# Various Approaches to a Human Preference Analysis in a Digital Signage Display Design

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**Abstract**

This article is concerned with various ways of analyzing the subjective assessment of displaying digital signage content. In the beginning, the brief description of the signage system evolution is described; next, the carried out experiment is depicted. The preferences of the 32 subjects were obtained using pairwise comparisons of the designed screen formats. Then the priorities were derived by applying the Analytic Hierarchy Process framework. The gathered data were modeled and analyzed by means of the analysis of variance, multiple regression, and conjoint and factor analyses. The results suggest that the application of different methods of preference analysis may provide additional information that could facilitate more in-depth understanding of the given preference structure. © 2011 Wiley Periodicals, Inc.

**Keywords:** Subjective assessment; Digital signage; Analytic Hierarchy Process

## 1. INTRODUCTION

The process of human decision making is often influenced to a large extent by individuals' preferences. Because this phenomenon is observed in many areas, the preferences are subject to investigation by numerous researchers from various fields of science, including, for instance, biology, economy, medicine, psychology, sociology, and human factors. The present study is directly focused on the various ways of analyzing human preferences toward different display designs used in digital signage systems, which are not only becoming commonplace, but are also evolving toward more and more interactive solutions. Hence, the scientific examination in this area may be carried out from the perspective of the human–computer interaction (HCI) field of study, where the investigation of people's attitudes and subjective feelings are also one of the major areas of interest.

The next section presents some general information about the evolution of signage systems. Later, a brief description of the preference evaluation is provided. Then, the experimental data related to the digital signage display design preferences are used to conduct analyses by means of various methods. They include the classical analysis of variance (ANOVA), multiple regression, as well as conjoint and factor analyses. The discussion and concluding remarks are given in the remainder of the article.

## 2. EVOLUTION OF SIGNAGE SYSTEMS

Signage systems have been a popular way of conveying information for hundreds of years. Posters, bills, banners, flags, and many other conventional means of still image communication (Access Displays, 2006) have

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Received: 8 December 2010; revised 20 January 2011; accepted 21 January 2011

View this article online at wileyonlinelibrary.com/journal/hfm

DOI: 10.1002/hfm.20295

been extensively used not only in almost any branch of industry or services but also for charity and social projects. Even in the contemporary computerized world, the paper-based graphical message is willingly taken advantage of, especially in various widely understood marketing activities.

During the years of experience in this area, a number of innovations that aimed at attracting peoples' attention more effectively were introduced, for instance, pop-up displays, spinning and swing signs (Warpfive International, 2009; Sign Spin, 2007), and roll-up screens (Exact, 2010). Further technical improvements resulted in constructing systems that allow for changing the display content mechanically, for example, by scrolling multiple posters (Bei Dou Xing Science & Technology Development, 2010) or by rotating the triangular louvers that enable showing different messages as the three faces are exposed (Triple Sign System AB, 2010). The information technology revolution has recently provided new opportunities for advertisers. For many years, marketing practitioners and researchers focused on the digital solutions based on the Internet that are usually tailored to an individual consumer. The technology progress in digital displaying devices, along with the networks becoming widespread, facilitated the development of electronically based solutions for out-of-home advertising. These digital signage solutions were probably originated by comparatively simple monochromatic LED signs that were able to scroll text, present simple graphics, and provide greater flexibility. These solutions were later considerably enhanced and now are available in numerous versions (e.g., Signs Plus LEDs, 2010). As the costs of producing LCD or LED panels were continuously decreasing, the panels were gaining more and more interest among advertisers. The process of replacing conventional billboards with the digital display solutions is especially intensive in more urban areas, where the electricity supply and access to computer networks is not a problem and there is are more potential customers. Thanks to the Internet network connections, the individual electronic displays could form a digital signage network used to present marketing information to consumers at various places in a specific way. Such a solution provides great flexibility in distributing the content to be displayed and allows for so-called advertisement narrowcasting (Harrison & Andrusiewicz, 2004), which enables advertisers to prepare the appropriate message for the particular segment of customers in given place and time. For example, content targeted at business travelers will be displayed at an airport on Monday mornings, and family-aimed messages might appear on Friday afternoons. The ongoing technology progress also gives completely new, electronically based opportunities to the marketing sector. Some of the modern experimental technologies include mid-air displays (Rakkolainen, 2008; Rakkolainen & Lugmayr, 2007), emergent displays that are blended with their environment (Chandler, Finney, Lewis, & Dix, 2009), or the digital equivalent of the cylindrical sidewalk signboard (Lin et al., 2009).

Easy access to more and more sophisticated and relatively inexpensive video and computer devices and the pressure to win people's attention incorporates some forms of interaction between digital signage equipment and potential consumers. On one hand, advertisers tend to use digital signage technologies not only for conveying information, but also as a way for eliciting data about potential customers. The gathered data may then allow for the adaptation of the display content to the passersby (Chen et al., 2009; Storz, Friday, & Davies, 2006). On the other hand, people more and more often are able to communicate with the signage system using, for instance, touch-sensitive screens, mobile devices (Cheverst et al., 2005), or even hand gestures (Chen et al., 2009). Other interesting forms of interaction may be found at Valli (2010).

Although digital signage systems are becoming similar to interactive systems, they differ considerably from the standard man–machine solutions, especially when the context of use is concerned. As the described domain is relatively new, the design recommendations are based mostly on practitioners' heuristics, for example, proposed by Bunn (2009). Some of the design problems concerned with digital signage were also presented in the documentary film *Helvetica* (2007) directed by Gary Hustwit and focused on typography and graphic design analyzed from the perspective of global visual culture. There is, however, little scientific systematic research regarding the perception of various kinds of solutions specific to digital signage systems. In the next section, the preference evaluation process used in this investigation is described.

## 3. PREFERENCE EVALUATION

There is no doubt that, in the advertising domain, customer contentment is considered especially significant, hence this study is devoted to the user's preferences toward various versions of the digital signage display design. Moreover, peoples' preferences are directly connected with satisfaction, which is one of the main dimensions of assessing the usability of interactive systems in the field of HCI (ISO 9241, 1998; ISO 9126, 1998).

It is known from psychology that preferences may be quite complex and strongly depend on the context. Therefore, taking advantage of various approaches to determine the preference structure seems to be reasonable. There are multiple ways of obtaining preference data from people and analyzing them. The most popular ways of collecting preferences include direct ranking and pairwise comparisons. In the former method, the user assesses all objects (products, services, alternatives) simultaneously, whereas the latter one requires the evaluation of two items at a time. In this research, the pairwise comparison approach was applied. The technique is usually easier for the user to perform and allows for considerably better accuracy of stimuli estimation (Koczkodaj, 1998). One must remember, however, that in this case the number of necessary comparisons grows rapidly with the increasing number of analyzed variants. After collecting responses from the subjects, the hierarchy of preferences needs to be derived by means of available procedures. The most popular methods of calculating a priority vector from the numerical pairwise comparison matrix include the eigenvalue/eigenvector approach and the logarithmic least squares procedure (Dong, Xu, Li, & Dai, 2008). There is no agreement among the researchers as to which of the techniques is better (compare, e.g., Barzilai, 1997, and Saaty & Hu, 1998).

For the purpose of this investigation, the approach advocated by Thomas Saaty (1977; 1980) within the framework of the Analytic Hierarchy Process (AHP) was applied. According to this method, the prioritization of people's relative preferences is carried out by finding the principal eigenvector corresponding to the maximal eigenvalue of the symmetric and reciprocal pairwise comparisons matrix. The principal eigenvector computed for every person is normalized in such a way that the sum of all its values equals one. The higher the obtained value of relative weight, the bigger the preference there is for a given alternative. According to the AHP, there is also a possibility of calculating for every subject taking part in the investigation the so-called consistency ratio (CR). Higher values of this parameter indicate bigger inconsistencies in pairwise comparisons. Generally, a CR value less than 0.1 is considered acceptable.

The idea of using the principal eigenvector was used in the presented research to derive relative subjective preferences toward the analyzed designs. The priority vectors were computed individually for every subject and were treated as a main dependent measure. The obtained preferences were next analyzed by means of four different techniques, namely, ANOVA, multiple regression, conjoint analysis, and factor analysis. In the following paragraphs, general information about these methods is demonstrated.

Both the classical ANOVA as well as the multiple regression with all their modifications are commonly applied by researchers in various areas. ANOVA is used to verify whether the differences in mean values for specific groups are statistically significantly different from each other. In turn, the general purpose of the multiple regression group of methods is to analyze the relationship between a dependent variable and independent predictors. In the context of this study, the derived preferences are treated as a dependent variable whereas the digital signage display design attributes are independent factors.

By means of the conjoint analysis, it is possible to decompose the overall preference assessment of a given profile into partial contributions assigned to attributes taken into account during the experiment (Krantz & Tversky, 1971; Luce & Tukey, 1964). Moreover, this method enables the researcher to calculate the partworths for all attribute levels and the importance of examined attributes. For several decades, the conjoint analysis has been exploited in a variety of research encompassing preference evaluations in many fields of science (Green, Krieger, & Wind, 2001). Among them, marketing and consumer research used the technique particularly extensively (Green & Srinivasan, 1978; 1990).

The main purpose of the factor analysis is the search for hidden common factors that best account for the covariance structure of the examined variables. The rationale supporting this approach is that in real studies the directly observed factors are quite often influenced by some other effects that are not directly measured. Mulaik (1986) provides the detailed review of the factor analysis evolution from 1940 until the mid-1980s. In the work of Steiger (1994), the later developments are presented. In this study the factor analysis allows us to get the fuller picture of participants' preferences and to examine if they are influenced by the specified attributes differently than it was assumed by the experimental design.

# 4. METHODS

## 4.1. Subjects

Nineteen women (59%) and thirteen men (41%) of an average age of 23.3 years (standard deviation = 1.5 years) took part in this experiment. The youngest participant was 19, and the oldest was 27 years old. The volunteers were from the Computer Science and Management Faculty of the Wrocław University of Technology (17 students, 53%) and from the Form Design Department of the Wrocław Academy of Art and Design (15 participants, 47%). The subjects reported spending from 3 to 16 hours a day operating the digital devices, with the mean equal to 8.5 hours (standard deviation = 2.1 hours).

## 4.2. Experimental Design and Procedure

Two independent factors were analyzed in our research: the space between three parts of the screen layout used for informative purposes and the type of background visible between these areas of data presentation. The first variable was specified at three categorical levels: small, medium, and large. In the second factor, three different backgrounds were used: (1) vivid colors with a gaudy texture, (2) simple rectangular and colorful shapes, and (3) a uniform color. The three gap sizes along with the three various background types produced nine variants. The full factorial design of this simple experiment allowed estimating interaction effects between factors. The experimental conditions of all studied digital signage screen profiles are illustrated in Figure 1. A standard, within-subjects model design was used to investigate the participants' preferences, thus all prepared variants of the digital signage screens were evaluated by every participant. Before the study began, the detailed purpose and scope of the research were explained. After answering personal data questions, the subjects were comparing pairwise the screen layouts. All possible combinations of the screen design pairs were demonstrated in random order.

The experiments were conducted in teaching laboratories on similar personal computers equipped with 17" LCD monitors. The resolution was set at 1280 by 1024 pixels. Microsoft Office PowerPoint 2003 software was used to display the images of the screen versions, and a paper version of a questionnaire was used to gather information about the subjects' preferences and to obtain answers to personal questions. The exemplary slide layout along with

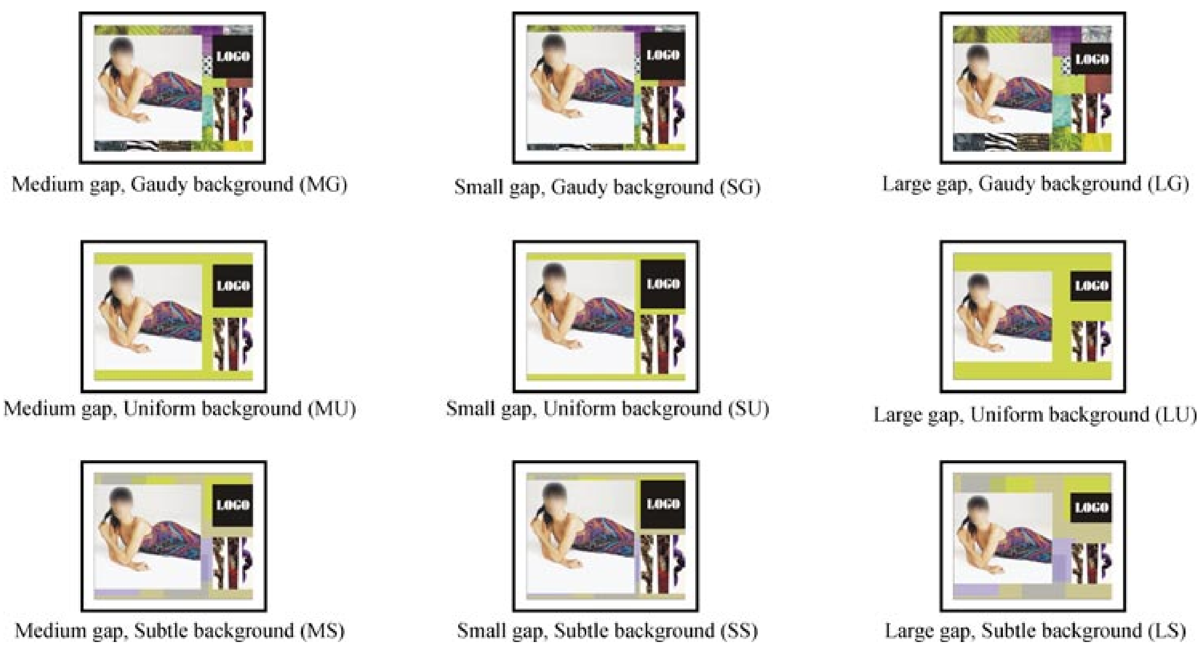


**Figure 1** All nine studied digital signage screen layout profiles.


a)

| | Extremely preferred | Very strongly preferred | Strongly preferred | Moderately preferred | No preference | Moderately preferred | Strongly preferred | Very strongly preferred | Extremely preferred | |
|---|---|---|---|---|---|---|---|---|---|---|
| SU | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | MS |
| SS | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | LU |
| MU | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | LG |

b)

**Figure 2** Exemplary presentation slide a) and first three rows from a questionnaire form used in the AHP b).

several rows of the paper questionnaire are given in Figure 2.

## 5. RESULTS

### 5.1. Preference Weights and Consistency Analysis

The consistency of pairwise comparisons performed during the research was assessed by CR values calculated according to the Saaty procedure. This indicator ranged from 0.031 to 0.537. The overall average was 0.173 (standard deviation = 0.122). The one-way ANOVA showed no differences in mean CR values between subjects from the two universities ($F(1{,}30) = 0.4$, $p = 0.53$). Also, the age of the participants did not considerably influence the analyzed coherence level ($F(7{,}19) = 1.81$, $p = 0.144$). The CR values, however, were significantly lower for men than for women ($F(1{,}30) = 11.1$, $p = 0.0023$). The average value for men was 0.098 (mean standard error [MSE] = 0.016), whereas for women if was more than two times higher (0.225; MSE = 0.029).

In the AHP, the CR is required to not exceed 0.1. It should be noted, however, that this threshold was recommended by Saaty arbitrarily. Moreover, in the full AHP, if the CR exceeds that limit, the subject is allowed to repeat and correct the preferences, if necessary. In this study this was not the case, so the dropoff value of CR was arbitrarily set at the level of 0.2. The application of this criterion resulted in exclusion of 12 persons from further preference examination, and thus the results of only 20 participants were subject to research in the next analyses. They included 12 men and 8 women, 11 persons were from the Wrocław University of Technology and 9 from the Wrocław Academy of Art and Design. The basic descriptive statistics of the obtained relative preferences for all screen profiles are given in Table 1.

According to the calculated arithmetic and geometric mean as well as a median value, the most preferred was the screen version with the medium gap and gaudy background (MG). In contrast, taking into account the same parameters, the least liked was the variant with large gap and uniform background (LU). The biggest standard deviation was registered for the medium gap and uniform background (MU), whereas the smallest was computed for the large gap and uniform background (LU). The biggest range (0.398) was observed for the screen with the large gap and subtle background

**TABLE 1.** Descriptive Statistics of the Relative Preferences for all Screen Variants

| Profile | Gap | Background | Mean | Geometric Mean | Standard Deviation | MSE | Min | Max | Median |
|---|---|---|---|---|---|---|---|---|---|
| MG | Medium | Gaudy | 0.167 | 0.115 | 0.121 | 0.027 | 0.023 | 0.406 | 0.170 |
| SG | Small | Gaudy | 0.152 | 0.094 | 0.128 | 0.028 | 0.011 | 0.401 | 0.141 |
| LG | Large | Gaudy | 0.132 | 0.090 | 0.104 | 0.023 | 0.014 | 0.375 | 0.111 |
| MU | Medium | Uniform | 0.084 | 0.063 | 0.066 | 0.015 | 0.011 | 0.229 | 0.063 |
| SU | Small | Uniform | 0.099 | 0.069 | 0.097 | 0.022 | 0.015 | 0.363 | 0.066 |
| LU | Large | Uniform | 0.060 | 0.048 | 0.039 | 0.009 | 0.009 | 0.131 | 0.048 |
| MS | Medium | Subtle | 0.097 | 0.071 | 0.074 | 0.016 | 0.018 | 0.238 | 0.053 |
| SS | Small | Subtle | 0.097 | 0.065 | 0.081 | 0.018 | 0.010 | 0.304 | 0.059 |
| LS | Large | Subtle | 0.112 | 0.066 | 0.113 | 0.025 | 0.011 | 0.409 | 0.072 |

(LS), whereas the smallest range (0.122) occurred for the large gap and uniform background (LU) variant.

## 5.2. ANOVA

Two-way ANOVA was used to verify whether the effects of the gap size, background type, and the interaction between these two variables considerably influenced the mean relative preferences. The obtained results are demonstrated in Table 2 and reveal that only the background factor was statistically significant ($p = 0.00034$).

The graphical illustration of the mean AHP weights along with the MSE values for the statistically significant factor is presented in Figure 3.

The graph indicates that the gaudy backgrounds were rated the highest, whereas the uniform type was the least preferred option for the subjects. The difference between the uniform and subtle versions was much smaller (25%) than between the gaudy and uniform (85%) or gaudy and subtle ones (48%). To check whether these discrepancies are statistically significant,

**TABLE 2.** Two-Way ANOVA Results of the Relative Weights

| Factor | SS | *df* | MSS | *F* | *p* |
|---|---|---|---|---|---|
| Gap size | 0.0086 | 2 | 0.0043 | 0.47 | 0.62 |
| Background* | 0.15 | 2 | 0.076 | 8.4 | 0.00034 |
| Gap size × Background | 0.022 | 4 | 0.0056 | 0.62 | 0.65 |
| Error | 1.5 | 171 | 0.0091 | | |

* $p < 0.0005$.

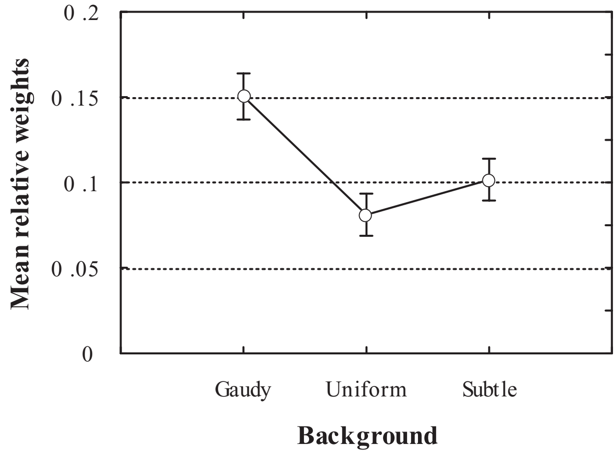


**Figure 3** Mean relative weights depending on screen background type, $F(2,171) = 8.4$, $p < 0.0005$. Vertical bars denote MSE values.

**TABLE 3.** Least Significant Difference Post Hoc Probabilities for the Background Effect

| Factor Level | Gaudy | Uniform | Subtle |
|---|---|---|---|
| Gaudy | × | *0.00010 | **0.0057 |
| Uniform | | × | 0.24 |
| Subtle | | | × |

* $p < 0.0005$.
** $p < 0.01$.

the post hoc type of analysis was additionally used. The results are shown in Table 3.

The least significant difference post hoc analysis showed that there was not any statistically significant difference between mean preferences for the profiles with uniform and subtle backgrounds. The tests also revealed that the screen designs with the gaudy background were substantially better perceived by the subjects in comparison with both the uniform and subtle backgrounds.

## 5.3. Multiple Regression

Multiple regression in this investigation was used to obtain the relationship between the independent variables gap dimension and background type and the dependent measure of the preferences. The two independent factors analyzed in the study were categorical, so the artificial coding was applied (Dielman, 2001). In both cases, the values −1, 0, and 1 were applied to represent all levels for the independent effects. The geometric means of preference weights calculated in accordance with the AHP served as the dependent variable. The parameters of the regression model were estimated by means of the least square method. The obtained model took the following form:

$$\textit{\textbf{Geometric Mean Weights}} = 0.076 - 0.0041 \cdot \textbf{Gap} - 0.020 \cdot \textit{\textbf{Background}}$$

For the presented model, the determinant coefficient amounted to 74%, which means that the variates included in the model explain 74% of the dependent variable variance. The $R^2$ considerably differed from zero [$F(2,6) = 8.7$, $p < 0.017$]. The observed preferences, along with values calculated from the constructed model, are illustrated in Figure 4.

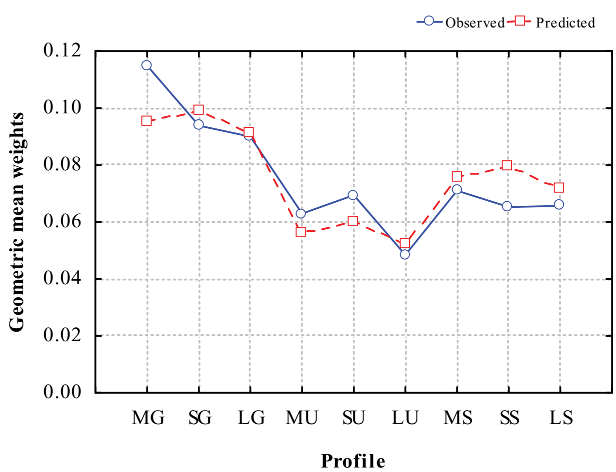


**Figure 4** Predicted and observed geometric means of relative weights for all screen variants. The regression model with two variables. $R^2 = 74\%$, $F(2,6) = 8.7$, $p < 0.017$.

**TABLE 4.** Multiple Regression Results for Relative Weights as a Dependent Variate and Gap and Background as Independent Variables

| Variate | Parameter | Standard Error | *t* Statistic | *p* Value |
|---|---|---|---|---|
| Intercept* | 0.076 | 0.0039 | 19.3 | 0.000001 |
| Gap | −0.0041 | 0.0048 | −0.84 | 0.43 |
| Background** | −0.020 | 0.0048 | −4.1 | 0.0064 |

*$p < 0.00001$.
**$p < 0.01$.

A standard procedure of analyzing the quality of the proposed model includes the verification of whether the parameters differ significantly from zero. The results of this analysis are demonstrated in Table 4, and they show that the Gap variate parameter was statistically insignificant ($p = 0.43$).

After excluding the Gap factor, the model took the following form:

$$\textit{\textbf{Geometric Mean Weights}} = 0.076 - 0.020 \cdot \textit{\textbf{Background}}$$

In this case the $R^2$ equalled 71.4%, adjusted 67.3% [$F(1,7) = 17.5$, $p < 0.005$], and all the parameters were considerably different from zero ($\alpha < 0.005$). The characteristics of the model are given in Table 5, and the graphical illustration of the predicted and observed geometric means of relative weights is presented in Figure 5.

## 5.4. Conjoint Analysis

The conjoint analysis in this study was conducted by applying the dummy variable regression for every participant. The AHP relative weights were used as the aggregate response for the individual profile of the digital

**TABLE 5.** Multiple Regression Results for Relative Weights as a Dependent Variate and Background as an Independent Variable

| Variate | Parameter | Standard Error | *t* Statistic | *P* Value |
|---|---|---|---|---|
| Intercept* | 0.076 | 0.0038 | 19.7 | 0.000001 |
| Background** | −0.020 | 0.0047 | −4.2 | 0.0041 |

*$p < 0.00001$.
**$p < 0.01$.

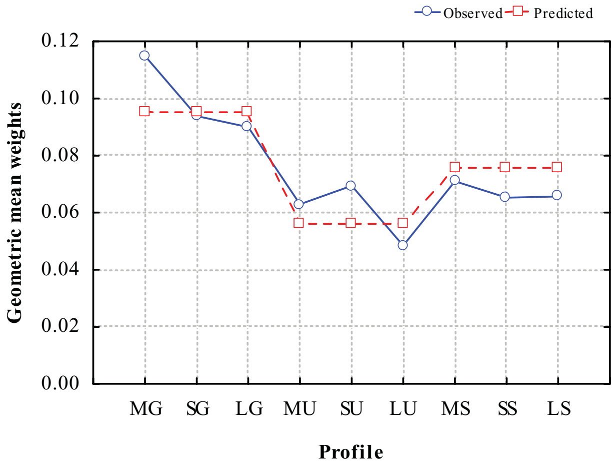


**Figure 5** Predicted and observed geometric means of relative weights for all screen variants. The regression model with one variable. $R^2 = 71.4\%$, $F(1,7) = 17.5$, $p < 0.005$.

signage screen format. The individual-level outcomes along with the basic statistical parameters are put together in Table 6.

The average relative importances along with the mean part-worths were calculated, and the results are demonstrated in Table 7.

The $R^2$ values calculated for every subject's regression served as a goodness-of-fit criterion, and the average value of this parameter equalled 83%. Mean $F$ statistics for all of the regressions amounted to 7.84, whereas the average significance level was $p = 0.086$.

The analysis results allow for choosing the most preferred digital signage screen version. There are several possible decision rules that can be applied. Among the most popular are the first-choice model (FCM), Bradley, Terry, and Luce (BTL) probability choice model, and logit probability model (LPM). In the FCM the decision is being made on the basis of the percentage of subjects that have rated the given variant the highest. In the BTL model, the choice probability for a given person is calculated by dividing the utility of this profile by the sum of utilities of all profiles. Then the individual probabilities are averaged across all subjects. According to the recommendation formulated in the AHP, the geometric instead of arithmetic means were used in this choice simulation method. The LPM estimates the choice probabilities in a way similar to the BTL approach, but, before making the division, the numerator is computed by raising the Euler's constant to the power of the appropriate utility, and the denominator is a sum of the Euler's constants raised to the power of all utilities. In this study, all persons for whom any

**TABLE 6.** Estimated Partial Utilities for Individual Subjects Together with Basic Statistics

| Variables | Estimated partial utilities for individual subject | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
| Gap size | | | | | | | | | | | | | | | | | | | | |
| Medium | 0.043 | 0.031 | −0.047 | −0.029 | 0.007 | 0.012 | −0.015 | 0.031 | −0.014 | −0.013 | −0.020 | 0.049 | 0.030 | −0.008 | 0.010 | −0.029 | 0.037 | −0.025 | 0.008 | 0.037 |
| Small | −0.032 | 0.024 | −0.096 | 0.015 | 0.052 | 0.074 | 0.045 | −0.023 | −0.029 | −0.019 | −0.007 | 0.001 | −0.004 | 0.034 | 0.023 | −0.017 | 0.009 | −0.017 | 0.060 | 0.009 |
| Large | −0.011 | −0.055 | 0.143 | 0.014 | −0.059 | −0.086 | −0.029 | −0.008 | 0.043 | 0.032 | 0.027 | −0.050 | −0.026 | −0.026 | −0.033 | 0.046 | −0.046 | 0.042 | −0.068 | −0.045 |
| Background | | | | | | | | | | | | | | | | | | | | |
| Gaudy | 0.108 | 0.059 | −0.006 | −0.064 | −0.090 | 0.121 | 0.144 | 0.027 | 0.077 | 0.018 | 0.145 | 0.146 | 0.022 | −0.078 | 0.146 | 0.132 | 0.123 | −0.075 | −0.090 | −0.077 |
| Uniform | −0.025 | −0.099 | −0.034 | −0.039 | 0.104 | −0.047 | −0.066 | −0.061 | −0.036 | −0.092 | −0.047 | −0.069 | 0.044 | −0.047 | −0.058 | −0.071 | −0.047 | −0.026 | 0.102 | 0.017 |
| Subtle | −0.083 | 0.040 | 0.040 | 0.103 | −0.014 | −0.074 | −0.078 | 0.035 | −0.041 | 0.074 | −0.098 | −0.077 | −0.066 | 0.126 | −0.088 | −0.060 | −0.075 | 0.102 | −0.012 | 0.060 |
| $R^2$ | 79% | 81% | 73% | 89% | 74% | 77% | 88% | 65% | 92% | 85% | 96% | 77% | 89% | 93% | 97% | 83% | 82% | 84% | 82% | 81% |
| $F$ | 3.8 | 4.4 | 2.7 | 8.3 | 2.8 | 3.4 | 7.3 | 1.9 | 11.4 | 5.8 | 21.7 | 3.3 | 7.9 | 13.2 | 35.6 | 4.9 | 4.6 | 5.2 | 4.5 | 4.2 |
| $p$ | 0.112 | *0.091 | 0.180 | **0.032 | 0.168 | 0.132 | **0.040 | 0.280 | **0.018 | *0.058 | **0.006 | 0.139 | **0.035 | **0.014 | **0.002 | *0.078 | *0.085 | *0.069 | *0.089 | *0.095 |
| Gap part-worths | 28% | 35% | 76% | 21% | 36% | 45% | 25% | 36% | 38% | 24% | 16% | 31% | 33% | 23% | 19% | 27% | 30% | 27% | 40% | 37% |
| Background part-worths | 72% | 65% | 24% | 79% | 64% | 55% | 75% | 64% | 62% | 76% | 84% | 69% | 67% | 77% | 81% | 73% | 70% | 73% | 60% | 63% |

*$p < 0.1$.
**$p < 0.05$.

**TABLE 7.** Aggregate-Level Relative Importances and Part-worth Estimates

| Variables | Relative Importance | Part-worth Estimates |
|---|---|---|
| Gap size | 32.5% | |
| Medium | | 0.00478 |
| Small | | 0.00501 |
| Large | | −0.00978 |
| Background type | 67.5% | |
| Gaudy | | 0.0393 |
| Uniform | | −0.0299 |
| Subtle | | −0.00939 |

**TABLE 8.** The Choice Simulation Results for Different Models

| Profile | Gap | Background | FCM | BTL | LPM |
|---|---|---|---|---|---|
| MG | Medium | Gaudy | 20% | 0.0807 | 0.1128 |
| SG | Small | Gaudy | 15% | 0.1033 | 0.1134 |
| LG | Large | Gaudy | 15% | 0.1008 | 0.1148 |
| MU | Medium | Uniform | 5% | 0.0404 | 0.1053 |
| SU | Small | Uniform | 10% | 0.0328 | 0.1059 |
| LU | Large | Uniform | 0% | 0.0641 | 0.1071 |
| MS | Medium | Subtle | 10% | 0.0901 | 0.1126 |
| SS | Small | Subtle | 10% | 0.1010 | 0.1134 |
| LS | Large | Subtle | 15% | 0.0865 | 0.1147 |

of the negative predicted value equalled zero were excluded from computations both in the BTL and LPM models. The results of the three described simulation models are demonstrated in Table 8.

Application of the maximum utility criterion as a decision rule would result in selecting the profile with a gaudy background and a medium gap. The BTL model would recommend the SG profile (small gap with gaudy background), whereas the LPM would recommend the LG screen (large gap and gaudy background). Thus, generally, it can be said that the presented models suggest using the screen design with gaudy background; however, the choice between gap types is not clear-cut and depends on the choice model.

## 5.5. Factor Analysis

To analyze the obtained experimental results from a different point of view, the factor analysis was used as a classification method (Hill & Lewicki, 2007). The relative weights obtained by means of the AHP for all digital signage screen variants were used as input values. The covariance matrix that shows relationships between the design profiles is presented in Table 9.

Based on these data, multiple factor analyses with the maximum likelihood method of factors' extraction followed by the normalized orthogonal varimax rotation were conducted to find possibly the best factor loading structure. The findings of the ANOVA and multiple regression showed that the gap factor influenced the subjects' preferences only to a small degree, so it was checked whether the covariance matrix structure could be reasonably explained by a single factor related with the type of the background. Such a factor could be called "degree of gaudiness," for instance. The results of this approach are given in the fourth and fifth column of Table 10.

The interpretation of factor analysis results are usually troublesome, because there is no agreement among researchers as to what value of a factor loading can be treated as high and what is the threshold for suppressing the factor loading. Some investigators suggest 0.3 as the minimum loading of an item (Hair, Anderson, & Tatham, 1987, 1998; Tabachnick & Fidell, 2001). Other researchers classify factor loadings of 0.70 or above as high, the values between 0.51 and 0.69 as medium, and 0.5 or lower as low (Kaufman, 1994). One of the most common proposals, applied also in this study, involves treating the absolute value of 0.4 as a cutoff, and interpreting the factor loading absolute value of 0.6 as high (Hair et al., 1998; Stevens, 1986; 1992; 2002). Apart from the presented rules of thumb, some interesting results were obtained by Peterson (2000). He compared the real factor analysis metadata with randomly generated data, and advised not to use factor loadings less than 0.3. Moreover, he recommends pursuing the solutions in which the variance explained by the factors exceeds 50%. The quality of the factor analysis can additionally be evaluated by analyzing the obtained commonalities. Velicer and Fava (1998) suggest that values greater than 0.8 for this parameter are considered high. Costello and Osborne (2005) argue, however, that low to medium commonalities between 0.4 and 0.7 are more common in real life data and only variables with commonalities lower than 0.4 are not acceptable.

In light of the described recommendations, the factor loadings obtained in this study for the one-factor structure are not satisfying. The correlations between the screen variants with a uniform background (MU, SU, LU) do not exceed the 0.4 cutoff threshold, and

**TABLE 9.** Covariance Matrix of Preference Weights Computed for all Studied Profiles that Served as an Input to the Factor Analysis

| | MG | SG | LG | MU | SU | LU | MS | SS | LS |
|---|---|---|---|---|---|---|---|---|---|
| MG | 0.0145 | | | | | | | | |
| SG | 0.0108 | 0.0163 | | | | | | | |
| LG | 0.0033 | 0.0032 | 0.0108 | | | | | | |
| MU | −0.0033 | −0.0034 | −0.0030 | 0.0043 | | | | | |
| SU | −0.0058 | −0.0052 | −0.0058 | 0.0055 | 0.0093 | | | | |
| LU | −0.0002 | −0.0012 | 0.0006 | 0.0008 | 0.0002 | 0.0015 | | | |
| MS | −0.0052 | −0.0053 | −0.0042 | −0.0001 | 0.0014 | −0.0011 | 0.0055 | | |
| SS | −0.0058 | −0.0059 | −0.0043 | −0.0002 | 0.0018 | −0.0011 | 0.0053 | 0.0066 | |
| LS | −0.0084 | −0.0093 | −0.0006 | −0.0007 | −0.0015 | 0.0006 | 0.0036 | 0.0037 | 0.0127 |

**TABLE 10.** Factor Loadings, Commonalities, and Proportion of Variance Explained Obtained by Maximum Likelihood Factor Analysis Followed by Normalized Varimax Rotation for One, Two, and Three Factors' Structure

| Screen Variants | | | One-Factor Structure | | Two-Factors' Structure | | | Three-Factors' Structure | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Label | Gap | Background | F1 | Com. | F1 | F2 | Com. | F1 | F2 | F3 | Com. |
| MG | Medium | Gaudy | ***0.654*** | **0.428** | **−0.559** | **0.515** | **0.578** | −0.396 | 0.195 | ***−0.750*** | **0.758** |
| SG | Small | Gaudy | ***0.630*** | 0.397 | **−0.539** | **0.492** | **0.533** | −0.357 | 0.131 | ***−0.805*** | **0.792** |
| LG | Large | Gaudy | **0.551** | 0.304 | **−0.556** | **0.406** | **0.475** | **−0.567** | **0.465** | −0.117 | **0.551** |
| MU | Medium | Uniform | −0.054 | 0.003 | ***0.960*** | 0.243 | ***0.980*** | ***0.950*** | 0.260 | 0.120 | ***0.985*** |
| SU | Small | Uniform | −0.276 | 0.076 | ***0.906*** | −0.030 | ***0.821*** | ***0.929*** | −0.087 | 0.084 | ***0.879*** |
| LU | Large | Uniform | 0.326 | 0.106 | 0.220 | **0.408** | 0.215 | 0.140 | **0.591** | 0.205 | **0.412** |
| MS | Medium | Subtle | ***−0.942*** | ***0.888*** | 0.215 | ***−0.900*** | ***0.856*** | 0.122 | ***−0.745*** | **0.520** | ***0.841*** |
| SS | Small | Subtle | ***−0.934*** | ***0.873*** | 0.196 | ***−0.945*** | ***0.930*** | 0.120 | ***−0.827*** | **0.502** | ***0.950*** |
| LS | Large | Subtle | **−0.474** | 0.225 | 0.022 | **−0.470** | 0.221 | −0.217 | 0.019 | ***0.907*** | ***0.870*** |
| **Proportion of variance explained:** | | | **36.7%** | | **31.0%** | **31.3%** | | **27.4%** | **21.5%** | **29.3%** | |

Factor loadings in absolute values greater than 0.6 are in italics and bolded, and between 0.4 and 0.6 are bolded. Communalities >0.8 are bolded and in italics, and the values between 0.4 and 0.8 are bolded.

for two others (LG and LS) the medium scores were computed. The proportion of explained variance was merely 37%, and only in three cases (MG, MS, SS) were the commonalities greater than 0.4.

The conjoint analysis outcomes presented earlier in this article indicate that both of the factors specified in the experimental design are considerably important for the elicited relative preferences. To verify that view, the factor analysis with assumed two factors was applied. Again, however, the results, which are given in columns 6–8 of Table 10, show little support for this viewpoint. The high factor loadings were computed only for four variables (MU, SU, MS, SS). Although the proportion of variance explained by the two factors was decent (62.3%), there were multiple and considerable cross-loadings for the screen designs with a gaudy background (MG, SG, LG). Additionally, the levels of commonalities left a lot to be desired: Two of them were unacceptable (LU, LS), and only four were greater than 0.8. The results obtained for the three-factors structure demonstrated in the last four columns of Table 10 seem to be of much better quality than those of the previous two analyses. All the commonalities are above the minimal level, and the proportion of the common variance explained by the three factors was close to 80%.

**TABLE 11.** Secondary and Primary Factor Loadings Obtained by Applying the Hierarchical Analysis of Oblique Factors

| Label | Gap | Background | Secondary 1 | Primary 1 | Primary 2 | Primary 3 |
|---|---|---|---|---|---|---|
| MG | Medium | Gaudy | ***−0.647*** | 0.254 | −0.005 | **−0.524** |
| SG | Small | Gaudy | ***−0.634*** | 0.216 | −0.066 | **−0.582** |
| LG | Large | Gaudy | **−0.478** | **0.465** | 0.323 | 0.043 |
| MU | Medium | Uniform | 0.255 | ***−0.899*** | 0.331 | 0.040 |
| SU | Small | Uniform | 0.396 | ***−0.848*** | 0.026 | −0.044 |
| LU | Large | Uniform | −0.125 | −0.167 | **0.554** | 0.247 |
| MS | Medium | Subtle | ***0.694*** | 0.030 | **−0.531** | 0.277 |
| SS | Small | Subtle | ***0.723*** | 0.039 | ***−0.604*** | 0.250 |
| LS | Large | Subtle | **0.430** | 0.316 | 0.160 | ***0.748*** |

Factor loadings in absolute values greater than 0.6 are in italics and bolded, between 0.4 and 0.6 are bolded

Although the factor loadings seem to be reasonably high, the significant cross-loadings between the first and second factor for the LG screen variant, as well as between the second and third factor for MS and SS profiles, make the findings look ambiguous and difficult to interpret.

The most interesting outcomes were obtained by applying the hierarchical analysis of oblique factors (Schmid & Leiman, 1957; Thomson, 1948; Thurstone, 1947) to the covariance matrix of preferences from Table 9. The resulting factor loadings computed according to this approach and demonstrated in Table 11 suggest that there are three primary factors that characterize the analyzed variables. There also appears to be one additional, and more general, secondary factor, which is considerably correlated with the second and third primary factors and much less related with the first one.

The presented structure seems to best represent the set of screen variants analyzed in this study, because the primary factor loadings are moderate or high (none is below the 0.4 threshold), and the cross-factor distribution is not meaningful. The proposal, however, is definitely more complex than the structures that could be expected from the experimental design applied in this research.

## 6. DISCUSSION AND CONCLUSIONS

Unquestionably, people's preferences play a significant role in a decision-making process, thus examining, modeling, and determining the real structure of them is essential in many areas. Understanding users' attitudes and finding the best possible ways of analyzing them seems to be important also in the field of usability of interactive systems, especially in its satisfaction dimension.

The main focus of this study was to thoroughly examine users' preferences toward some of the screen characteristics of digital signage displays using various methods. The analyzed graphical solutions were differentiated by two factors: the background type and the amount of the free space between different visual components of the screen layout. For retrieving the relative preferences, Saaty's AHP framework was applied. The obtained findings show that, depending on the approach, the investigator may come to various conclusions and make different practical decisions.

The results of ANOVA proved that neither the gap factor nor the interaction between the gap and background type had a substantial influence on the obtained mean preferences. The further post hoc analysis demonstrated that there was not any meaningful difference between the uniform and subtle backgrounds. These findings would recommend the researcher to choose any of the screen layouts with a gaudy background. A similar suggestion was obtained in the multiple regression approach, where the AHP preference weights were presented as a function of the independent variables. The initial two-variable model proved to be inadequate due to the insignificance of the Gap parameter. Therefore, the final formula included only the background as a dependent variate. This result supported the view of taking into consideration mainly the background type while neglecting the gap size factor in the design of digital signage graphical layouts. The findings yielded from the conjoint analysis are only partly in concordance with the previous ones. They still show that the background variable is the most significant, with the relative importance equal to 67.5%, but the relative importance of 32.5% acquired for the gap size indicates that this factor could have a significant impact on the users' preferences as well. The series of conducted factor analyses provided some evidence that the preference structure in this research could be much more complicated than it was observed by means of the three techniques described earlier on. In particular, the hierarchical analysis of the preference weights covariance matrix resulted in as many as three primary latent factors and one, more general, secondary factor. These findings indicate that the preferences concerned with the examined factors may be interrelated or may be influenced by some other factors that were not controlled in this study. This interpretation could have been omitted relying solely on the outcomes of the regression analysis, where the interaction between the examined factors was statistically insignificant. The brief summary of the findings, along with the conclusions resulting from the individual methods applied in this study, are put together in Table 12.

**TABLE 12.** Summary of the Results from all of the Methods Used

| Method | Results | Conclusions |
|---|---|---|
| ANOVA | • Background: significantly important ($p < 0.0005$)<br>• Gap and the Gap-Background interaction: statistically insignificant ($\alpha = 0.05$)<br>• Post hoc analysis for Background:<br>–Gaudy significantly better perceived than Uniform ($p < 0.0005$) and Subtle ($p < 0.01$)<br>–The difference between Uniform and Subtle was not meaningful ($\alpha = 0.05$) | • Do not take into consideration the Gap effect<br>• Focus on the Gaudy background, which is the best, and do not differentiate between the Uniform and Subtle backgrounds. |
| Multiple regression | • The regression formula after excluding the Gap variate because of the its statistically insignificant parameter ($\alpha = 0.05$):<br>Geometric Mean Weights<br>= 0.076–0.020 • Background<br>• $R^2 = 71.4\%$, $F(1, 7) = 17.5$, $p < 0.005$ | • Do not take into account the Gap effect<br>• Gaudy backgrounds are better perceived than Subtle ones, and Subtle backgrounds are rated higher than Uniform ones. |
| Conjoint analysis | • Relative importances (RI) and part-worth estimates (PW):<br>–Gap: RI = 32.5%; PWMedium = 0.00478, PWSmall = 0.00501, PWLarge = −0.00978<br>–Background: RI = 67.5%; PWGaudy = 0.0393, PWUniform = −0.0299, PWSubtle = −0.00939<br>• Best variants according to choice simulation models:<br>–FCM: medium gap with gaudy background (MG)<br>–BTL: small gap with gaudy background SG<br>–LPM: large gap with gaudy background (LG) | • The Background variable is far more important than the Gap one, but the Gap should also be included during making practical decisions.<br>• According to choice simulators one should choose the layout with gaudy background. The simulators, however, are inconsistent when the Gap is concerned and provide different recommendations. |
| Factor analysis | • Series of various factor analyses provided no clear structure of the factor loadings. The best was the three-factors structure; however, because of the significant cross-loadings, the outcome was not acceptable. | • The results indicate that this method might probably be inappropriate for the gathered data. |
| Hierarchical factor analysis | • Suggests three primary factors and one more general secondary factor, which is considerably correlated with the second and third primary factors and much less related with the first one. | • The application of this method revealed of the quite clear general structure of the preferences, which is however different from the design of the experiment. It suggests that the perception of the examined layouts depends on different aspects of the analyzed layouts than it was initially assumed in this experiment. |

Generally, in light of the conducted analyses, both of the investigated effects had significant impact on the users' perception of the examined screen layouts. The results also indicate that the background was far more important than the gap variable; however, from the hierarchical factor analysis, it can be seen that they might be subject to some more general secondary factor.

There are of course many limitations related to this research. First, the inclusion of other factors related with the digital signage screen design could broaden the analysis, which could be of great value, especially to practitioners. Also adding more levels to the investigated factors could be interesting. Because of the not fully clear preference structure obtained in this research, future investigations might include, for example, examination of the optimal geometrical properties and interrelations between the graphical components of digital signage displays. Possibly, finding the existence of so-called golden sections between some of them (Gielo-Perczak, 2001) could result in elaborating the appropriate design recommendations.

The present study was carried out on a comparatively small sample, and the reader should be cautious in generalizing the obtained results because of the considerable inconsistencies that were observed, particularly in women, which decreased the number of subjects used for further examination. Furthermore, in the conjoint analysis, the regression models obtained for some individuals were statistically not significant, and some others were significant merely at the level of 0.1. Taking into account the small number of participants in this research, they were not excluded, but it may be argued whether this was justifiable. The application of the cluster analysis to the conjoint data may be worth noting, provided that a bigger sample is available. In applying the factor analysis, it is also possible to use other than in this study rotational approaches or threshold values, which could lead to different preference structure proposals. Moreover, the conducted analyses can be supplemented by using, for instance, some version of the path models originally proposed by Wright in 1921.

Despite these limitations, the study undoubtedly shows that, even for a quite straightforward experimental set-up, the structure and interpretation of users' preferences may be problematic. It is naturally hard to recommend one best approach because each of the techniques used in this study has its advantages and limitations. Therefore, it may be reasonable to apply various methods of subjective data analysis whenever possible to get a fuller picture of the preference structure. They should rather be used as complementary instead of as mutually exclusive. Such a comprehensive approach, in turn, may help to make correct practical decisions and facilitate future research objectives. Furthermore, it seems that the presented discussion and conclusions are not only confined to the digital signage, and could have practical implications in other areas, especially those concerned with visual communication.

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