Audience Measurement of Digital Signage: Quantitative Study in Real-World Environment Using Computer Vision

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We present a quantitative study of digital signage audience measurement using computer vision. We developed a camera-enhanced digital signage display that acquires audience measurement metrics with computer vision algorithms. Temporal metrics of a person’s dwell time, display in-view time and attention time are extracted. The system also determines demographic metrics of the gender and age group. The digital signage display was deployed in a real-world environment of a clothing boutique, where demographic and viewership data of 1294 store customers were recorded, manually verified and analysed. The analysis shows that 35% of customers specifically looked-at the display, having the average attention time of 0.7 s. Interestingly, the attention time was substantially higher for men (1.2 s) than for women (0.4 s). Age group comparison reveals that children (1–14 years) are the most responsive to the digital signage. Finally, the analysis shows that the average attention time is significantly higher when displaying the dynamic content (0.9 s) when compared with the static content (0.6 s).

Keywords: digital signage; audience measurement; quantitative study; computer vision

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1. INTRODUCTION

Modern applications of digital signage are interfaces to public or internal information, advertising, brand building and making enhanced customer experience (Krumm, 2011; Lundström, 2008; Müller et al., 2011a; Schaeffler, 2008). Digital signage displays have the advantage over static signs because they can display the multimedia content such as images, animations, video and audio. The content can be adapted in real time to a different context and audience (Bauer and Spiekermann, 2011), making it attractive for use at airports, hotels, universities, retail stores and various outdoor public spaces. However, the displayed content is frequently generic and uninteresting for observers causing the effect of Display Blindness (Müller et al., 2009). To make digital signage more effective as an information interface, the displayed content should be informative, dynamic and attractive.

The actual attention that people pay to public displays is one of the key parameters of digital signage. The comparative case study of Huang et al. (2008) reveals that paying attention to public displays is a complex process, which depends on several criteria such as positioning of the display, display size, content format and content dynamics. Therefore, to maximize the attention to digital signage, these parameters should be considered already during the design phase of the digital signage system. Research in digital signage today is aimed at exploring designs and options for delivering engaging and interactive content in public places. Michelis and Müller (2011) introduced Audience Funnel, a framework for audience interaction generalization. Various interaction modalities are proposed, including body position, speech, facial expression, body posture, gaze and touch (Müller et al., 2010). Chen et al. (2009) describe a prototype system for interaction with digital...
signage using hand gestures. Also, adaptive and interactive digital signage is permeating urban life and architecture (Kuikkaniemi et al., 2011) as well as ubiquitous computing (Krumm, 2011). However, ubiquitous monitoring (Moran and Nakata, 2010) can lead to negative responses. Little and Briggs (2009) address the problem of receiving personal information in public spaces via personalized interaction. Grobelny and Michalski (2011) focus on digital signage content design. By performing pairwise human preferences comparison analysis, they show that different layout structures, background and content positioning can significantly affect the user’s perception of the digital signage content.

Digital signage can yield a remarkable impact in commerce. A generalization study by Burke (2006, 2009) reveals that in-store digital signage increases customer traffic and sales. Indeed, the shoppers are the most responsive to messages that relate to the task at hand and their immediate interest. A qualitative study using questionnaires by Dennis et al. (2010) shows that digital signage is an effective stimulus, adding to positive perceptions of the mall environment, the emotions and the approach behaviour. Finally, digital signage screens also improve the image of shopping malls and create a favourable shopping atmosphere (Newman et al., 2010).

Digital signage, clearly, is a strong contributor in various processes and fields; however, most of the measured impact was observed using qualitative methods. Nearly, all reported studies collected data by using interviews and questionnaires. Some of these publications address the inherent limitation of such approach and propose further research to determine whether people’s actual behaviour really reflects their stated beliefs (Müller et al., 2009; Newman et al., 2010). Therefore, envisaging a quantitative method, with means for determining various audience measurement metrics could open a completely new window to digital signage, allowing for maximum interaction and continuous context awareness.

In this paper, we present a computer vision-enhanced digital signage system for monitoring the actual activity of the audience in front of the system and collect quantitative data on the audience, that is demographic metrics of a person’s dwell time, display in-view time, attention time, gender and age group. The use of this system enables a new methodological approach to audience measurement in front of digital displays which gives quantitative data on all observed customers. We performed a quantitative field study in a real-world environment of a clothing boutique to test the methodology as well as the performance of the developed system. The collected data were then used for audience analysis of customers. The outline of the paper is as follows: Section 2 presents the audience measurement metrics and the computer vision-enhanced digital signage system, Section 3 elaborates the audience measurement field study, Section 4 presents experimental results, Section 5 provides a further analysis and discussion of the results and Section 6 gives final conclusions.

2. COMPUTER VISION-ENHANCED DIGITAL SIGNAGE

A real-time audience measurement system was developed for application in digital signage. The system is based on computer vision methods for detecting and tracking persons’ faces from video. The video is captured by a digital camera that accompanies the digital signage screen. From the video, the system automatically computes various metrics and generates quantitative statistics of detected persons. The following temporal and demographic audience measurement metrics are determined: (i) dwell time which represents the sum of all time intervals when an observer was present in the same room or area as the display, (ii) in-view time which represents the duration of all time intervals when an observer was facing the display screen (without necessarily paying attention to the screen), (iii) attention time which is a part of the in-view time when an observer is actually looking at the display and (iv) the gender and age group which are demographic characteristics of each individual customer.

Our digital signage system consists of four video analysis modules, each designed for the determination of one of the metrics. Figure 1 illustrates the scheme of video analysis modules that are described in more detail below.

2.1. Dwell time

Object segmentation is used to determine the dwell time of each observer that enters the store. We employ a background
Audience Measurement of Digital Signage

2.2. In-view time

A frontal face detection algorithm is used to determine whether observers are facing the display. We use the Viola and Jones (2004) frontal face detector that runs in real time. The hit rate of this face detection method is reported to be 98% (Lienhart et al., 2003), which is suitable for our purposes in terms of detection accuracy and speed. Using this face detector, we get the location of all present faces regardless of their position and scale down to the size of 20 × 20 pixels.

2.3. Attention time

The orientation of the observer’s head is the central parameter in the determination of the attention time (when the observer is actually looking at the display). We use the multi-view active appearance model (AAM) method to register all detected faces. The AAM simultaneously models the intrinsic variation in shape and texture of the deformable visual object, a human face in this case, as a linear combination of basis modes of variation (Matthews and Baker, 2004). Although linear in both shape and appearance, overall, AAMs are non-linear parametric models in terms of the pixel intensities. Fitting an AAM to an image consists of minimizing the error between the input image and the closest model instance; i.e. solving a non-linear optimization problem. The reported convergence rate of this method is 98% (Saragih and Göcke, 2009). Using multi-view AAM registration and estimated observer’s 3D position, we determine the observer’s head orientation and consequently, if the head is oriented towards the display, this denotes the person’s attention.

2.4. Gender and age group classifiers

The demographic metric of age and gender is determined within seven age groups: 1–14, 15–24, 25–34, 35–44, 45–54, 55–64 and over 65 years, all either male or female. We apply the support vector machine (SVM) learning algorithm for the age and gender classification (Moghaddam and Yang, 2002). The FERET database (Phillips et al., 2000) was used as a learning set for gender and age classifiers. The FERET database comes fully annotated including facial images and the corresponding gender and year of birth data for 856 individuals. We use the AAM facial registration method described in Section 2.3 to register a face and warp it to the normalized frontal form of size 50 × 50 pixels. Normalized FERET faces were used to train SVM classifiers for gender and age. Using this approach, we achieved 91% classification accuracy on the FERET testing set.

3. FIELD STUDY

A field study of the proposed digital signage system was performed in a real-world environment, specifically focusing on

Figure 2. Field study. (a) Typical camera image from the clothing store where we performed the field study. (b) Customer observing the shop apparel. (c) Customer watching the screen. (d) Image of observer after object segmentation using background subtraction.
the attention of the observers, i.e. their time metrics. We used a 24-inch Sony Vaio VPCL135FX/B computer display enhanced with a Logitech WebCam Pro 9000 camera. The digital signage system was positioned into a small clothing boutique in the city center of Ljubljana, capital of Slovenia, with a population of 300,000. The floor plan consisted of a main area (∼35 m²) situated between the entrance and the cashier’s desk (see Fig. 2a) with an additional room in the back used for changing.

We have selected for the field study on purpose a small retail shop so that the entire retail space could be covered by a single-camera unit. We should mention that the shop sells higher priced sports fashion clothing and apparel, which can affect the demographic and behaviour characteristics of the customers.

To achieve the highest attention rates of our signage display, we optimized different criteria according to Müller et al. (2009) and Huang et al. (2008). To optimize the position, the display was mounted at eye level on a special shelf next to the cashier’s desk, facing directly the entrance. For the eye-catching criterion, the shelves immediately next to the display were filled with small textile goods that were of immediate eye-catching interest.

To obtain data for assessment of the animated content criterion, the static and dynamic content was displayed at the signage display during the field study. The static content consisted of a slide show with 20 slides shown in 10 s intervals. The slides showed pictures of distinctive sportsmen and sportswomen wearing attire from the shop’s assortment (Fig. 3a). The dynamic content consisted of three video clips, which showed various sports and entertainment situations (Fig. 3b). The slide show and the videos were designed also to maximize the colourful content criterion, the emotional content criterion and the aesthetic look criterion.

3.1 Privacy aspects

Privacy-by-design (Brey, 2005; Langheinrich, 2001) as well as privacy-by-architecture (Spiekermann and Cranor, 2009) principles is incorporated in our computer vision-enhanced digital signage architecture, to ensure secure and appropriate handling with the acquired personal data. By design, all image processing is performed by the display unit in real time, therefore no visual records are stored or distributed over network. The display unit discards video image immediately after processing, storing only audience measurement metrics that are sent to the central server using encrypted data transfer. Using the proposed approach, we can acquire relevant audience data and perform a generalized behavioural analysis without the need to single out or even identify individual customers which is typically needed for a qualitative analysis using interviews or questionnaires.

Although the system processed video data in real time during the field study, video was recorded solely for the purpose of data verification by human reviewers. The manual annotation was performed within 3 days, discarding video afterwards. All customers in the shop were notified of the video recording, in compliance with the national privacy legislation.

3.2 Verification of results

The field study was performed within 23 daily sessions, consisting of a totally 214 h of video recordings. The tested digital signage system acquired characteristics and attention responses of 1294 people. To ensure the ecological validity of collected data, all automatically obtained data (temporal and demographic metrics) were manually verified by two human reviewers. We devised a video annotation programme for manual processing, following guidelines for effective video annotation proposed by Chen et al. (2008). Cohen’s kappa coefficient κ was used for the evaluation of the inter-rater agreement (Carletta, 1996) of demographic metrics. Based on the data collected in this study, we determined \( \kappa_{\text{gender}} = 1.0 \) for gender classification and \( \kappa_{\text{age group}} = 0.91 \) for the estimation of observers’ age groups.

The accuracy of automatically obtained parameters was compared with annotated data. The comparison shows that the system performs with a high accuracy, giving gender classifier 86.6% and age classifier 77.1% classification accuracy. The performance benchmark shows that the system is capable of video processing at 21 FPS using two cores of Intel Q8400 (2.66 Ghz) processor making it suitable for broadcasting adaptive content in real time.

We performed also a Kruskal–Wallis (K–W) test to determine the statistical significance of specific audience measurement metrics (Spurrier, 2003). The K–W test is a non-parametric method for testing whether measured data originate from the
The full results of the analysis are presented in Table 1. Note, over half an hour, which expectably results in high present: the number of analysed observers/customers (tent. Further, for dwell, in-view and attention time, the columns formed for the audience metrics of gender, age group and con- that the table summarizes the results of three general tests per- formed for the audience metrics of gender, age group and con-

4. RESULTS

The full results of the analysis are presented in Table 1. Note, that the table summarizes the results of three general tests performed for the audience metrics of gender, age group and content. Further, for dwell, in-view and attention time, the columns present: the number of analysed observers/customers (N), aver- age dwell/in-view/attention time (mean), median (median) and standard deviation of mean (SD). Results of the two-tailed K–W test (α = 0.05) are presented with: mean rank, test result value (H), degrees of freedom (DF) and the representative P-value.

Table 1 shows a large standard deviation in all three time metrics: dwell, in-view and attention time, which interestingly implies strongly varying behaviour of shop customers. Indeed, some people stayed in the shop for <20 s, whereas others were there for over half an hour, which expectably results in high standard deviation.

We next present individually each of the three time metrics.

4.1. Dwell time

The overall mean of dwell time, the time when a person is in the same room as the display, is 144 s (see Table 1, row 14, column 4). On average, each observer re-entered the scene 1.8 times. More specifically, the distribution of dwell times for all observers is presented in Fig. 5.

Comparison of the mean dwell time for gender reveals that male shoppers have a higher mean dwell time (156 s) than women (137 s) (see Table 1, rows 3 and 4, column 4). Also, the K–W test confirms the significant difference in mean ranks distribution (H(1) = 4.25, P = 0.039). Age comparison shows that the age group of 15–24 years has the mean dwell time substantially below average (101 s when compared with average 144 s). The difference in distribution is also confirmed using the K–W test (H(6) = 20.4, P = 0.002). Indeed, this quantitatively confirms that the boutique aims at an older target age group, between 25 and 55 years; which is also evident from Fig. 4. According to the mean comparison and the K–W test (H(1) = 1.48, P = 0.223), content type has no significant effect on the dwell time.

Interpreting the results, we could reason that the observed difference in the distribution of dwell time between males and females is due to the difference in the number of short shopping visits. Indeed, there are 51% of all females and only 44% of all males that have dwell time <60 s.

4.2. In-view time

In-view time analysis shows that the display comes into the field of view of an average person 4.9 times. The corresponding average of total in-view time is 17.6 s (see Table 1, row 27, column 4), indicating that the average person (customer) was facing the display for 12% of the total (dwell) time when the person spent in the room with the display. Distribution of the in-view time is presented in Fig. 6.

Gender comparison reveals higher in-view time for males. A significant difference in distributions is also confirmed by the K–W test (H(1) = 32.4, P ≤ 0.0001). No significant effect on the in-view time is found for the metrics of age (H(6) = 6.77, P = 0.343) and displayed content (H(1) = 0.85, P = 0.357).

4.3. Attention time

The analysis reveals that 35% of all people entering the store looked at the display at least once, 12% looked at the display at least twice and 6% three times or more. The corresponding total average attention time of an average person was 0.7 s (see Table 1, row 40, column 4). The conversion rate between people engaging with the display and the ones not paying any attention to it at all was 35%, which relates well with the conversion rate of 33% reported by Michelis and Müller (2011). Distribution of attention time is presented in Fig. 7.
Table 1. Quantitative results of the digital signage audience measurement field study

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<tr>
<td>35–44</td>
<td>323</td>
<td>0.42</td>
<td>0.0</td>
<td>1.19</td>
<td>589.7</td>
<td></td>
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<tr>
<td>45–54</td>
<td>251</td>
<td>0.67</td>
<td>0.0</td>
<td>1.69</td>
<td>647.5</td>
<td></td>
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<tr>
<td>55–64</td>
<td>153</td>
<td>0.68</td>
<td>0.0</td>
<td>1.73</td>
<td>659.9</td>
<td></td>
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<tr>
<td>65+</td>
<td>81</td>
<td>0.66</td>
<td>0.0</td>
<td>1.29</td>
<td>660.9</td>
<td></td>
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<tr>
<td>Content</td>
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<td></td>
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<tr>
<td>Slides</td>
<td>665</td>
<td>0.60</td>
<td>0.0</td>
<td>1.49</td>
<td>625.8</td>
<td></td>
<td>5.71</td>
<td>1</td>
<td>0.017</td>
</tr>
<tr>
<td>Video</td>
<td>629</td>
<td>0.86</td>
<td>0.0</td>
<td>2.27</td>
<td>670.4</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Overall</td>
<td>1294</td>
<td>0.72</td>
<td>0.0</td>
<td>1.91</td>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>

Values of mean, median and standard deviation are given in seconds.

Interestingly, males are more attracted to digital signage than females: 48% of all males and only 27% of all females looked at the display at least once. The overall average attention time for males was 1.2 s and for females 0.4 s (see Table 1, rows 29 and 30, column 4). Significant difference in distribution was also confirmed using K–W analysis ($H(1) = 71.9, P \leq 0.0001$). Observing evident difference in the mean attention time for the 1–14 age group (see Table 1, row 31, column 4), we performed a two-tailed Steel–Dwass–Critchlow–Fligner multiple pairwise comparison post hoc test (Hollander and Wolfe, 1999) which confirms statistically significant difference between the 1–14 group and all other age groups. We believe that the reason for the youngest age group being so distinctive is in shop goods. Retail assortment offered
nearly only adult apparel and children therefore directed their attention rather to the digital display.

Content type has no significant effect neither on dwell time nor on in-view time; however, it has an effect on the attention time (see Table 1, rows 38 and 39). The evaluation confirms that the dynamic content draws \( \sim \)1.5 times more attention than the static content. More specifically, the average attention time increased for 43% when broadcasting dynamic
content. The results agree well with the qualitative digital signage observations (Dennis et al., 2010; Huang et al., 2008; Müller et al., 2009) as well as with psychological studies on attention capture (Hillstrom and Yantis, 1994; Remington et al., 1992). Statistical significance was also confirmed using the K–W test ($H(1) = 5.71, P = 0.017$).

4.4. Summary of analysed metrics by gender, age and content type

Gender: gender has a significant impact on all three observed temporal metrics. Men are more receptive for digital signage than women, having on average higher dwell time, in-view time and attention time (see Table 1).

Age: age has no effect on in-view time; however, it affects dwell time and attention time. Children (1–14 years) demonstrate the highest attention time, whereas the age group of 35–44 shows the lowest attention time.

Content: content (static or dynamic) does not affect the dwell and in-view time. However, broadcasting dynamic content shows a strong increase (43%) in attention time.

5. DISCUSSION

5.1. Interaction graph analysis

To better understand how the studied metrics are interrelated, we performed an interaction graph analysis (Jakulin and Bratko, 2004). Interaction graphs are based on entropy, which is a measure of the uncertainty in information theory. Each node in the graph corresponds to one of the observed metrics. The information gain of each metric is expressed as a percentage of eliminated uncertainty, written below the metric’s name. Edges represent interaction between nodes as a value of their relative mutual information. A negative interaction edge, presented with an undirected dashed line, implies that the two metrics provide partly the same information. A positive interaction edge, presented with solid bidirectional arrows, indicates the amount of novel information added by the pair of connected metrics (Jakulin and Bratko, 2004).

The interaction graph of the data acquired in our field study was calculated using the Orange machine learning framework (Curk et al., 2005) and is illustrated in Fig. 8. Attention time (as a continuous variable) was replaced with a binary class variable looked-at that indicates whether one has looked-at the display or not. The continuous metrics (dwell time and in-view time) were discretized using entropy MLD discretization. To ensure better legibility of the interaction graph, only the most significant edges of each metric are shown.

The most important metric is in-view time that alone removes 24.3% of class entropy. A negative interaction edge between these two metrics (dashed line) indicates that in-view num reduces class entropy by only $24.3 - 22.8 = 1.5\%$ on its own, once we have already accounted for in-view time. Gender alone provides 5.27% of information, but if we account for the positive interaction between in-view time and gender (solid bidirectional arrow), they together eliminate $28.7 + 5.27 + 1.73 = 35.7\%$ of class entropy.

The most informative metrics are: in-view time (28.7%), in-view num (24.3%), dwell time (18.9%) and dwell num (11.3%). We explain this by reasoning that the longer person stays in shop or the longer the display is in his/her field of view, the higher is the probability of observing the screen. There is also a strong negative interaction between these metrics indicating significant amount of shared mutual information between them.

Metrics gender (5.27%), age group (4.47%) and content type (4.15%) are also all informative. Positive interactions between them and positive information gain imply that they...
are inter-dependent. Thus by knowing gender and content type, we eliminate 10.5% of class uncertainty.

The remaining metric day indicates the day of the week when the observer visited the shop. This node was added to the interaction graph to illustrate the validity of the proposed analysis. We can strongly believe that the day of the week does not correlate with the fact whether a shopper did look at the screen or not. The interaction graph analysis confirms this assumption since by knowing the day of the week, we eliminate only 0.17% of class entropy.

5.2. Limitations and benefits of the proposed digital signage system

There are several limitations but also benefits that one should consider when evaluating the presented results. The proposed methodology gives us detailed and measurable data on the behaviour of all observed subjects. Therefore, the number of customers analysed in such quantitative fashion is much larger than the number of customers typically covered within the framework of a qualitative analysis using interviews or questionnaires. It does not, however, offer an explanation of their behaviour. To fully explain and understand the social aspects of diverse attention rates, a quantitative audience measurement field study should be performed in parallel with collection of qualitative data from the same population. Having access to exact behavioural quantitative data on attention, one can improve also the preparation of questionnaires and interviews for qualitative studies.

An interesting result in our experiment which asks for an explanation is that males are more attracted to digital signage than females (Section 4.3). This finding could be explained, for example, using interviews or questionnaires. We could also test a hypothesis with the help of our quantitative methodology. For example, the observed result in our field study that men were more attracted to digital signage could be a consequence of the topic of the displayed dynamic content, mainly sports in our case. To test this hypothesis, we could replace the sport topics with, for example, family activities, to see if the corresponding attention data would change. We believe, however, that in order to explain such observations, the analysis of customer behaviour should go even deeper. A customer must first select an item, then she or he can make a decision to buy it and, finally, by paying for the item ending the whole purchase process. When a group of customers comes in a shop these roles for selecting, buying and paying can be distributed among different people in the group. The explanation for the above observation could therefore be that, in the framework of this field study, women were on the average more involved in the selection of clothing goods than men. Men who were part of a group of customers could be, in the meantime, more responsive to the whole store environment, including digital signage. Since the selection phase in the whole purchasing process typically takes longer than all other purchasing phases, this could also explain the collected statistics of attention time. By analogy, in a more technically oriented store, we would probably observe a reversal of gender statistics.

The broadcasting of information by means of the digital signage system in the presented field study was nearly optimal due to the highly controlled environment. The digital signage display and the complete broadcasting area were indoors, ensuring constant lightning conditions. Since computer vision is sensitive to changes in illumination, audience measurement errors would increase in an outdoor environment. The display was positioned on a prominent location at eye-level height where the camera was able to cover almost the entire shop area. All these and other parameters can hardly be optimal in an arbitrary real-world situation and can adversely affect the results of the proposed audience measurement system.

The performance of the proposed system also depends on technical characteristics. Real-time video processing requires a certain amount of processing power. The proposed system utilizes two cores of Intel Q8400 processor which means that the system is suitable for implementation on embedded devices. By using more complex computer vision algorithms or more expensive hardware components, such as infrared sensors or multiple cameras for stereo vision, the system’s accuracy could be improved. However, we believe that the proposed system set up offers a good price–performance ratio and can operate in real time on low-priced hardware. Selected computer vision algorithms are also copyright free, which makes the proposed system setup suitable for commercial deployment in large numbers.

It is probably already within technical means that camera-equipped digital signage systems could remember and identify individual customers by their appearance. But this would require establishing customer databases which would run against most privacy regulations. Although most customers are quite willing to identify themselves through various loyalty cards when they actually make a purchase, identifying themselves by merely stepping into a store is a completely different issue.

6. CONCLUSION

An advanced digital signage system is presented, consisting of a display screen, a digital camera and audience measurement software. Computer vision and machine learning methods were implemented for an automatic assessment of the audience measurement time and demographic metrics. The field study that we performed shows that, if the environment is optimally controlled, computer vision is at a stage where it can give fully reliable data for audience measurement research.

The digital signage system was applied in a field study for customer research in a clothing boutique, enabling a full quantitative audience measurement research. The attention time quantifier reveals that, on average, men pay attention
to the digital signage display for 1.2 s, whereas women only 0.4 s. Age group comparison shows that attention time to digital signage is the highest (2.4 s) in the children age group (1–14 years) when compared with the all average attention time of 0.7 s. Interestingly, the average attention time is the lowest in the 35–44 years age group (0.42 s). The contents quantifier, dynamic or static, shows that broadcasting dynamic and not static digital signage content increases attention time for 43%.

More generally, these results are aimed to improve the future design of digital signage systems. The proposed architecture can be implemented on new or existing digital signage systems. Providing proper privacy care, it could serve as an advanced quantitative tool for various types of audience measurements. Additional social implications could be inferred and a wider behavioural analysis could be performed based on this non-invasive approach. We believe that using the proposed methodology, detailed audience measurement analysis can be performed continuously on all observed customers and at large number of points in parallel which could offer new ways of customer communication in marketing and advertisement. In this way, future digital signage systems could automatically adapt themselves to different types of retailers, to different customer bases and to different localities using the type of analysis of collected measurements which was used in this article only post hoc. Since demographic metrics are obtained in real time, they could be used to adapt content also in near real time to reflect actual variations in customers during a single day. Attention behaviour analysis and the possibility of designing adaptive scenarios could lead to a further evolution in content development for digital signage systems. Therefore, we plan to study in the future what kind of feedback mechanism would be the most efficient and simple enough for adaptive digital signage systems. Finally, as the next steps towards maximum-impact scenarios could lead to a further evolution in content development for digital signage systems. Thus, the cooperation and support of the boutique store in performing the field study.

REFERENCES


