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Using MWD: A Business Intelligence System for Tourism Destination Web*

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The importance of Internet as mass media in the field of tourism is that it constitutes an important channel of marketing institutions and business network of the tourist destinations. But very few subsequent processes of management, maintenance, improvement, and exploitation of this appearance are deeply studied. The interactive nature of the website, as both transmitter of information and receiver, has attracted the attention of scholars since the interaction allows opening new approaches to the study of the network traffic (the pages user has visited, order them, the time that it has been in them, the actions carried out...) and cyber behavior. Information flows from the physical to the cyber world, and vice versa, adapting the converged world to human behavior and social dynamic. The business intelligence systems based on Internet enable organizations intelligent actions to address time-sensitive business processes and benefit from analytics. As result provides the opportunity to anticipate and estimate visitor habits in a changing environment. This paper presents the research and technological fields which have been incorporated to study of the destination web, a business intelligent tool based on Internet that it aims to increase the performance of the local manager or tour operator by providing an enhanced insight through the behavior of visitors on the website and future trends in research are expressed.

Keywords: tourism destination web monitor, web mining, web analytics, business intelligence system

A System Within the Business Intelligence Based on Internet

The present time has been recognized as a technology-mediated world, with computing and communication entities interacting among themselves, as well as with users. In this technology-rich scenario, real-world components interact with cyberspace thus driving towards what some scholars have called the Cyber-Physical World (CPW) convergence (Conti et al., 2012). Information flows from the physical to the cyber world, and vice versa, adapting the converged world to human behavior and social dynamics.

In this new technology-mediated world, information about the physical reality is seamlessly conveyed into the cyber world. However, it is not obvious about how to transfer information and knowledge from the cyber world toward the physical one. This opens up the field for the creation of innovative research and advanced services to better understand and interact with the surrounding physical world as well as the social activities.

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In fact, information technology and business intelligence, provide a novel direction to support enterprise business in a new way (Chaudhuri, Dayal, & Narasayya, 2011). Business intelligence based on Internet is one of the most robust trends that trigger the awakening of a growing interest in the field of strategic management and e-science (Teo & Choo, 2001; Du Toit, 2003).

At this moment it is seeing a confluence of practices and technologies into business that enable organizations intelligent actions to address time-sensitive business processes and benefit from analytics. As a result, the new situation provides the opportunity to anticipate and estimate consumer habits on a changing environment (Shih, Liu, & Hsu, 2010; Alzua-Sorzabal, Gerrikagoitia, & Torres-Manzanera, 2013).

The change has brought new means of communication, characterized by a decentralized set of communication networks allowing fast, economical, direct and ubiquitous collections and generation of information (Kahn et al., 1997; Pérez, Rodríguez, & Rubio, 2003). Hence, people are empowered to express, share, create, consume, and organize information in a new manner (Pisani, 2008). Thus, the mass media come into view as a suitable tool to develop communication strategies within the context of strategic marketing (Varadarajan, 2010).

The importance of Internet as mass media in the field of tourism is that it constitutes an important channel of marketing institutions and business network of the tourist destinations, providing huge volumes of information available to potential tourists (Wang & Fesenmaier, 2006; Buhalis & Law, 2008).

The traditional communication channel (TV, newspapers, radio etc.) is replaced by websites that allow access to all information (Abou-Shouk, Lim, & Megicks, 2012); enabling web users to get prices of products and tourism resources in a transparent and dynamic (Lanquar, 2001). The new technology-mediated environment not only provides destinations a new means of promotion and enhancement of tourist activities, but also, new means of learning about the tourist taste and preferences. Advance solutions, tolls, and metrics, play a very important role in this process of developing a deep understanding of the present and future visitor. Beyond traditional web analytics, destination's stakeholders are needed of innovations to support the intelligent monitoring of the visitors, in order to anticipate and improve their performance. Destination management organization (DMO) must find out to whom, to what, to how, and to when to refer to the visitor.

In this context, Centre for Cooperative Research in Tourism (CICtourGUNE) has designed an enhanced system within the business intelligent based on Internet for measurement, analysis, and modelling of destination digital visitors named destination web monitor (DWM). This paper presents the research and technological fields which have been incorporated in recent years on the web sites of the DMOs, it defines the DWM and future trends in research within the scope of the DMO's website are expressed.

Related Work

The DMOs invest many resources: time, effort, and money in order to have a presence on the internet; but very few of them are studying the subsequent processes of management, maintenance, improvement, and exploitation of this appearance (Wang & Fesenmaier, 2006).

The interactive nature of the website, as both transmitter of information and receiver, have attracted the attention of scholars since the interaction allows to open new approaches to the study of the network traffic (the pages user has visited, order them, the time that it has been in them, the actions carried out...) and cyber behavior.

Furthermore, new disciplines appeared in the last decade, such as, web mining in order to move forward in discovering and analyzing useful information from web sites (Agarwal, 2010). It implies areas and technologies related to information management and retrieval, artificial intelligence, machine learning, natural language processing, network analysis, and integration of information (Cooley, Mobasher, & Srivastava, 1997; Wang, Abraham, & Smith, 2005). Currently three approaches can be recognized: web usage mining, web content mining, and web structure mining.

Web usage mining techniques are based on the process of discovering patterns of usage on web data (Srivastava, Cooley, Deshpande, & Tan, 2000; Iváncsy & Vajk, 2006). It is about getting users profiles inferring unobservable information about the user from their observable information (Arbelaitz et al., 2012a). It is particularly interesting to discover the paths that are rarely followed by the visitor or the crossing of them among the most visited pages (Shahabi, Zarkesh, Adibi, & Shah, 1997). Thus, the resulting indicators facilitate the optimal design of a DMO's website (Spiliopoulou, Faulstich, & Winkler, 1999).

Within the second group, the web content mining techniques define processes that try to discover useful information from the content of web pages (Srivastava, Desikan, & Kumar, 2005). The contents hosted on a web page can be text, images, videos, data stream, metadata, and hypertext (text, language marches, hyperlinks) (Weiss, Vélez, & Sheldon, 1996). At present, researches are turning their attention to web multimedia mining techniques, which seek to recognize and select the images (Rodríguez-Vaamonde, Ruiz-Ibáñez, & González-Rodríguez, 2012) and video sections of interest (Ocaña, Martos, & Vicente, 2002).

Web structure mining techniques are focused on inferring knowledge from websites through the "links" that they host. In this context we underline the work carried out by Piazzi, Baggio, Neidhardt, and Werthner (2011) and Merinero, Rodríguez, and Pulido Fernández (2009).

The existing literature on the diverse web mining techniques applied to tourism destination shows that the acquired information about the behavior of visitors, allows to customize the navigation scheme and/or the content to new visitors according to previously defined behavior patterns (Das & Vyas, 2011; Perona, Arbelaitz, Gurrutxaga, & Muguerza, 2010; Pierrakos, Paliouras, Papatheodorou, & Spyropoulos, 2003). Thus, web personalization strategies have been developed in order to optimize and enrich visitor's experience.

There are a large volume of professional solutions in the market (Google Analytics, Piwik, AWStats) which incorporate the capture of the digital footprint and a process of web analytics. Web analytics is the science that covers statistics, information technologies, as well as the economy, management, marketing principles and several experts systems from other fields.

A diverse set of tracking tools, which capture the interaction of visitors, is needed to obtain the information automatically on the digital footprint left by the visitor on the website. Currently, tracking tools work at different levels: (1) server, using server logs; (2) client, by a remote agent (JavaScripts or Java Applet) or by modifying the source code of a web browser; and (3) proxy, through an intermediate level where it stores data between web browsers and web server (Srivastava et al., 2000). Most of the published studies are based on tools and server logs (Cooley et al., 1997; Srivastava et al., 2005; Zaïane, Xin, & Han, 1998; Arbelaitz et al., 2013); although more recent studies are using the implementation of a script on the websites (Shao & Gretzel, 2010; Pitman, Zanker, Fuchs, & Lexhagen, 2010; Plaza, 2011; Arbelaitz et al., 2013).

The DWM System

Definition

For this research the following definition of DWM has been adopted: a system to measure, analyze, and model the behavior of visitors in different virtual areas (region, territories, tourist brands, associations, capitals, districts, municipalities) in which a destination is promoted and with the objective of providing benchmarking ratios that facilitate strategic surveillance and intelligent marketing policies.

DWM contributes to gaining a holistic understanding of the destination, which facilitates the extraction of explicit and tacit knowledge of the networked system comprising different sites in its two aspects: relations between them and the interaction of the visitor in each of them.

The design of the DWM satisfies the five levels of the web analytics maturity model (WAMM) (Gassman, 2008); a set of best practices covers the entire lifecycle of a product or service from conception to delivery and maintenance.

General Architecture of DWM

Figure 1 shows the general stages of the processes within the DWM. The user accesses the destination website through a PC, a smartphone, a tablet, or a PDA, and at that moment, it is when the capture of its interaction with the site starts.

The collected data are processed in external servers to later convert it into useful information that will be monitored. Once the monitoring of results is available, it proceeds to analyze and evaluate in order to draw conclusions on the consumer profile about the destination.

Figure 1. General stages of DWM.

The technical platform starts capturing data before the visitor accesses the destination web page, recording the search engine and the search word that has led the destination, in the case that the access is not direct. It is possible to incorporate a small JavaScript code that must be hosted on each destination website. It records in real time all the actions that the user makes and these are stored in a MySQL[1] database belonging to the web analytics tool.

After installing the tracking code on the web pages of the DMO, it proceeds to check the status of the implementation.

Once the data are stored in the MySQL, an Extract, Transform and Load (ETL) process transports it to another SQL server[2] database on a daily basis. All the raw data need a cleaning process, for instance, to

[1] Oracle and affiliates database.
[2] Microsoft corporation database.

remove sessions generated by robots (Tan & Kumar, 2004).

When the cleaning process is finished, an analysis services[3] project generates a cube with its dimensions and fact tables to be able to interact with the obtained data. The project facilitates the design, creation, and management of multidimensional structures that contain aggregated data from the SQL server database.

So far it has data in clean tables, which can be exploited through simple reports. To obtain answers to more elaborate issues, the tables are transformed in order to work on the data easily with mathematical packages that allow applying knowledge discovery in databases (KDD) techniques. This is a non-trivial process to discover knowledge and useful information within the data contained in any repository of information (Fayyad, Piatetsky-Shapiro, & Smyth, 1996).

The most common techniques of KDD employed in the domain of the website are: (1) characterization to find rules that outline the general characteristics of the data obtained; (2) comparison to discover discriminatory rules, for example, to determine the behavior of web robots; (3) associations and correlations of data where the presence of a set of them implies the presence of others; (4) the prediction that seeks to predict a value or values of an attribute based on its relevance to the rest; (5) the classification which compares sequences from a group within a segment of users that show similar patterns of navigation; (6) the time series analysis that recognizes patterns, characteristics, trends, differences, similarities intervals along a time sequence; and (7) the sequence of behavior that is based on obtaining the patterns by which the presence of a set of data is followed by another in temporal order (Zaïane et al., 1998).

Each action URL is assigned a topic because the combination of action and use provides a better understanding of the real interest of the visitor (Arbelaitz et al., 2012b).

This assignment can be performed via specifications of interest found in the profiles of the users (Ravindran & Gauch, 2004), open directory project (ODP) (Open Directory Project, 2013), or through the analysis of the visited web pages (Sugiyama, Hatano, & Yoshikawa, 2004).

The first classification addresses in a fast and successful way the main menu topics of the website. Its appearance is usually done in a standardized manner with values between 0 and 1. The information obtained is displayed in a simple and clear way through reports and/or graphics that are incorporated into a SharePoint[4] solution. This web solution allows fast access from anywhere platform.

All these techniques within the scope of web usage mining can be completed with the analysis of web site content, web content mining, and studying the structure of the site, web structure mining. The set of processes contributes to the system network that makes up different sites and the relationships between them through the interactions of visitors that will help to achieve a holistic understanding of the destination as a whole.

Definition and Measurement of Variables

Professional web analytics tools, whose degree of maturity is positioned in the technical details (Level I), respond to basic questions such as: fractional number of visits by nationality and location; engine search references other websites, direct traffic, social networking; number of unique users; number of new visits versus number of concurrent visits; number of hits per page, number of visited pages, pages viewed by language, ratio of pages per visit, bounce rate number... (Peterson, 2006).

In addition, the maturity level of the DWM base allows formulating more elaborated questions, as the one

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[3] This allows processing online analytical (OLAP) and data mining processes.
[4] Microsoft content management platform.

collected in Table 1. These enriched answers are displayed on a scoreboard that displays data on the performance, behavior and, trends and predictions. The generic indicators of performance include workload, efficiency, effectiveness, and productivity. The behavior indicators respond to the behavior of visitors and the generic indicators over trend and prediction are focused on discovering new preferences and projections focusing on the visitor and the behavior.

Table 1

Questions That Are Answered by Applying KDD Techniques to DWM

Questions	Technical
What do our users?	Sequential patterns
What do they like most and which least?	Association rules or patterns frequently
How have they found? (Entry platform...)	Analysis of classification
Are there groups differentiated by origin?	Analysis of clustering and classification analysis
What are the most common profiles by origin/topic?	Association rules or patterns frequently
Are there behaviors differentiated by origin/topic?	Clustering and other statistical techniques
What are the most common tour paths?	Sequential patterns
What is the user behavior over time? Comparison between periods, trends...	Other statistical techniques
What are the buying habits of tourists?	Analysis of classification and association rules or patterns frequently
What are the features they have in common successful products and services?	Association rules or most frequent patterns and other statistical techniques

The scoreboard developed by the DWM displays data on the performance (see Figure 2), behavior (see Figure 3) and, trends and predictions (see Figure 4). Generic indicators of performance include workload, efficiency, effectiveness, and productivity. The behavior indicators respond to the behavior of visitors and the generic indicators over trend and prediction are focused on discovering new preferences and projections focusing on the visitor and the behavior.

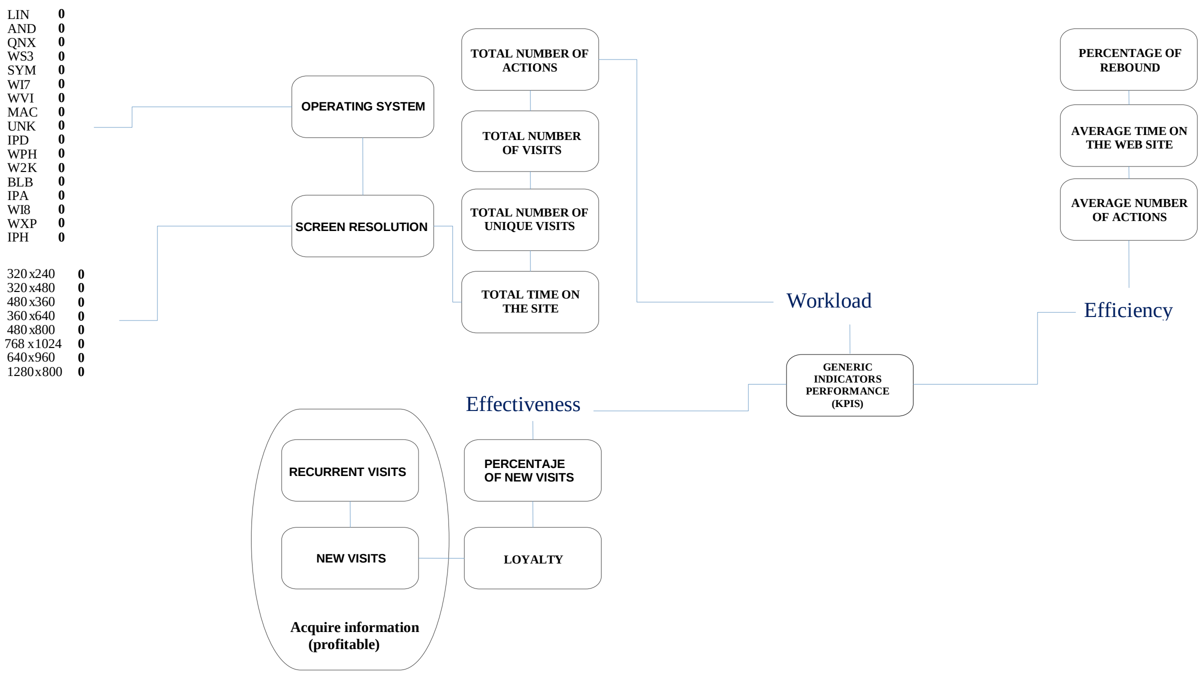

Figure 2. MWD performance indicators.

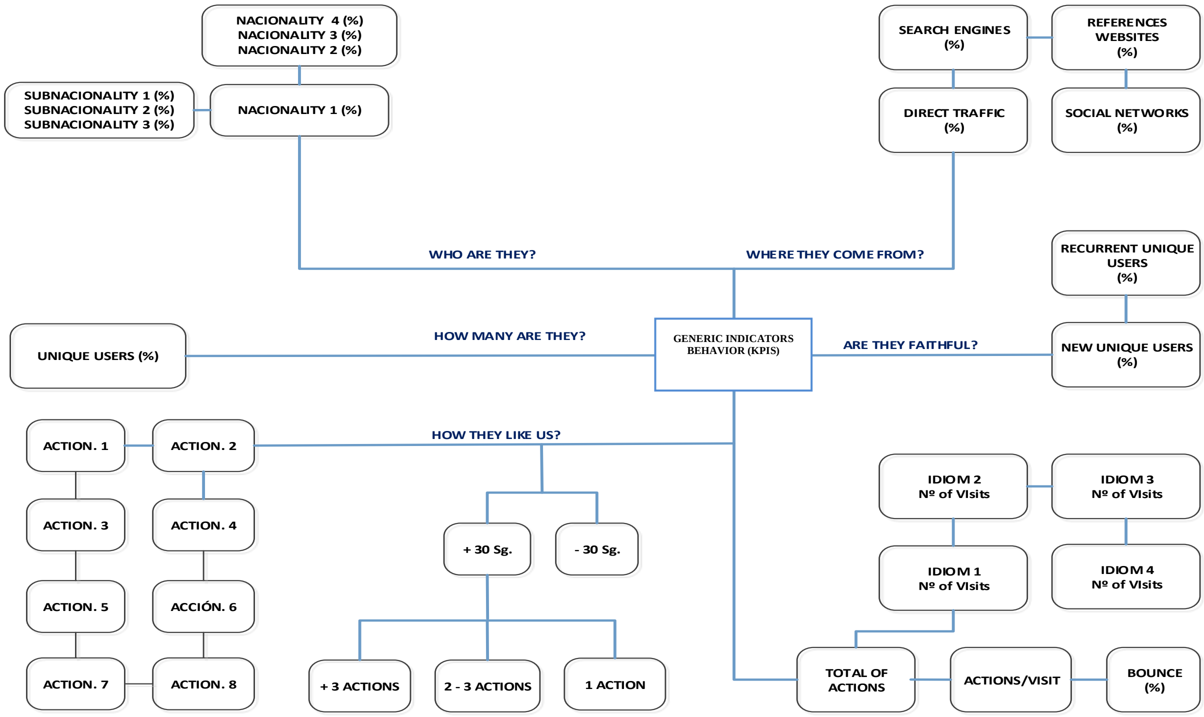

Figure 3. MWD behavior indicators.

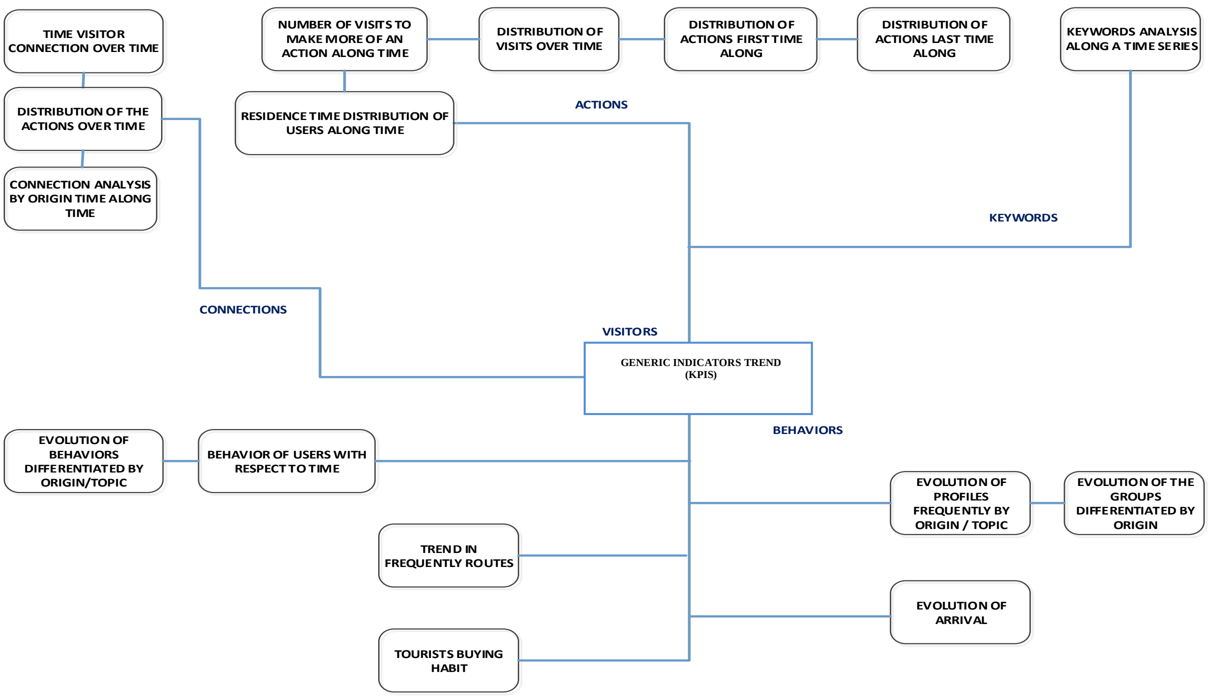

Figure 4. MWD trend indicators.

Discussion on the Different Studied Web Analytics Tools and MWD

Currently there is a large volume of vendors and solutions in the market, which apart from achieving the gathering of the digital footprint are responsible for performing web analytics processes, such as Google

Analytics, Piwik, AWStats, Adobe Analytics, etc..

In this section the discussion will focus on the first three ones that are the most widely used. Nonetheless, significant methodological and technical differences can be identified among them. Respecting the extraction of information, it can be done through server logs or using a script hosted on the website.

AWStats collects the navigation trace left in server logs; not allowing direct access to the data but exposing them through a web reports. In obtaining the attributes to capture, the mentioned system does not register the visited pages that they are hosted on the server cache. And so, it is not easy tracking the individual cookies and queries to data hosted on the server, and the user time spent on visiting a page is inferred by an algorithm.

Google Analytics and Piwik accomplish the capture of the digital footprint through a script, which should be hosted on the website of the DMO, and whose implementation requires the involvement of the prescriber of the web. The script transforms the user interaction in recognizable actions in a database, but does not enable to capture the page reloads or clicks the button return (Srivastava et al., 2000).

Another significant difference should be noticed between Google Analytics and Piwik. In Google Analytics data are housed on Google servers; so direct access to data is not facilitated. However, access to an API or through a manual export to spreadsheets or simple text format is supported. The main limitation is that data are allotted by day and do not cover the navigation attributes. To the contrary, Piwik provides full access to the data and support further analytical possibilities. In this case, the data are disaggregated and related to the time at which the action is performed. In addition, Piwik, allows data imports from Google Analytics.

Due to the described improvements the technological environment of DWM has been developed upon Piwik in order to capture the digital footprint from the DMOs web pages. Moreover, customizing capture DWM allows catching variables that are not available by default in Piwik, for example, the used device.

In DWM, it aims to increase the performance of the local manager or tour operator by providing an enhanced insight through the behavior of visitors on the website. It is a clear improvement of the existing solutions since it assists on audience segmentation according to the reason of the visit; facilitates the selection of the clusters of tourism products in the interest shown by visitors: culture, sports, landscape, ecology, alternative, etc.. The information generated by the monitor supports decision-making processes in increasing in the number of followers and provides the most suitable periods of the year for a more effective communication campaign. Because it is capable of responding to complex issues where only are able to respond those tools whose maturity level is five.

Ultimately, DWM enables optimization and design of tourism web sites in a time sensitive framework.

Conclusion and Future Work

Internet and the web presence of the DMOs have broken heavily on custom and everyday uses for travel research as well as moderator of the image formation and the willingness to travel to a destination. Intelligent systems in the tourism, as it is the case with DWM, support tourism organizations to better understand the business environment and potential customers. The new generation of information systems provides a novel way to identify the most relevant information, greater decision support, greater mobility and ultimately, greater and enjoyment of the tourist experience (Gretzel, 2011).

The DWM as a platform for competitive intelligence improved online marketing strategies. The DMO’s decision-making will be supported by evidences on the effect of marketing strategies as far as on attracting new customers, increasing the degree of loyalty of the visitors and launching programs to encourage the spontaneous recommendations. In this way, the user is at the center of the system and their behavior with the DMO site is interpreted in a quantitative and qualitative mode.

Future efforts in the investigating of the architectures and the algorithms that exploit the data within DWM promise to lead us to the next generation of intelligence within website of the DMO.

By the 2014 it is expected to exceed the current figure of four billion mobile devices around the world; with a higher number of mobile devices connected to the Internet than desktop computers (Martín, López-de-Ipiña, Alzua-Sorzabal, Lamsfus, & Torres-Manzanera, 2013). The mobile device becomes a window on the information in real time and having this accurate information is changing tourist behavior at the destination would be crucial to enhance destination management and customer expectations. The developed system, DWM, will support this new challenge, since it would facilitate through new developments to study the visitor behavior on a destination through mobile applications and linked it to previously conduct a virtual visit to destination.

Furthermore, DWM, foresees a new data storage structure that allows new connections between different big data systems (Lohr, 2012). Because the highly disaggregated level of the data, DWM will make possible a better adjustment with reality; more accurate, enabling complex answer questions related to multiple attributes of tourism.

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