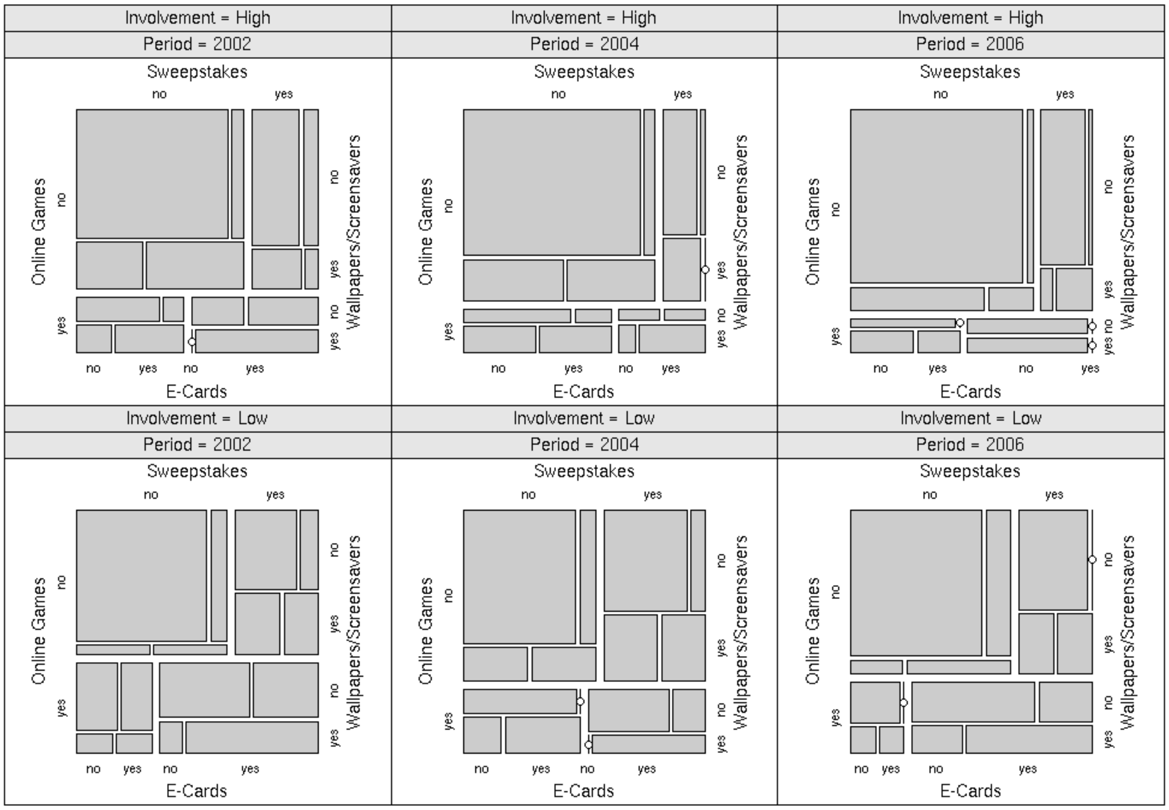

Figure 5. Comparison of Instrument Occurrence by Involvement and Time

Splitting the sample by involvement and time makes it possible to compare the various instrument combinations at low/high involvement companies and their evolution over time (Figure 5). While the proportion of websites which used none of the instruments at all (the top left box of each mosaic plot) clearly increased for high involvement companies, it is smaller for low involvement companies and remains comparatively stable. For high involvement companies the combination of e-cards, online games and sweepstakes (represented by the two bottom areas of the quadrant in the lower right) disappeared over time. While in 2002 every high involvement website which used online games, sweepstakes and wallpapers/screensavers also used e-cards (area in the lower right), this combination does not exist anymore in 2006. However, this combination of instruments can still be found on websites from low involvement companies.

We tested a number of different log-linear models to discover relations between different instruments. In line with our exploratory approach, we strive to detect whether companies prefer certain combinations and whether their usage of the instruments depends on involvement and time. A model is essentially a function of cell frequencies, i.e. the expected frequency of websites using a specific combination of instruments (Knoke and Burke, 1991). For an abbreviated description of the model's input parameters, we use the following abbreviations:

E: E-Cards
S: Sweepstakes
O: Online Games
W: Wallpapers and Screensavers

In a first step, the saturated model is formulated, which includes all possible effect parameters for the estimation. Eta (η) is the geometric mean of the number of cases in each cell and is commensurate with the intercept term of a regression model (Knoke and Burke, 1991),while tau (τ) represents effects from variables on cell frequencies.

$$F_{ijkl} = \eta \tau_i^E \tau_j^S \tau_k^O \tau_l^W \tau_{ij}^{ES} \tau_{ik}^{EO} \tau_{il}^{EW} \tau_{jk}^{SO} \tau_{jl}^{SW} \tau_{kl}^{OW} \tau_{ijk}^{ESO} \tau_{ijl}^{ESW} \tau_{ikl}^{EOW} \tau_{jkl}^{SOW} \tau_{ijkl}^{ESOW}$$

The saturated model allows for interactions between all variables and therefore always perfectly reproduces the sample data. The number of effects in the saturated model corresponds to the number of cells (Knoke and Burke, 1991). We now create log-linear models by estimating the frequency, when the number of interactions is reduced gradually (Agresti and Finlay, 1986). The most restrictive model includes all explanatory variables but eliminates all interaction terms, thus not allowing for any interdependence.

$$F_{ijkl} = \eta \tau_i^E \tau_j^S \tau_k^O \tau_l^W$$

In the following, we use a short notation for the models, with letters in brackets representing interactions. The model without interactions is therefore represented by the notation {E}{S}{W}{O}, and the saturated model is written as {ESOW}. The models are tested by comparing the estimated cell frequencies to the observed frequencies. Two measures are available that express how well the model is able to reproduce the data: the Pearsons chi-square statistic and the likelihood-ratio statistic (Everitt, 1977). Since the model is fitted by maximum-likelihood estimation, we use the likelihood-ratio statistic (L2), which is recommended by Knoke and Burke (1991). L2 follows a chi-square distribution with degrees of freedom equaling the number of effect parameters eliminated from the saturated model (Everitt, 1977). For each L2, a p-value is calculated, indicating the level of significance. In search for a good fitting model, we try to decrease the number of effects (increase the degrees of freedom), without obtaining a significant value of L2. As a rule of thumb, models with a p-value (probability of a type 1 error) between 0.1 and 0.35 can be accepted. At higher levels, the model is likely to contain unnecessary parameters ("too good a fit") (Knoke and Burke, 1991).

Nr	Model	L^2	D.f.	$P(L^2)$
1	{ESOW}	0.00	0.00	1.00
2	{ESO}{ESW}{SOW}{EOW}	1.11	1.00	0.29
3	{ESW}{SOW}{EOW}	3.15	2.00	0.21
4	{ESO}{SOW}{EOW}	2.41	2.00	0.30
5	{ESO}{ESW}{EOW}	10.95	2.00	0.00
6	{ESO}{ESW}{SOW}	1.38	2.00	0.50
7	{SOW}{ESO}{EW}	3.11	3.00	0.37
8	{SOW}{EWO}	7.00	4.00	0.14
9	{SOW}{ESW}	19.45	4.00	0.00
10	{SOW}{EW}{EO}{ES}	5.21	4.00	0.27
11	{SOW}{EW}{EO}	8.53	5.00	0.13
12	{SOW}{EO}{ES}	72.57	5.00	0.00
13	{SOW}{EW}	30.23	6.00	0.00
14	{EO}{EW}{SO}{SW}	24.07	7.00	0.00
15	{E}{S}{O}{W}	204.85	11.00	0.00

Table 1. Model Fit (Whole Sample)

Table 1 shows selected models and their corresponding L2-values, degrees of freedom (d.f.) and p-values. We used a stepwise approach and systematically reduced the number of interactions. Only those models which exhibit a non-significant value of L2 (i.e. they do not deviate significantly from the saturated model) were retained. The saturated model {ESOW} (1) with its perfect fit to the data always has a L2 of 0. The model {E}{S}{O}{W} (15), which was depicted in Figure 4, does not allow for any interaction and significantly differs from the data ($p < .05$). It is therefore discarded.

In order to search for a parsimonious model which is able to reproduce the cell frequencies, we gradually increase the degrees of freedom. We start by eliminating the interactions between all four variables, but allow for all interactions between triples of them, and obtain a model which does not significantly deviate from the saturated model (2). We further eliminate specific interactions between the triples (3-6). The significantly high L2 for the model {ESO}{ESW}{EOW} (5) indicates that this model cannot provide satisfactory estimations. Since this model lacks the interaction between the triple {SOW}, we assume a strong relation between sweepstakes, online games and wallpapers/screensavers. By systematically eliminating further interactions we found a number of valid models all including {SOW} as triple interaction (7-9). Finally we found a model {SOW}{EW}{EO} (11) with 5 degrees of freedom that is able to deliver acceptable estimations of our sample data. A further increase in the degrees of freedom did not produce any satisfactory results (12-14). We therefore conclude that model (11) is the most parsimonious model that adequately represents our data structure.

In the next step we examine differences between high and low involvement companies (Table 2). For sake of brevity, we only concentrate on those models which provide sufficient explanatory power and skipped models 1, 2, 8, 12 and 13.

Nr	Model	L^2	D.f.	$P(L^2)$		L^2	D.f.	$P(L^2)$
		High Involvement				Low Involvement		
3	{ESW}{SOW}{EOW}	2.09	2.00	0.35		2.28	2.00	0.32
4	{ESO}{SOW}{EOW}	4.94	2.00	0.08		0.24	2.00	0.89
5	{ESO}{ESW}{EOW}	1.96	2.00	0.37		9.45	2.00	0.01
6	{ESO}{ESW}{SOW}	1.29	2.00	0.53		0.24	2.00	0.89
7	{SOW}{ESO}{EW}	6.44	3.00	0.09		0.24	3.00	0.97
9	{SOW}{ESW}	9,85	4,00	0,04		10,96	4,00	0,03
10	{SOW}{EW}{EO}{ES}	7.26	4.00	0.12		2.32	4.00	0.68
11	{SOW}{EW}{EO}	9.03	5.00	0.11		2.66	5.00	0.75
14	{EO}{EW}{SO}{SW}	22.73	7.00	0.00		10.14	7.00	0.18
15	{W}{E}{O}{S}	117.12	11.00	0.00		86.74	11.00	0.00

Table 2. Model Fit (Split by Involvement)

Generally speaking, the low involvement sub-sample resembles the relations we found in the overall sample. In contrast to the high involvement sample, the low involvement group was able to deliver more accurate estimations. It was even possible to further increase the degrees of freedom. The model {EO}{EW}{SO}{SW} (14), which was not accepted for the overall sample, exhibits a non-significant value of L2 and was the most parsimonious model for the low involvement group. The opposite is true for high involvement companies. The poor fit of the model {ESO}{SOW}{EOW} (4) indicates a high importance of the interactions between e-cards, sweepstakes and wallpapers {ESW}. Additionally, we tried to fit the model {SOW}{ESW} (9), but did not obtain a satisfactory result. The results indicate the existence of stronger relations between various combinations of instruments for low involvement than for high involvement companies.

In order to analyze the development of instrument usage over time, we split the sample according to our points of data collection. Table 3 shows selected models for the three points in time 2002, 2004, and 2006. Again we excluded those models which do not provide additional explanatory power (1, 2, 8, 12, 13). No unambiguous development can be identified. Model 8, 10, and 11 are acceptable for the year 2002 and are highly reliable for 2004. The values for 2006 indicate also reliable estimations, but not at the same high level as in 2004. Model {SOW}{EW} (13), which is significant in 2002 and 2004, turns out to be insignificant in 2006. Conversely, model {EO}{EW}{SO}{SW} (14) is able to deliver satisfactory results in 2002, but loses power in 2004 and 2006.

Nr	Model	L^2	D.f.	$P(L^2)$		L^2	D.f.	$P(L^2)$		L^2	D.f.	$P(L^2)$
		2002				2004				2006		
3	{ESW}{SOW}{EOW}	5.09	2.00	0.08		3.32	2.00	0.19		2.84	2.00	0.24
4	{ESO}{SOW}{EOW}	5.99	2.00	0.05		1.28	2.00	0.53		2.96	2.00	0.23
5	{ESO}{ESW}{EOW}	5.19	2.00	0.07		6.19	2.00	0.05		6.83	2.00	0.03
6	{ESO}{ESW}{SOW}	4.65	2.00	0.10		0.90	2.00	0.64		3.81	2.00	0.15

7	{SOW}{ESO}{EW}	6.00	3.00	0.11		1.44	3.00	0.70		3.82	3.00	0.28
8	{SOW}{EWO}	8.40	4.00	0.08		4.69	4.00	0.32		3.62	4.00	0.46
10	{SOW}{EW}{EO}{ES}	6.72	4.00	0.15		3.92	4.00	0.42		4.00	4.00	0.41
11	{SOW}{EW}{EO}	8.40	5.00	0.14		4.70	5.00	0.45		4.83	5.00	0.44
13	{SOW}{EW}	25.04	6.00	0.00		11.32	6.00	0.08		5.22	6.00	0.52
14	{EO}{EW}{SO}{SW}	9.24	7.00	0.24		12.10	7.00	0.10		16.97	7.00	0.02
15	{W}{E}{O}{S}	76.40	11.00	0.00		66.36	11.00	0.00		79.61	11.00	0.00

Table 3. Model Fit (Split by Time)

Analyzing the development over time we cannot find evidence for a steady increase in relations between different combinations of instruments. The relations grew stronger between 2002 and 2004, but this increase was not carried forward until 2006. The assumption that over time a single best combination of instruments will emerge cannot be supported. However, the changing popularity of different combinations over time indicates the existence of short-term trends.

CONCLUSIONS AND MANAGERIAL IMPLICATIONS

In this exploratory study we analyzed the use of various hedonic instruments on company websites. We focused on the four most popular instruments: e-cards, sweepstakes, online games, and wallpapers/screensavers, all of which can be used by companies to appeal to customers' hedonic predispositions. A website analysis reveals that the overall usage of hedonic instruments decreased between 2002 and 2006. Companies which produce or sell low involvement goods typically used hedonic instruments on their websites more frequently than high involvement companies.

We were able to show that the different instruments are not used independently from each other. We found evidence that companies prefer different combinations of instruments. In particular, low involvement companies, which have to especially motivate potential customers to visit their websites, show more distinctive patterns than high involvement companies. We did not find a single steady trend toward certain combinations of instruments. Instead, the relations among such instruments seem to change over time. We therefore assume the existence of short-term trends regarding instruments and their combinations. Also, the significant reduction in e-cards – while other instruments remained relatively constant – is an indicator for such trends.

Companies that want to support their web activities with hedonic instruments should consider using them in combination. Since we only looked at empirical relations between hedonic instruments found on websites, further research is needed to assess the perceived impact on users and customers, i.e. which instrument might be useful to attract certain customer segments. Hedonic instruments should therefore be implemented in combination with each other rather than separate from each other. A customer-centered approach could also identify if there are specific user groups who show a particular affiliation to certain combinations of hedonic instruments on websites. Future research may improve the external validity of the results by carrying out replication studies in different industries and in different countries.

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