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RESEARCH ARTICLE

INTEGRATION OF SOCIAL MEDIA, REGIONAL AND SERVICE FACTORS IN QUANTITATIVE E-COMMERCE WEBSITES EVALUATION

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ABSTRACT

The effectiveness of an E-commerce website is vital to E-business success. Therefore, it is important to accurately evaluate the performance of E-commerce websites. Many website evaluation methods have been proposed and used. However, though these tools have covered remarkably broad factors, social media as well asregional and service-relatedfactors are usually not taken into consideration. In this paper, a new model is proposed, integratingsocial media (i.e., Twitter data), website rank, website functionality, regional and service-related data in order to quantitatively evaluate the performance of E-commerce sites. By adopting those new factors, we try to provide a new model to better assess the compounding effect of website performance. The proposed model is applied to54 selected E-commerce websites in Saudi Arabia, and the evaluation results show the benefit of the new model. The proposed model can be used to improve the site performance and help decision makers to better understand their business.

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INTRODUCTION

The impact of E-commerce on markets, retailers, and consumers in developed countries has been noticed in the past decade and will continue to rise (AlGhamdi, Drew, and Alhussain 2012). The E-commerce practice began in most developing countries in early 90's. Such practice is commonly acknowledged to be an index of economic progression (Al-Hudhaif and Alkubeyyer, 2011). In 2002, the global spending growth resulting from E-commerce transactions reached around 0.27 trillion USD and significantly jumped to 10 trillion after a decade (AlGhamdi *et al.*, 2012). The global retail E-commerce sales reached1.5 trillion USD in 2015 and are projected to reach 4 trillion USD in 2020(Anon, 2016b). The performance of E-commerce websites is tremendously important since it affects the compatibility, usability, and growth of the business. Qualitative approaches using principals and/or criteria were often used to evaluate the overall quality of an E-commerce site. However, the qualitative evaluation performed by a domain expert can be subjective and is very time-consuming. A number of websites evaluation methods using quantitative approach have been proposed; each method was designed with one or a few particular evaluation purposes.

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For examples, some methods are designed for general websites, whilesome are customized for specific domains (Alotaibi, 2013); some methods are used for redesign decisions, while others are used for strategic decisions related to business or marketing (Alotaibi, 2013). Researchers or field engineers usually extend an existing foundation model like ServQual (Parasuraman *et al.*, 1988), WebQual (Rodríguez-Pineda, 2000) or WebQEM (Olsina and Rossi, 2002) by adding new criteria or new factors to meet their own evaluation purposes. The tools mentioned above usually take a set of predefined factors for evaluation without providing a way to take other important factors into account. These existing models or tools often report only a set of parameters such as the speed, accessibility, link analysis and page ranking, which may not be the most effective indictors for the growth of the business. There are many globally recognized recent phenomena and new factors affecting E-commerce performance include, but are not limited to, social media, mobile usage, payment methods, and government regulations (AlGhamdi *et al.*, 2012; Alghamdi, Nguyen, and Jones, 2013; Alghamdi *et al.*, 2011; Al-Hudhaif and Alkubeyyer 2011). It is also a well-known fact that the factors influencing E□commerce adoption and implementation are highly related to the country/region and culture under investigation (AlGhamdi *et al.*, 2012; AlGhamdi, Nguyen, and Jones 2013; Alghamdi *et al.*, 2011; Al-Hudhaif and Alkubeyyer, 2011; Makki and Chang, 2015c). These new factors, social media, region and culture differences, must be considered in a modern E-commerce websites evaluation model. Therefore, a new tool that better tackles fore mentioned problems is indeed needed.

Briefly, the goal of this paper is to provide an enhanced model to quantitatively evaluate E-commerce websites using the factors that were widely used in the past along with unused oneslike social media, regional and service-related factors.To design an effective model for the performance evaluation of E-commerce websites that takes social media, regional and servicesfactors into account, we have selected a developing country, which is Saudi Arabia, as a case study. A recent article reported that mobile shopping and social media have driven E-commerce traffic higher (Maple, 2015). Other studies also reported a remarkable growth of internet, very high possession rate of mobile devices, and social media usage in developing countries like Saudi Arabia (Anon 2014). Our previous research has conducted a comprehensive survey from the perspective of the consumers to identify a set of factors affecting the performance of E-commerce sites in Saudi Arabia (Makki and Chang, 2014, 2015a, 2015b, 2015c). Based on the analysis of our survey data and other reports, new factors were identified, namely, social media (Twitter data was used), web ranking, web functionality, regional and service-related factors (e.g., regional coverage, local payment and delivery methods, multi-lingual content, aftersales services and available sales currencies). Therefore, in this paper, we propose a new website evaluation model consisting of four different sub-modules to better assess the compoundedeffectiveness of E-commerce sites quantitatively. We will use the data we have collected pertaining to the consumers and the E-commerce websites in Saudi Arabia (Makki and Chang 2014, 2015a, 2015b, 2015c). Figure 1 shows the process of our data collection.

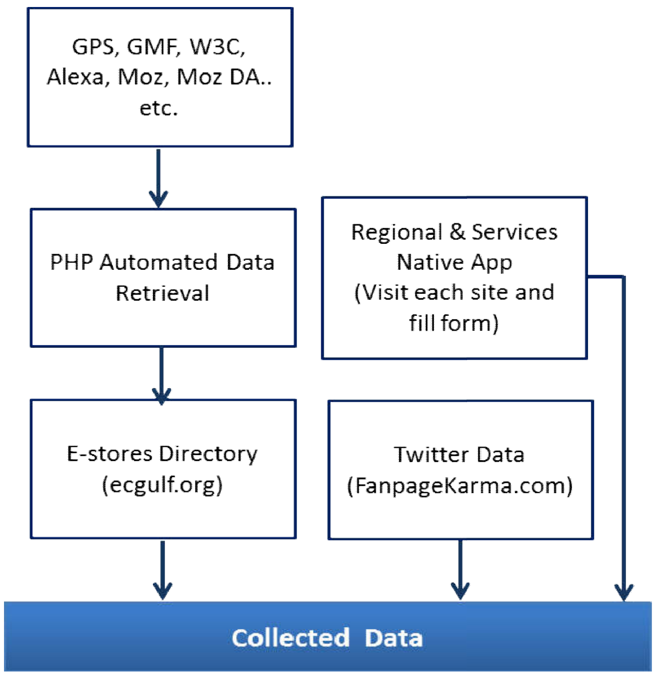

Fig.1. Data collection process

MATERIALS AND METHODS

In this section, we will first describe the data used in this study and the performance evaluation indexes that we propose for each sub-module: 1) Twitter; 2) Web Rank; 3) Web Functionality; and 4) Regional and Services. Second, we will briefly describe the data analysis methods used. The Principle Component Analysis (PCA) is used to de-correlate the identified factors in each sub-module, and K-mean clustering algorithm to classify the performance of E-stores into four classes, i.e., Excellent, Good, Average and Pooror four grades, i.e., 4, 3, 2, and 1 respectively.

Selected Region

We have chosen Saudi Arabia to be our case study for several reasons. First, it is the biggest country in the Gulf region in terms of population and land and it has always been regarded, due to historical and cultural reasons, as the role model to be followed by fellow Gulf countries. With an estimated population of 31.5 million according to the 2015 census; a Gross Domestic Product per capita at 21,312.82 million USD in 2015 (Anon, 2016a), Saudi Arabia is definitely a good choice for this study because of the potential it represents when it comes to E-commerce, for both E-retailers and consumers-wise. It is also interesting to find out the reasons behind the difficulties E-commerce is witnessing to gain popularity among the internet users and consumers. Another good reason that we use this country in our study is its very rapid growth in social media usage. In “The State of Social Media in Saudi Arabia 2013 | The Social Clinic” report, Saudi Arabia was ranked number one in the world in Twitter and YouTubeusage (Anon, 2014).

Twitter Data Collection

Tweets of each E-commerce website from January 1st toOctober 31st 2016 were gathered using FanpageKarma.com, a website that offers statistical tools for social media analytics. The total number of original tweets collected during this 300-day period is 144,510, which represents the sum of tweets from our 54 selected E-stores. In addition, the following data were collected for each E-store: number of the followers, total 300-day period tweets, number of tweets per day, conversations (engagement with followers), retweets and likes, average number of retweets per tweet, growth rate, and total lifetime tweets.

Website Data Collection

In our previous research, where we analyze the website performance affected by mobile compatibility and social media involvement of E-commerce sites in Saudi Arabia, we have developed a dynamic website (ecgulf.org) to collect data of E-stores (Makki and Chang, 2015c). Data collected there will be usedfor the other 3 sub-modules. As shown in Figure 1, the website data was collected from several remote services and some data was entered manually after visiting each E-store.For each E-store, the following information will be obtained:business category, location, website link, social media accounts links, delivery methods, accepted payment methods, languages of website, currencies accepted, mobile compatibility, etc. We have also developed PHP programs that can automatically retrieve statistical data ofeach site in our system on a daily basis. Our website consists of more than 140 major online stores in Saudi Arabia. The actual number of E-stores in our site can vary as we regularly add new E-stores or remove the ones out-of-business. At the time of this paper is written, the number of E-stores in our website is 143.For this paper, we used 54 E-stores that have higher number of followers in Twitter.

Website Ranking (WR) Data Collection

Three different website ranking data is extracted from ranking websitesusing our PHP programs for Alexa Rank, Moz Rank, and Moz Domain Authorization (DA). These ranks provide a general view on the websitesin either search engines based on a set of criteria or in their own directory using their own algorithms for a certain purpose.

Web Functionality (WF) Data Collection

Web functionality datawascollectedand saved in our website withthe following information for each E-store: Native Mobile App availability, Google Mobile Friendly (GMF) status and score, W3C HTML Errors and Google Page Speed (GPS) scores. Mobile App data was collected manually by visiting each website and looking for the availability of a native mobile application. For the rest of data, we developed an automated web program to access the API's for each E-store and save the informationon our website as shown in Figure 1.

Region and Services (RS) -RelatedData Collection

We have collected regional and services-related data that include payment methods, delivery methods, aftersales services, regional coverage, website languages, and accepted currencies. Data was collected manually by visiting each E-store and saved to our website. For each factor in this module, we applied a pre-defined weighting scheme which as described in our previous studies (Makki and Chang 2015b, 2015c, 2016).

E-Commerce Website Evaluation Indexes

As the site performance is indeed a compounding effect of many factors,we will describe the factors that we have identified and used in each sub-module, then analyze these factors to compute a performance index for each sub-module.

1.Twitter (TW) Performance Index

To measure the performance index of Twitter accounts,the following factors were proposed and computed using the collected data. The score of each factor presented here is normalized, so the value of each factor is ranged between 0 and 100. In general, a higher score indicates a better performance.

a.Tweets Activity (TA)

The TA score depends on the average daily tweets reflecting how often the account tweets. A Microsoft's Excel function PERCENTRANK.EXC (PER), which returns the rank of a value in a data set as a percentage, is used to calculate the percentile of one account compared to the average of all accounts. The TA score can be calculated according to the following formula using the PER function:

$$TA = PER\left(\frac{T}{Y}\right) \times 100$$

where T is the number of tweets within a period and Yis the number of days in the same period.

b.Account Popularity (AP)

The AP score depends on the number of tweets, the retweets percentages, the like percentages, the growth rate percentage, and the number of followers. The AP score reflects how popular the account is, and can be calculated by the following formula:

$$AP = \left(\frac{PER(T \times F) + PER\left(\frac{T}{R+L}\right) + PER(C) + PER(O) + PER(F)}{5}\right) \times 100$$

where T is the number of tweets within a period, F is the number of followers, R is the retweet percentage, L is the number of likes, C is the percentage of retweets per tweet and O is the growth rate percentage.

c.Account Reach (AR)

The AR score depends on the total number of tweets and the number of followers that reflects how many tweets has been sent to how many followers. We recognize that the number of retweets may contribute to the score of this factor, but due to the difficulty to track the followers of each follower who retweeted, we have decided not to include it here but use it in our previousfactor. The AR score can be calculated using the following formula:

$$AR = PER(T \times F) \times 100$$

where T is the number of tweets within a period and F is the number of followers.

d.Account Conversation (AC)

The AC score depends on the percentage of replies that reflects how many times out of tweets an account replied to a follower during the observed period. The AC score can be calculated according to the following formula:

$$AC = \left(\frac{PER(J) + PER(F)}{2}\right) \times 100$$

where Jis the reply tweet ratio and F is the number of followers.

2.Website Functionality (WF) Performance Index

The WF score depends on the number of W3C HTML Validation Errors (V), the Google Page Speed score (G), the native mobile app (A), and GMF score (M). If there is a native mobile app, the value of A equals to 100, otherwise 0. The WF score can be computed as the average value of those 4 factors according to the following formula:

$$WF = \left(\frac{PER(V) + PER(G) + M + A}{4}\right) \times 100$$

3.Website Rankings (WR) Performance Index

The WR score depends on the factors Alexa rank (X), the Moz rank (N), and the Moz Domain Authority rank (Z). The WR score can be computed as the average value of those 3 factorsaccording to the following formula:

$$WR = \left(\frac{PER(X) + PER(N) + PER(Z)}{3}\right) \times 100$$

4.Regional and Services (RS) Index

The RS score depends on the payment methods (E), the delivery methods (D), the regional coverage (Q), the aftersales services (S), the website languages (U) and the accepted currencies (B). Obviously, these factors won't be equally important, and relative weight should be applied to each factor. Therefore, we defined a weighting scheme for these factors. The RS index can then be computed using the following formula:

$$RS = (E \times 3.5) + (D \times 2) + (Q \times 1) + (S \times 2.5) + (U \times 0.5) + (B \times 0.5)$$

Data Analysis

As described earlier, the proposed model consists of 4 sub-modules, so the goal of data analysis is how to combine all the factors in four modules to better assess the performance of E-commerce sites. The factors that we have identified and used in each module may be highly correlated. Hence, a method to carefully select which factors to use or extract new uncorrelated factors is required. Principal Component Analysis (PCA) is perhaps one of the most widely used statistical techniques for feature/factor extraction (Jolliffe, 2002). PCA was first performed on each module individually to get a new set of factors. The new set of factors (i.e., principle components) will be mutually uncorrelated, and the dimension of the data set will be then reduced. The principle components are sorted, and the larger components are used where the sum of selected components is greater than 85% of the sum of all components (i.e., to cover at least 85% of the information). After the PCA, the K-mean clustering algorithm (Ding and He, 2004) was used to classify the performance of E-stores into four different categories: Excellent, Good, Average and Poor, or scored at 4, 3, 2, and 1 respectively.

RESULTS AND DISCUSSION

The original factors that we proposed in the social media module were Tweets Activity, Account Popularity, Account Reach and Account Conversation. Intuitively, these factors are correlated and the PCA reveals this fact. After PCA, only one new factor was taken, since it already covers 88% of the information. There are 4 original factors in the web functionality that include Native App, GMF Score, W3C HTML Errors, and GPS Score. After the PCA, the dimension is reduced to 3. For the web page ranking module that includes 3 factors Alexa, Moz, and Moz DA, it was reduced to 2 new factors after PCA. For the regional and service modules, the original 6 factors are Payment,Delivery, Regional Coverage, Aftersales Services, Website Languages, and the Accepted Currencies; 5 new factors that are taken into account after the PCA. This indicates the factors we have identified previously for social media are highly correlated, but the factors in regional and service-related modules are not. Finally, we applied K-mean clustering to classify the performance of each E-store for each module.Table 1 shows the results of evaluation using each individual module ordered by best performance. It is clear that an E-commerce site may have good web functionality and page ranking but can be poor in social media and regional and services-related factors; we can mention the E-store *dokkanafkar* as an example.

Table 1. Performance evaluation result for each selected E-stores using different performance indexes

E-Store	TW	WF	WR	RS	Avg.
markavip	4	4	4	4	4.00
extrastores	4	3	4	4	3.75
namshidotcom	4	4	4	3	3.75
axiom_ksa	4	3	4	4	3.75
souqksa	4	3	4	3	3.50
matjarhk	4	3	3	4	3.50
jarirbookstore	4	2	4	3	3.25
carrefoursaudi	4	3	4	2	3.25
hungerstation	4	4	3	2	3.25
emall_ksa	4	2	4	2	3.00
dokkanafkar	3	4	4	1	3.00
gheeras	4	3	3	2	3.00
izoneksa	3	2	3	4	3.00
varietalcafe	3	2	3	4	3.00
tdeals	4	2	1	4	2.75
alwaneshop	3	2	2	4	2.75
goldenscentcom	4	1	3	3	2.75
lenoshop	3	2	2	4	2.75
nano_eshop	4	2	3	2	2.75
mangojazan	3	4	1	3	2.75
icafestore	3	4	2	2	2.75
vanillaeshop	4	1	2	3	2.50
pinktouch_ksa	3	1	3	3	2.50
alkhabeershop	3	2	3	2	2.50
etorsofit	3	1	2	4	2.50
lantanaashop	3	3	2	2	2.50
pattzstore	3	2	2	2	2.25
smartmallws	3	1	3	2	2.25
flourishopcom	3	2	2	2	2.25
matargraphics	1	2	2	4	2.25
gltsa	2	1	2	4	2.25
natamakan	3	1	2	2	2.00
layfootak	1	2	1	4	2.00
markat4u	3	2	2	1	2.00
rainbowshopksa	3	2	2	1	2.00
wardatstore	3	1	3	1	2.00
bouquetexp	2	2	2	2	2.00
othopshop	2	2	2	2	2.00
medicaloutfit	2	2	2	2	2.00
alhabib_shop	3	1	1	2	1.75
sahabmarkit	2	2	1	2	1.75
8rn_2moon	2	2	1	2	1.75
modahcafe	2	1	2	2	1.75
notahstore	3	1	1	2	1.75
glamoo	2	1	2	2	1.75
seerastore	2	1	2	2	1.75
doreeshop	1	1	2	3	1.75
netmall_sa	2	1	1	3	1.75
savvyshopsa	1	1	1	4	1.75
kernaf_sa	2	1	1	2	1.50
esokria	2	1	1	2	1.50
nv_ksa	1	1	1	3	1.50
madakha	2	1	1	1	1.25
a3dsti	1	2	1	1	1.25

In general, the E-stores that have more followers and higher conversation rates rank higher in overall quality of evaluation. This is because they are engaging more with their high volume of followers, which is the key role of using social media in E-commerce (Makki and Chang, 2015c). This result supports our selection of social media as a criterion in our E-commerce website performance evaluation method. Similarly, RS and WF, as criteria selection in our method, assist in knowing how each E-store is performing in the manners related to the website itself and user experience interacting with it.

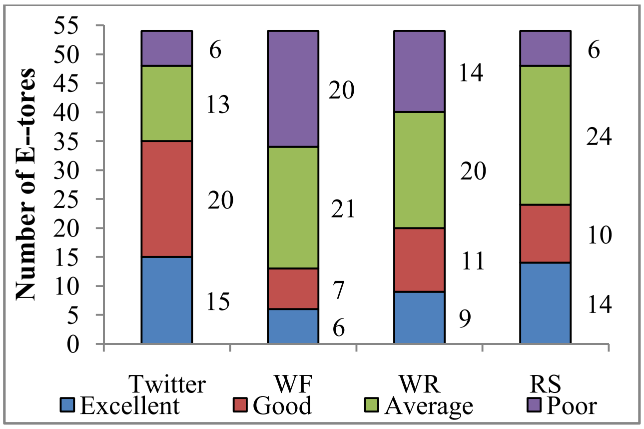

Fig.2. Summary of the performance classification result using K-mean and different performance indexes

Most of the WF factors we used, like GMF, GPS and W3C HTML error validations, are relatively new and not used before (together) in other website evaluation methods. In Figure 2, we summarize the performance classification result using the 4 different performance indexes. In Table 1, we have averaged these four indexes to provide an overall performance index. This simple weighted mean may not be an optimal approach to combine the indexes, and more sophisticated weighting schemes can be developed for different industries. For example, an online airline reservation system may have weight less for the social media, while an E-store selling electronics may weight more on its services.

Conclusion

The proposed E-commerce website evaluation method uses a quantitative approach to evaluate the performance of E-stores. By adding social media, cultural, regional, and services factors to our method, we are able to grade the performance of E-stores in the scale of 4-1 (excellent to poor). The use of relatively new factors in web functionality index,such as GPS, GMF, and W3C HTML error validations, added more value to the method. The proposed model can also be used to evaluate websites in other domains than E-commerce, like universities and banks, and with modified regional and services-related factors.The proposed performance evaluation model can be used by the E-commerce sites not only in Saudi Arabia, but in other countries or regions also, with a possible different set of factors that have to be properly identified in advance.

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