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Reputational intelligence: innovating brand management through social media data

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Abstract

Purpose – Companies are currently facing the challenge of understanding how their business is affected by the large volume of opinions continually generated by their stakeholders in social media regarding their intangible assets (experiences, emotions and attitudes). With this in mind, the purpose of this paper is to present an innovative management model, named E2AB, to measure and analyse reputational intangibles from digital ecosystems and their impacts on tangible assets.

Design/methodology/approach – The methodology applied was big data and business intelligence techniques. These methods were used in the computing process to obtain daily data from every asset guarantees that the model is validated with robust data. This model has been corroborated using data from the banking sector, specifically 402,383 net data inputs from the digital ecosystems.

Findings – This study illustrates the existence of a holistic influence of intangible assets over tangible assets. The findings demonstrate complex relationships between tangible and intangible assets, determined not only by the type of variable but also by its valence and intensity.

Practical implications – These findings may help chief communication officers and general managers a better understanding of how intangible assets extracted from online users' opinions are related to their organisation's tangible assets plus a chance to find out about their impact and how to manage them for a practical and agile decision making in real time.

Originality/value – It is a pioneering work in establishing a model, which demonstrates transversal and holistic relationships between relational intangible and tangible assets of firms from digital ecosystems, using business intelligence techniques.

Keywords Business intelligence, Social media data, Reputational intelligence, Reputational model, Intangible management, Customer perceptions

Paper type Research paper

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Introduction

All organisations are interested in controlling their reputation, but this is becoming increasingly difficult due to the big data expressed by society on social networks (Ji *et al.*, 2017). It has already been stated in the literature on the subject that reputation, even though it has much influence on the creation of value and economic benefits for organisations (De Quevedo *et al.*, 2005), is difficult to measure (Groenland, 2002). This is because it is constructed from the perceptions that interest groups have of companies, based on the experiences, emotions and attitudes that these provoke in their audiences (Fombrun and Gardberg, 2003). Such perceptions are often transmitted and published verbally in various online and offline media (Arbelo and Pérez, 2001).

Even when academic studies exist that define some measurements of reputation in online contexts (Azzeh, 2017; Casimiro and Coelho, 2017; Dutot and Castellano, 2015), they do not study how the perceptions of stakeholders extracted from the internet could influence the business of organisations. These perceptions, which are very difficult to measure, are part of the so-called intangible assets of companies, while their business is framed within their tangible assets. From a management perspective, intangible assets are defined as the intellectual capital that provides a company with a competitive advantage (Edvinsson and Malone, 1997). Of particular importance among such assets is relational capital, this being understood as the set of relationships that companies maintain with their stakeholders (Bontis *et al.*, 2000). This capital is extracted from the experiences, emotions and attitudes of individuals in the context of the relations they maintain with organisations (Diefenbach, 2006). As for tangible assets, these basically comprise the economic resources that are a part of the company's balance sheet (Garcia-Parra *et al.*, 2007), the stock market price or the price of shares being particularly important as both are relevant indicators of a company's value (Ansotegui, 2010).

One important question is how could we measure the impact of relational intangibles from digital ecosystems on the companies' tangible assets? Due to the immediacy and the large volumes of data handled in digital conversations, measurement tools should incorporate not only data in real time but also offer robust and representative data. Companies have often used online data simply to monitor their reputation in this context. However, the way of integrating all this information and using it as a business performance indicator remains an unresolved matter. This is precisely where the originality of this work lies: the construction and validation of a model that analyses the relationship of intangible assets with each other and with the stock market price. This is possible thanks to big data and business intelligence techniques, which allow us to extract a large volume of qualitative data from the internet and convert them into quantitative data that are integrated into the proposed model.

Conceptual background

Models to manage the relational intangibles assets in digital environments

There is extensive literature on how to construct models to manage perceptions (Elshwikh, 2017; Ingenhoff and Buhmann, 2016; Money *et al.*, 2010) and much research has been done on reputation management (Eckert, 2017). Reputation models have identified the causes of this in terms of the good or bad experiences of stakeholders with firms, and their consequences in terms of favourable or unfavourable attitudes towards the brand, but without considering the economic impact (Ponzi *et al.*, 2011; Money *et al.*, 2010). Other authors have been content to establish relationships between intangibles and tangibles, albeit without proposing a model (Brown *et al.*, 2009; Gabbioneta *et al.*, 2011; Stuebs and Sun, 2011; Wang *et al.*, 2010). None of the studies discuss how these tangible and intangible relational capital assets can influence each other, nor their holistic effect on the company as a whole and on different business areas (Eckert, 2017; Ponzi *et al.*, 2011).

According to Ingenhoff and Buhmann (2016), the methodology most commonly used by the authors to validate both the models and the relationships between assets is the structural equation model (PLS–SEM) or regression and correlations approaches (Vig *et al.*, 2017). Although these methodologies may establish multiple relationships between variables, they present fragmented and static views of reality. Therefore, a reputational intelligence model is needed and it should include all the intangible and tangible assets obtained from big data in real time through digital sources. Moreover, it should use business intelligence techniques, data mining (Tsai *et al.*, 2016) and online analytical processing (OLAP) (Wrembel and Koncilia, 2007) to analyse the transversal and holistic relationships and measure influences between these assets.

Variables that determine reputation

According to the literature, corporate reputation, as the main relational intangible capital, comprises experiences, emotions and attitudes from audiences towards the brand (Ponzi *et al.*, 2011). Experiences have been studied not only from the consumer perspective, but also considering the experience of the remaining stakeholders (Davis *et al.*, 2000). Fombrun and Gardberg (2003) and Ponzi *et al.* (2011) state that audiences mainly express an opinion on companies' work regarding six aspects: products and commercialisation; work environment (labour environment); ethical behaviour; social responsibility; business management (direction); and solvency and profitability.

Emotions, the second intangible, are feelings experienced by the different audiences as a subjective reaction to their experiences with their environment. Emotions are composed of three variables: valence, intensity and quality (Scherer, 2005). They reflect a great deal of information about the relationship with the individual, as well as internal thoughts concerning this relationship (Scherer, 2005). These reactions come with innate organic changes, influenced by experiences.

Attitude, the third intangible, is defined as predisposition towards a brand; this can be acquired through your own or someone else's experiences/emotions, and generates behaviour that affects company business (Ajzen and Fishbein, 2005). Attitude is determined by recommendations expressed by influencers, for example, financial analysts, and can generate favourable or unfavourable behaviour from the public towards the brand (Fombrun and Gardberg, 2003).

Finally, these three intangibles have an impact on business, a tangible variable. The relationship between intangible and tangible variables provides a value indicator showing the results of the relationship between company and its stakeholders. These value indicators are expressed in financial terms, market shares, revenue volume, etc. (Black *et al.*, 2000). With all the data generated using these variables, it is possible to establish relevant indicators to determine the influence of intangibles on business.

Reputational intelligence model proposed and hypothesis

Based on the variables being described, a new reputational model is proposed for digital ecosystems. This model considers the transversal and holistic relationships between intangible and tangible relational variables. On the one hand, this model includes the main relational capital extracted from the digital environment: experiences among the public with brands, subdivided into six dimensions (product, ethic, social, profitability, direction and labour); emotions that the environment and its different agents perceive about brands; and attitude towards the brand. On the other hand, it includes a tangible or business asset: the share price. This model, presented in Figure 1, is called E^2AB and is defined by the initials of each variable: Experience and Emotion (E^2), Attitudes (A) and Business (B).

E^2AB model aggregates new relationships and items to the cause-and-effect reputational model from MacMillan *et al.* (2005). Specifically, it is building up with a new variable

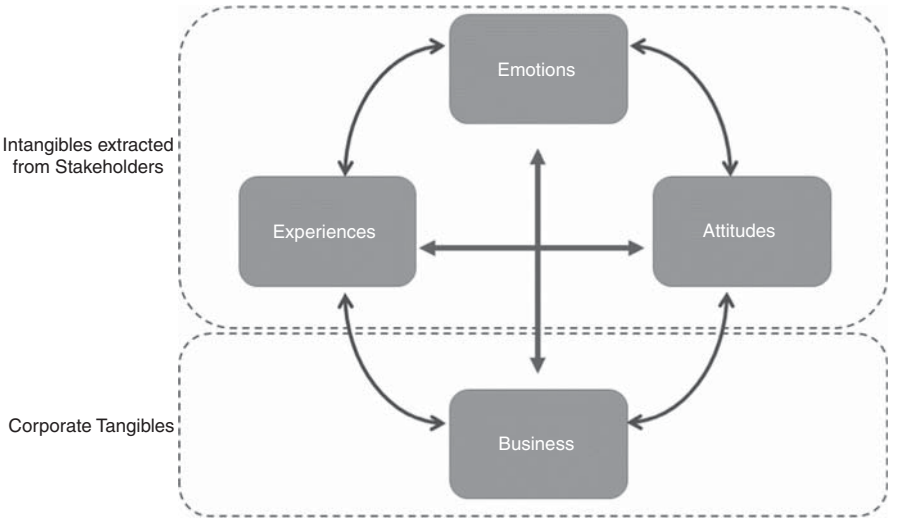

Figure 1. A reputational intelligence model for digital ecosystems

(the tangible asset called business) and with reciprocal relationships between relational intangible assets (experience, emotion and attitude) and tangible assets. The inclusion of this new variable has been supported in some studies that empirically demonstrated relationships between both types of assets, albeit in a fragmented way and in diverse contexts. These authors generally believe that a good brand reputation generates economic benefits (Brown *et al.*, 2009; Gabbioneta *et al.*, 2011; Stuebs and Sun, 2011; Wang *et al.*, 2010).

Regarding the types of relationship between assets, the model proposed outperforms previous intangible models, which have documented the impact of experiences, emotions and attitudes in just one direction, by measuring the impacts of each intangible variable with a brand's business separately (Thomson *et al.*, 2005; Ponzi *et al.*, 2011). However, it tends to be more complex in real life. In fact, the relationship between them can be transversal or holistic. A transversal impact describes the situation where a variable influences another intangible and/or tangible variable. Holistic influences are identified among all intangible and tangible variables as a whole. Additionally, in a digital context with dynamic conversations, where the stakeholders interact with each brand continuously, these variables fluctuate and influence each other very quickly (Dutot and Castellano, 2015; Karjaluoto *et al.*, 2016). Considering the above, to empirically validate the model proposed, the first two working hypotheses, dealing with the differential characteristics of the model, are proposed:

H1. Experiences, emotions and attitudes have a reciprocal transversal impact.

H2. Experiences, emotions and attitudes have a holistic influence towards the tangible asset.

With the aim of enriching the interpretation of the model, the type of relationship that intangible assets maintain with each other is examined in depth, establishing their polarity. It is particularly interesting to analyse this relationship because it has not yet been tested using big data or business intelligence techniques in the online environment, which constitutes the contexts of the model proposed. Second, the impact of experiences and emotions linked to a brand on financial analysts' recommendations remains an unresolved relationship in the literature. For example, it is worth wondering whether a high number of negative news and comments complaining about the bad experiences that clients are having with a banking service have any influence on financial analysts when it comes to

recommending the purchase or sale of the bank's shares. In this sense, la mainstream opinion states that society's unfavourable emotions and experience generate unfavourable social recommendations towards a brand (Jiang *et al.*, 2016; Lee and Wu, 2015; Verhagen *et al.*, 2013). However, some authors (Bollen *et al.*, 2011; Gabbioneta *et al.*, 2011) have considered that these unfavourable social emotions and experiences do not always generate unfavourable recommendations among certain influencers in the business, such as the financial analysts. A third hypothesis emerges here:

H3. Negative experiences and emotions do not always generate negative influencers' recommendations towards brands.

Methodology applied

The data sample

To test the initial working hypothesis, we used a study applied to the Spanish banking sector. Specifically, seven large banks were chosen. Given that this is a new model, a sector has been chosen where there is plenty of data available, continuously and in real time, to apply it to each of its variables. In this respect, the banking sector is considered ideal for four reasons: it is a sector where public opinion usually generates a large volume of data on the net; it generates many recommendations from financial analysts; it is a concentrated sector because the seven largest banks represent el 90 per cent revenue volume (Cambio16, 2018) for the whole banking sector; and it can get real time data on continuous real time fluctuations of share values on the stock market.

The sources from which opinions are extracted, from digital ecosystems in the Spanish market, are online mass media, forums, chats, Twitter, blogs, multimedia channels and stock exchange platforms. These data are in text format, in Spanish, and have been collected from 2,500 websites. We extracted 633,162 banking inputs read within 2016 and a total of 402,383 net data inputs. The net data inputs are the data, which is related to the brands being studied and their contexts. For some of the entities being studied, all 365 days of the year being analysed were taken into consideration. It was not possible to obtain data on some national or local holidays. This situation occurs in the case of the variable that measures attitudes. To overcome this issue, all the days in this situation were attributed the "not completed" value and were excluded from the analysis. Consequently, information about these days does not appear in the tables.

Procedure

E^2AB is a model that establishes transversal and holistic relationships between intangible assets (experiences, emotions and attitudes) and the tangible asset stock market price. This model has been designed to be used with big data and business intelligence techniques. It is possible with these techniques to extract a large volume of qualitative data poured into the online environment and convert them into quantitative data. Finally, these quantitative data are used to validate the working hypotheses, that is, to analyse the reciprocal transversal relations between intangible assets, the holistic relationship between intangible and tangible assets and, finally, the influence of experiences and negative emotions on the attitudes of financial analysts. When it comes to putting all of this into effect, the phases applied in the methodology are: data gathering, Extract, Transform and Load (ETL), data warehouse, data analysis and report management.

Data gathering

The data-gathering phase is responsible for selecting the sources, compiling the information and cleansing it to answer questions in the analysis phase. The sources of

information were located using web crawlers (Chau and Chen, 2003). Then, they were validated by a group of four experts using in-depth interviews, in order to guarantee the veracity and importance of the information. In addition, this validation was complemented with official studies and audience rankings (the Diffusion Justification Office Index, the General Media Study, etc.).

Subsequently, the information collection process began. This process was different for each information source. Extracting the share price data did not present any major problems, since it is public data that were obtained from the website of the Spanish Securities and Exchange Commission (www.cnmv.es) and the Madrid Stock Exchange. The intangible assets data were extracted from the relevant communications, which are those that refer to the experiences, emotions and attitudes associated with each of the banks analysed in the sample. For this purpose, all published information containing the name of each bank was extracted from online sources. For the tweets, the actual Twitter API was used; for the online news, new services APIs were used; and for the remaining sources, the extraction was carried out by means of Web Scraping processes (Web Crawling, Screen Scraping and Web Extraction), as has been done in other works (Chan *et al.*, 2016; Peláez *et al.*, 2019).

In order to clean up the data, the stored communications were analysed by the analysis service that uses the Python NLTK (Tobergte and Curtis, 2013) library and a set of logical rules that define the actor to which an analytic must be performed. For example, if we wanted to analyse communications related to product experiences with Bank A, such as an online commentary like "Bank A loans are the best", we would previously define the rules that allowed us to extract it, through the occurrence of keywords and their connectors. In this case, the occurrences taken into account were the likes of "Bank A", "Bank A loans", "Bank A" and "loans", etc.

Finally, a semantic analysis was performed. The purpose of performing a semantic analysis in this phase was that of accelerating the analyses of subsequent phases, obtaining metadata for subsequent processing. One example of metadata that is stored along with the information is feeling. This semantic analysis was performed using a classification algorithm based on an Artificial Neural Network, with supervised training. The training uses a corpus of communications, previously classified according to their valence (positive, neutral and negative). This corpus is endorsed by the Spanish Society for Processing Natural Language (SEPLN). It contains 70,000 phrases and it used the TensorFlow convolutional neural networks training library. Figure 2 shows an example of the communications and the valence of feeling.

Communications sample:

Communications

Date	Communication	Valuation	Label
12 February 2015	(BANCO) elegida mejor banca privada de España en 2015 por Euromoney. (BANK) chosen as best private banking in Spain in 2015 by Euromoney.	Positive (+)	
28 February 2015	(BANCO) Gracias a vosotros por la rápida respuesta. ¡Que os sea leve el domingo! (BANK) Thank you for the quick answer. Have a nice sunday!	Positive (+)	
03 May 2015	Los sinvergüenzas de (BANCO) cobran 2 € por extraer dinero en sus cajeros automáticos! Boicot! Those dishonest folks from (BANK) claim 2 € for getting money out from their ATMs! Boycott!	Negative (–)	
17 August 2015	(BANCO) son ustedes unos ladrones me acabáis de robar 28 euros de comisiones sin explicaciones. (BANK) you are a bunch of thieves who just stole me 28 euros in commissions with no further explanation.	Negative (–)	
28 October 2015	(BANCO) son unos sinvergüenzas. Te obligan a hacerla por el cajero que esta a tope y el ventanilla sin faena y encima te cobran. (BANK) are dishonest people. They force you to the ATM that is full and the counter without work and they even charge you	Negative (–)	
23 November 2015	Muchisimas gracias al departamento de communicación de (BANCO) por sus rapidas gestions y su preocupación por el cliente.:) Lost of thanks to the communications department of (BANK) for their quick management and their customer support.:)	Positive (+)	
31 December 2015	37 céntimos por hacer una transferencia en (BANCO). Propóstio de año nuevo: Cerrar la cuenta en (BANCO) 37 cents for transfering money in (BANK). New year's resolution: Closing my account in (BANK)	Negative (–)	
07 January 2016	(BANCO) lo suyo es una tomadura de pelo, es una verüenza, para cerrar una cuenta he ido 3 días a sus oficians y nada. Ya está bien. (BANK) what you are doing is pulling our leg out, a disgrace, I have been in 3 offices in order to close my account and nothing. That's enough.	Negative (–)	
20 March 2016	(BANCO) Gracias! Parece que ya teneis la solución a mi petición (BANK) Thanks! It looks like you have the solution to my question	Positive (+)	
30 April 2016	Excelente la resolución de incidencias de (BANCO). Gracias AM Excelent conflict resolution from (BANK). Thank you AM	Positive (+)	

Figure 2. Communications with their valence

Extract, Transform and Load

The ETL phase is fundamental in any business intelligence process, as its function is to give value to the data that have been extracted and cleansed in the previous phase. One of the problems we found when designing a business intelligence system is the diversity of information sources and, consequently, the variety of data formats and scales. This means that we have to perform a unification process on them (Santos and Ramos, 2009), to be able to construct a data warehouse. Only textual data have been used in this work, so their unification posed no special difficulties. However, the unification of the scales was more complex, since the transformation process is not linear (Santos and Ramos, 2009).

The data were transformed into two types of scales. The emotion and experience data are represented on a continuous scale and attitudes on a discrete scale. This difference in the type of scales is due to the fact that whilst experiences and emotions are expressed with different intensities, using a whole host of expressions, attitudes are based on recommendations that can be summarised in specific categories. Linguistic tags have been used for both scales, in order to make it easier for decision makers to interpret the information (Herrera and Herrera-Viedma, 2000).

Figure 3 shows the continuous scales of level scores that evaluate the experiences and the emotions with the semantic interpretation and the discrete scale with five scores is drawn up, measuring the attitudes that meet the granularity defined by Miller (1956), 7 ± 2. Likewise, we have opted for a symmetric label scheme for the semantic interpretation of continuous values (Herrera and Herrera-Viedma, 2000). These five values include a semantic explanation to interpret them (see Figure 4): hate, reject, indifference, acceptance and admiration. In the case of attitudes, they are expressed in a defined rating range by financial analysts or experts: sell (0), maintain sell (2.5); neutral (5); maintain buy (7.5) and buy shares on stock exchanges (10).

This labelling process generates the communication intensity metadata and it is associated with each of the communications. This metadata consists of a global linguistic label that combines the valuation of all the data, regardless of the information source. Consequently, Bayes Classifier trained with a corpus that contains the classes shown in Figure 3 was used to contextualise the final communications, before being stored in the data warehouse. Figure 4 shows the communications with their valence value and the linguistic intensity label.

Data warehouse

Construction of the data warehouse considers aspects such as independence of the operational databases (Inmon, 1996), along with multidimensional and temporal modelling

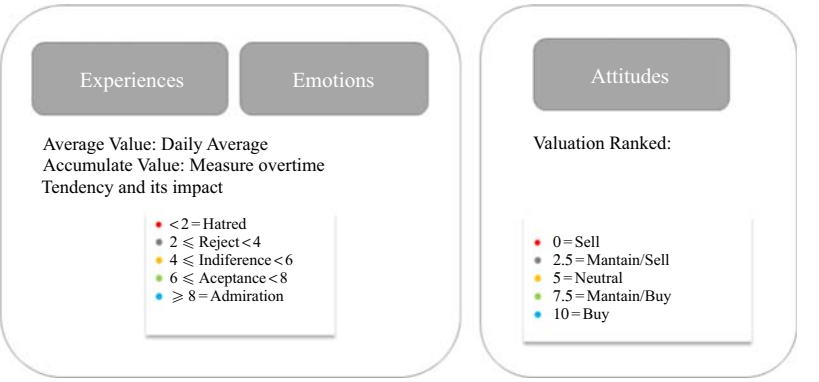

Figure 3.
Scales for measuring intangibles

Communications sample:

Communications

Date	Communication	Valuation	Label
12 February 2015	(BANCO) elegida mejor banca privada de España en 2015 por Euromoney. (BANK) chosen as best private banking in Spain in 2015 by Euromoney.	7	Acceptance
28 February 2015	(BANCO) Gracias a vosotros por la rápida respuesta. ¡Que os sea leve el domingo! (BANK) Thank you for the quick answer. Have a nice sunday!	7.5	Acceptance
03 May 2015	Los sinvergüenzas de (BANCO) cobran 2 € por extraer dinero en sus cajeros automáticos! Boicot! Those dishonest folks from (BANK) claim 2 € for getting money out from their ATMs! Boycott!	1	Hate
17 August 2015	(BANCO) son ustedes unos ladrones me acabáis de robar 28 euros de comisiones sin explicaciones. (BANK) you are a bunch of thieves who just stole me 28 euros in commissions with no further explanation.	2	Hate
28 October 2015	(BANCO) son unos sinvergüenzas. Te obligan a hacerla por el cajero que esta a tope y el ventanilla sin faena y encima te cobran. (BANK) are dishonest people. They force you to the ATM that is full and the counter without work and they even charge you	2.5	Reject
23 November 2015	Muchisimas gracias al departamento de communicación de (BANCO) por sus rapidas gestions y su preocupación por el cliente.:) Lost of thanks to the communications department of (BANK) for their quick management and their customer support.:)	9	Admiration
31 December 2015	37 céntimos por hacer una transferencia en (BANCO). Propóstio de año nuevo: Cerrar la cuenta en (BANCO) 37 cents for transfering money in (BANK). New year's resolution: Closing my account in (BANK)	3	Reject
07 January 2016	(BANCO) lo suyo es una tomadura de pelo, es una verüenza, para cerrar una cuenta he ido 3 días a sus oficians y nada. Ya está bien. (BANK) what you are doing is pulling our leg out, a disgrace, I have been in 3 offices in order to close my account and nothing. That's enough.	2	Hate
20 March 2016	(BANCO) Gracias! Parece que ya teneis la solución a mi petición (BANK) Thanks! It looks like you have the solution to my question	8	Admiration
30 April 2016	Excelente la resolución de incidencias de (BANCO). Gracias AM Excelent conflict resolution from (BANK). Thank you AM	9	Admiration

Figure 4. Communications with the communication valuation scale

(Santos and Ramos, 2009). It is built on a NoSQL database (it specifically uses the MongoDB database) making data integration easier, simpler and more dynamic, as each document in a collection can have different fields.

Data analysis

The aim of this phase is to analyse and understand the relationships between tangible and intangible assets with the data that were obtained and contextualised in the previous phase, through correlations between variables, business intelligence tools, OLAP and data mining techniques. The OLAP used in this study helps create cubes to analyse information about different perspectives (dimensions). The cubes allow us to analyse the facts available in the table of facts in the different dimensions considered in the modelling. The data mining techniques contribute to finding relationships, patterns or models that are implicit in the data stored in large databases (Santos and Ramos, 2009). This analysis uses a type of data mining technique: key influencers.

Report management

The results visualisation is the phase where analyst output should be defined as a way to contribute to control and the business and intangible assets, by developing a dashboard or preparing the structure of the report management. The dashboards and the report management are drawn up in the most appropriate form of graphs, text and tables to visualise the final results.

Empirical corroboration of the model and findings

To check whether the first research hypothesis is met, first the correlation between the variables of the model was studied. Table I presents the correlation between two pairs of variables and it is possible to identify the high level of correlation between all the experience dimensions, emotion, attitude and the share prices. The ethical experience has a lower value, which means that it has a lower impact.

To look in more detail at how these variables influence each other, the reciprocal transversal influence of experiences on emotions and emotions on attitudes will be studied. The results are based on the Naïve Bayes algorithm, which can be used for prediction or classification. The Bayes theorem can be used to calculate the probability that a hypothesis is met, taking into consideration given knowledge, expressed by the following equation:

$$P(h|d) = (P(d|h) \times P(h))/P(d), \quad (1)$$

Table I. Correlations between experiences, emotions and attitude cases

	EP	EL	EE	ES	ED	ER	EM	AT	QT
EP	1								
EL	0.798**	1							
EE	0.170**	−0.186**	1						
ES	0.800**	0.692**	0.025	1					
ED	0.910**	0.867**	0.196**	0.810**	1				
ER	0.896**	0.922**	0.033	0.817**	0.964**	1			
EM	0.818**	0.770**	0.290**	0.776**	0.963**	0.897**	1		
AT	−0.095**	−0.253**	0.098**	0.280**	−0.064**	−0.069**	0.001	1	
QT	0.233**	0.025**	0.543**	0.193**	0.344**	0.232**	0.442**	0.530**	1

Notes: AT, attitude; EL, laboural experience; ER, profitability experience; ES, social experience; EE, ethic experience; EP, product experience; ED, direction experience; EM, emotion; QT, quotation. $^{**}p < 0.01$

where $P(h|d)$ is the probability of hypothesis h given the data d. This is called the posterior probability; $P(d|h)$ is the probability of data d given that the hypothesis h was true; $P(h)$ is the probability of hypothesis h being true (regardless of the data). This is called the prior probability of h; $P(d)$ is the probability of the data (regardless of the hypothesis).

After the calculation, it is possible to select or identify the hypothesis with the highest value, more than 75 per cent probability, as presented in Table II. To do this, analysis was used on the key influencers from the whole sector, meaning the seven banks. In Table II, it can be observed, first, how the experience variables influence emotion, at least, with a 75 per cent impact, with the exception of ethical and work experience. However, correlation is significant for both types of experience with emotion, considering all intensities overall. Second, when the relationship between emotion and the hate value is analysed, it is found to favour a neutral attitude with an impact of 100 per cent.

Table III shows that this transversal relationship is reciprocal between the three intangible variables, experience, emotion and attitude. Regarding the relationship between attitude and emotion, the data show that this attitude, when it takes the hold/buy and neutral values, has a probability of influencing emotion with acceptance and hate values by 100 per cent. In addition, it is demonstrated that there is a reciprocal relationship between emotion and different experience categories. *H1*, which establishes the reciprocal transversal relationship between experiences, emotions and attitudes, is therefore accepted.

The procedure to test *H2* was similar to that used to test *H1*. Table IV thereby shows the relationships of experience, emotions and attitude variables with the tangible assets, respectively. It is seen that they all demonstrate an influence over 75 per cent in at least

Table II. Transversal influence from experiences on emotion and emotion on attitude

Variable	With the value	Impact (%)	Favours a variable with the value
Experiences			
ES	Indifference	100	EM Indifference
ER	Acceptance	100	EM Acceptance
ER	Admiration	100	EM Admiration
ED	Reject	100	EM Reject
EP	Hate	100	EM Hate
ED	Hate	89	EM Hate
ER	Hate	82	EM Hate
Emotion			
EM	Hate	100	AT Neutral

Notes: ES, social experience; ER, profitability experience; ED, direction experience; EP, product experience; EM, emotion

Variable	With the value	Probability (%)	Favours a variable with the value
Attitudes			
AT	To hold/buy	100	EM Acceptance
AT	Neutral	100	EM Hate
Emotions			
EM	Hate	84	EL Hate
EM	Acceptance	100	EL Acceptance
EM	Admiration	100	EL Admiration
EM	Indifference	100	ER Indifference
EM	Acceptance	100	ER Acceptance
EM	Admiration	100	ER Admiration
EM	Hate	100	ER Hate
EM	Hate	100	ES Reject
EM	Indifference	100	ES Indifference
EM	Acceptance	100	ES Admiration
EM	Reject	100	ES Hate
EM	Acceptance	100	EE Acceptance
EM	Hate	100	EE Reject
EM	Hate	100	EE Hate
EM	Reject	91	EP Reject
EM	Admiration	87	EP Acceptance
EM	Acceptance	100	EP Admiration
EM	Hate	100	EP Hate
EM	Reject	100	ED Reject
EM	Indifference	90	ED Indifference
EM	Indifference	96	ED Acceptance
EM	Acceptance	100	ED Admiration
EM	Hate	100	ED Hate

Notes: AT, attitude; EL, laboural experience; ER, profitability experience; ES, social experience; EE, ethic experience; EP, product experience; ED, direction experience; EM, emotion

Table III. Transversal influence from attitude on emotion and from emotion on experiences

Variable	With the value	Probability (%)	Favours stock market value (€)
EM	Hate	100	< 2.24
EP	Hate	100	< 2.24
ED	Hate	87	< 2.24
AT	To keep/sell	100	2.24–4.16
EM	Indifference	82	4.16–5.93
EE	Admiration	100	5.93–7.43
AT	Neutral	91	5.93–7.43
AT	To hold/buy	100	> 7.43

Notes: AT, attitude; EL, work experience; ER, profitability experience; ES, social experience; EE, ethic experience; EP, product experience; ED, direction experience; EM, emotion

Table IV. Holistic influence from intangibles on tangibles

one of the categories with the exception of work experience, social and profitability. However, the correlation of the three types of experiences with share price is significant, without distinguishing between its different categories (see Table I). It is thereby shown that, effectively, it is possible to talk about the existence of a holistic influence among the intangible assets over the tangible assets. This is the proposition in *H2*, which is therefore accepted.

To answer the third hypothesis, Table V extracts the outcomes of applying the OLAP technique. The table shows the number of days per year in which the predominant comments presented a certain combination. Since the combinations were many and varied, only the 25 that were repeated the most days are shown. Thus, for example, the first row of data in Table V indicates that in the case of Bank 5, there were 97 days in which the predominant situation for product, management and profitability experience and for emotion was a situation of hatred; that of work, ethical and social experiences was one of rejection; and the recommendations of the analysts were neutral.

It can be seen that not all the negative experiences and emotions have generated negative recommendations. Obviously, cases arise where, faced with comments featuring negative experiences and emotions, recommendations from the analysts have taken the same direction, with a value to keep/sell. This is the case of Row 12, in which for Bank 3 there were 44 days in which the recommendation was one of keep/sell and the general feeling in all experiences was negative, except in the ethical and management dimension. The case of Bank 5 is particularly striking as there were many days when the attitudes were neutral even when the experiences and emotions were hate and/or rejection (Rows 1, 3, 6 and 18). Along the same line, in the case of Bank 1, all the experiences and emotions, regardless of the valence, generate recommendations with a favourable hold/buy value (Rows 11, 21, 22 and 25). *H3* is therefore accepted since it has been shown that negative experiences and emotions do not always generate negative influencers' recommendations towards brands.

Table VI summarises the results obtained for each hypothesis, indicating the techniques used, the tables in which these results are reflected and the conclusions regarding the hypotheses put forward.

Discussion

Compared to models that only relate static information on management of relational capital intangibles (Ponzi *et al.*, 2011; O'Gorman and Pirner, 2006), the findings obtained from applying the proposed E^2AB model demonstrate that big data in real time can offer robust and representative data that can be considered as relevant management indicators, affecting not only their intangible variables but also corporate business variables (Casado and Peláez, 2014).

More specifically, this work demonstrates that intangible variables not only have a transversal impact on each other in a single direction, but that it is also reciprocal. Until now, the classic intangible management models had ignored this reciprocity. On the one hand, Park and Lee (2007) established the existence of a significant relationship between emotion and experiences in their social and labour dimension, albeit without establishing a cause-and-effect relationship between them. On the other hand, other authors who did establish a causal relationship did so by pointing to experiences as causes of emotions (MacMillan *et al.*, 2005), and emotions as causes of attitudes (MacMillan *et al.*, 2005; Ponzi *et al.*, 2011; Thomson *et al.*, 2005), but without demonstrating the effect in the other sense. Our research therefore takes the findings made so far a step further by demonstrating the reciprocity between these intangible assets.

In addition, the existence of a holistic influence of intangible assets over share price has been demonstrated. There are studies that prove the individual relationship of experience (Stuebs and Sun, 2011) emotion (Bollen *et al.*, 2011) and attitude (Brown *et al.*, 2009) with the share price. However, these are fragmented studies. The present study thus demonstrates that reality is indeed much more complex, especially in online environments, where stakeholders converse and influence each other very quickly, as other authors have found (Dutot and Castellano, 2015; Karjaluoto *et al.*, 2016). Similarly, the findings of this study are in line with the trend among scholars who explained that firms with better reputations are at less risk, as they experience fewer fluctuations in sales and net income, are less likely to fail

Table V. Relationships between experiences, emotion and attitude

Row	Bank	Experiences EP	EL	EE	ES	ED	ER	EM	Attitude Keep/Sell	Neutral	Hold/Buy
1	5	−−−	−	−	−	−−−	−−−	−−−		97	
2	6	+	0	+++	+	+++	+	+		87	
3	5	−−−	−−−	0	−	−−−	−−−	−−−		79	
4	7	0	0	0	+++	+	0	+			74
5	4	+	0	0	0	+	0	0		70	
6	5	−−−	−−−	+	−	−−−	−−−	−−−		69	
7	4	0	−	+	−	0	−	−		65	
8	7	−	−	+++	0	0	−	0		34	29
9	2	+++	+	+	+++	+++	+++	+		52	
10	6	0	−−−	+++	0	0	−	0		51	
11	1	0	0	+++	+	+	+	+			48
12	3	−	−	+	−−−	0	−	0	44		
13	6	+	+	+++	+	+++	+	+		42	
14	2	+++	+	+	+	+++	+	+		41	
15	2	+++	+	+	+++	+++	+++	+		38	
16	3	0	+	+	0	+++	+	+	37		
17	4	+	0	+	0	+	0	0		37	
18	5	−−−	−	−−−	−	−−−	−−−	−−−		35	
19	2	0	−	+++	0	0	−	0	32		
20	3	0	+	+	0	+	+	+	32		
21	1	−	−	+++	0	0	−	0			31
22	1	+	+	+	+	+++	+	+			30
23	4	−	−−−	+++	−	−	−	−			30
24	3	+	+++	+	+	+++	+++	+++	29		
25	1	−	−	+++	−	0	−	0			28

Notes: EP, product experience; EL, laboural experience; EE, ethic experience; ES, social experience; ED, direction experience; ER, profitability experience; EM, emotion. +++: admiration; +: acceptation; 0: indifference; −: reject; −−−: hate

Table VI.
Summary of results

Hypothesis	Techniques	Results	Tables	Conclusion
H1	Key influencers, correlations	Relation experiences/emotion	Tables I and II	Accepted
	Key influencers, correlations	Relation emotion/attitude	Tables I and II	
	Key influencers	Relation attitude/emotion	Table III	
	Key influencers, correlations	Relation emotion/experience	Tables I and III	
H2	Key influencers	Relation experiences/share price	Table IV	Accepted
	Key influencers	Relation emotion/share price	Table IV	
	Key influencers	Relation attitude/share price	Table IV	
H3	OLAP	Negatives experiences and emotions/neutral recommendations	Table V	Accepted

and have lower stock price volatility (Brown *et al.*, 2009; Gabbioneta *et al.*, 2011; Stuebs and Sun, 2011; Wang *et al.*, 2010).

This research also shows that not only is there a relationship between the different intangible variables of the proposed model, but also that their polarity is also important. Specifically, and despite the fact that some authors state that unfavourable emotions and experiences usually generate recommendations that are also unfavourable towards a brand (Jiang *et al.*, 2016; Lee and Wu, 2015; Verhagen *et al.*, 2013), this study does not confirm it. In fact, the findings show that negative experiences and emotions can generate neutral and even favourable recommendations from analysts. These results are more aligned with those studies on the financial sector that maintain that certain analysts do not necessarily match up their recommendations with what users express regarding their experiences and emotions (Bollen *et al.*, 2011; Gabbioneta *et al.*, 2011; Wang *et al.*, 2010). One possible explanation for this fact is that, although analysts use online publications and commentaries to take the pulse of the social context in relation to the company's activity, they also consider other, more specialised sources of information when making their recommendations (Klimczak and Dynel, 2018).

Conclusions

This research has illustrated transversal and holistic relationships between relational intangibles and tangibles assets and validated a conceptual research model outlining its determinants, denominado E^2AB. This should result in insights that could make an important contribution to extant knowledge and will help to validate and improve the findings in the related literature. Specifically, the existing theoretical framework has been enriched by taking into account the use of data extracted from online information sources and considering that the relations between intangibles are not only unidirectional, as has become customary (MacMillan *et al.*, 2005; Ponzi *et al.*, 2011; Thomson *et al.*, 2005). At the same time, the reputational model proposed also contemplates the relationship between intangible and tangible assets, a relationship that has been little explored so far, with some exceptions (Gabbioneta *et al.*, 2011; Wang *et al.*, 2010), albeit never integrated into a general model.

The main practical implication of this study is that, by demonstrating the interrelationship between all intangible assets, companies run the risk that negative comments about one very specific aspect of theirs will lead to negative comments about other different aspects. If one adds to this the snowball effect of the online environment (Bekkers *et al.*, 2011), managers must hurry and remedy those situations being debated and published on the internet. Managers' vigilance is all the more important given the holistic impact these intangibles have on the share price. Despite all this, managers, who are eager to see the value of their company's shares increase, should interpret the negative comments made on the net with caution, as the recommendations of financial analysts are not always in line with them.

However, these findings call for great caution when invoking our application in data from social media and over one sector. On the one hand, even when comments on where the big data is extracted are validated through findings shown with business intelligence techniques (Uncles, 2001), there is always a minimum semantic classification error for these comments. This limitation to our research is standard regarding the studies on opinions extracted from social media (Kirilenko *et al.*, 2018). On the other hand, our sample and the sector are appropriate to begin validation of the proposed E^2AB model, given the abundant amount of data available in real time and continuously in all its variables. However, validation is not possible in all sectors in our research.

Faced with these limitations, our model should be applied by scholars from different disciplines pursuing further research in this area to: optimise the semantic classifiers' success rate for the data extracted from social media; study the behaviour of intangible and tangible assets for the remaining sectors by applying the E^2AB model; extract reputational behaviour patterns in one sector and across sectors; and make progress towards predictive models on the influence of reputational capital intangibles over current and new business variables.

In summary, the findings of this study promise benefits in terms of developing dashboards for companies to integrate these assets, their relationships and influences on their business for practical and agile decision making in real time. The results of combining the model proposed here with big data processes and business intelligence will help maintain market sustainability for organisations and will encourage progress towards predicting social behaviour to develop an innovated and anticipated management model for companies in real time using robust data.

References

Ajzen, I. and Fishbein, M. (2005), "The influence of attitudes on behaviour", in Albarracín, D., Johnson, B.I. and Zanna, M.P. (Eds), *The Handbook of Attitudes*, Erlbaum, Mahwah, NJ, pp. 173-221.

Arbelo, A. and Pérez, P. (2001), "La reputación empresarial como recurso estratégico: Un enfoque de recursos y capacidades", paper presented at XI Congreso Nacional de ACEDE, Zaragoza, 16–18 September, available at: www.pymesonline.com/uploads/tx_icticontent/reputacion.pdf (accessed 24 June 2019).

Ansotegui, C. (2010), "¿En qué consiste crear valor?", *Harvard Deusto Finanzas y Contabilidad*, Vol. 98 No. 1, pp. 26-36.

Azzeh, M. (2017), "Online reputation model using moving window", *International Journal of Advanced Computer Science and Applications*, Vol. 8 No. 4, pp. 508-512.

Bekkers, V., Beunders, H., Edwards, A. and Moody, R. (2011), "New media, micromobilization, and political agenda setting: crossover effects in political mobilization and media usage", *The Information Society*, Vol. 27 No. 4, pp. 209-219.

Black, E.L., Carnes, T.A. and Richardson, V.J. (2000), "The market valuation of corporate reputation", *Corporate Reputation Review*, Vol. 3 No. 1, pp. 31-42.

Bollen, J., Mao, H. and Zeng, X. (2011), "Twitter mood predicts the stock market", *Journal of Computational Science*, Vol. 2 No. 1, pp. 1-8.

Bontis, N., Keow, W.C.C. and Richardson, S. (2000), "Intellectual capital and business performance in Malaysian industries", *Journal of Intellectual Capital*, Vol. 1 No. 1, pp. 85-100.

Brown, R., Chan, H. W. and Ho, Y. K. (2009), "Analysts' recommendations: from which signal does the market take its lead?", *Review of Quantitative Finance and Accounting*, Vol. 33 No. 2, pp. 91-111.

Cambio16 (2018), "Resultados de la banca española en 2017: Una temporada de flechas verdes", available at: www.cambio16.com/cambio-financiero/resultados-de-la-banca-espanola-en-2017/ (accessed 8 May 2017).

Casado, A.M. and Peláez, J.I. (2014), "Intangible management monitors and tools: reviews", *Expert Systems with Applications*, Vol. 41 No. 4, pp. 1509-1529.

Casimiro, M. G. and Coelho, A. (2017), "A causal relationship mode linking corporate reputation and customer-based brand equity: a customer perspective", *Academia-Revista Latinoamericana de Administración*, Vol. 30 No. 2, pp. 249-268.

Chan, H. K., Wang, X., Lacka, E. and Zhang, M. (2016), "A mixed-method approach to extracting the value of social media data", *Production and Operations Management*, Vol. 25 No. 3, pp. 568-583.

Chau, M. and Chen, H. (2003), "Comparison of three vertical search spiders", *IEEE Computer*, Vol. 36 No. 5, pp. 56-62.

Davis, R., Buchanan-Oliver, M. and Brodie, R.J. (2000), "Retail service branding in electronic-commerce environments", *Journal of Service Research*, Vol. 3 No. 2, pp. 178-186.

De Quevedo, E., De la Fuente, J.M. and Delgado, J.B. (2005), "Reputación corporativa y creación de valor. Marco teórico de una relación circular", *Investigaciones Europeas de Dirección y Economía de la Empresa*, Vol. 11 No. 2, pp. 81-97.

Diefenbach, T. (2006), "Intangible resources: a categorial system of knowledge and other intangible assets", *Journal of Intellectual Capital*, Vol. 7 No. 3, pp. 406-420.

Dutot, V. and Castellano, S. (2015), "Designing a measurement scale for e-reputation", *Corporate Reputation Review*, Vol. 18 No. 4, pp. 294-313.

Eckert, C. (2017), "Corporate reputation and reputation risk: definition and measurement from a (risk) management perspective", *Journal of Risk Finance*, Vol. 18 No. 2, pp. 145-158.

Edvinsson, L. and Malone, M.S. (1997), *Intellectual Capital: Realizing Your Company's True Value by Finding Its Hidden Brainpower*, Oxford University Press, New York, NY.

Elshwikh, Y. (2017), "A trust and reputation model for quality assessment of online content", *International Journal of Advanced Computer Science and Applications*, Vol. 8 No. 3, pp. 58-61.

Fombrun, C.J. and Gardberg, N. (2003), "Who's tops in corporate reputation?", *Corporate Reputation Review*, Vol. 3 No. 1, pp. 13-17.

Gabbioneta, C., Mazzola, P. and Ravasi, D. (2011), "Corporate reputation and stock market behavior", in Helm, S., Liehr-Gobbers, K. and Storck, C. (Eds), *Reputation Management*, Springer, Berlin, pp. 215-229.

Garcia-Parra, M., Simo, P., Mundet, J. and Guzman, J. (2007), "Intangibles: Activos y pasivos", *Intangible Capital*, Vol. 1 No. 1, pp. 70-86.

Groenland, E.A. (2002), "Qualitative research to validate RQ-Dimensions", *Corporate Reputation Review*, Vol. 4 No. 4, pp. 308-315.

Herrera, F. and Herrera-Viedma, E. (2000), "Linguistic decision analysis: steps for solving decision problems under linguistic information", *Fuzzy Sets and Systems*, Vol. 115 No. 1, pp. 67-82.

Inmon, W.H. (1996), "The data warehouse and data mining", *Communications of the ACM*, Vol. 39 No. 11, pp. 49-50.

Ingenhoff, D. and Buhmann, A. (2016), "Advancing PR measurement and evaluation: demonstrating the properties and assessment of variance-based structural equation models using an example study on corporate reputation", *Public Relations Review*, Vol. 42 No. 3, pp. 418-431.

Ji, Y.G., Li, C., North, M. and Liu, J.M. (2017), "Staking reputation on stakeholders: how does stakeholders' Facebook engagement help or ruin a company's reputation?", *Public Relations Review*, Vol. 43 No. 1, pp. 201-210.

Jiang, H., Liang, J., Wang, H. and Sun, P. (2016), "The interplay of emotions, elaboration, and ambivalence on attitude–behavior consistency", *Journal of Consumer Behaviour*, Vol. 15 No. 2, pp. 126-135.

Karjaluoto, H., Mäkinen, H. and Järvinen, J. (2016), "A firm's activity in social media and its relationship with corporate reputation and firm performance", in D'Ascenzo, F., Magni, M., Lazazzara, A. and Za, S. (Ed.), *Blurring the Boundaries Through Digital Innovation*, Springer, Cham, pp. 161-172.

Kirilenko, A. P., Stepchenkova, S., Kim, H. and Li, X. R. (2018), "Automated sentiment analysis in tourism: comparison of approaches", *Journal of Travel Research*, Vol. 57 No. 8, pp. 1012-1025.

Klimczak, K.M. and Dynel, M. (2018), "Evaluation markers and mitigators in analyst reports in light of market response to stock recommendations", *International Journal of Business Communication*, Vol. 55 No. 3, pp. 310-337.

Lee, Y. C. and Wu, W. L. (2015), "Effects of medical disputes on internet communications of negative emotions and negative online word-of-mouth", *Psychological Reports*, Vol. 117 No. 1, pp. 251-270.

MacMillan, K., Money, K., Downing, S. and Hillenbrand, C. (2005), "Reputation in relationship: measuring experiences, emotions and behaviours", *Corporate Reputation Review*, Vol. 8 No. 3, pp. 214-232.

Miller, G.A. (1956), "The magical number seven, plus or minus two: some limits on our capacity for processing information", *Psychological Review*, Vol. 63 No. 2, pp. 81-97.

Money, K., Rose, S. and Hillenbrand, C. (2010), "The impact of the corporate identity mix on corporate reputation", *Journal of Brand Management*, Vol. 18 No. 3, pp. 197-211.

O'Gorman, S. and Pirner, P. (2006), "Measuring and monitoring stakeholder relationships: using TRI* M as an innovative tool for corporate communication", in Margit, H. and Pallas, M. (Eds), *Customising Stakeholder Management Strategies*, Springer, Heidelberg and Berlin, pp. 89-100.

Park, N. and Lee, K.M. (2007), "Effects of online news forum on corporate reputation", *Public Relations Review*, Vol. 33 No. 3, pp. 346-348.

Peláez, J.I., Martínez, E.A. and Vargas, L.G. (2019), "Products and services valuation through unsolicited information from social media", *Soft Computing*, pp. 1-14, doi: 10.1007/s00500-019-04005-3.

Ponzi, L.J., Fombrun, C.J. and Gardberg, N.A. (2011), "RepTrak^{TM} pulse: conceptualizing and validating a short-form measure of corporate reputation", *Corporate Reputation Review*, Vol. 14 No. 1, pp. 15-35.

Santos, M. and Ramos, I. (2009), *Business Intelligence*, FCA Editora, Lisbon.

Scherer, K.R. (2005), "What are emotions? And how can they be measured?", *Social Science Information*, Vol. 44 No. 4, pp. 695-729.

Stuebs, M. T. and Sun, L. (2011), "Corporate social responsibility and firm reputation", *Journal of Accounting, Ethic & Public Policy*, Vol. 12 No. 1, pp. 33-56.

Thomson, M., MacInnis, D.J. and Park, C.W. (2005), "The ties that bind: measuring the strength of consumers' emotional attachments to brands", *Journal of Consumer Psychology*, Vol. 15 No. 1, pp. 77-91.

Tobergte, D.R. and Curtis, S. (2013), "Improving neural networks with Dropout", *Journal of Chemical Information and Modeling*, Vol. 53 No. 9, pp. 1689-1699.

Tsai, C., Lu, C.H., Hung, Y.C. and Yen, D.C. (2016), "Intangible assets evaluation: the machine learning perspective", *Neurocomputing*, Vol. 175, pp. 110-120.

Uncles, M. (2001), "Editorial: interactive electronic marketing and brand management", *Journal of Brand Management*, Vol. 8 No. 4, pp. 245-254.

Verhagen, T., Nauta, A. and Feldberg, F. (2013), "Negative online word-of-mouth: behavioral indicator or emotional release?", *Computers in Human Behavior*, Vol. 29 No. 4, pp. 1430-1440.

Vig, S., Dumicic, K. and Klopotan, I. (2017), "The impact on reputation on corporate financial performance: median regression approach", *Business Systems Research Journal*, Vol. 8 No. 2, pp. 40-58.

Wang, K., Smith, M. and Taken, S.K. (2010), "Does brand management of corporate reputation translate into higher market value?", *Journal of Strategic Marketing*, Vol. 18 No. 3, pp. 201-221.

Wrembel, R. and Koncilia, C. (2007), *Data Warehouses and OLAP: Concepts, Architectures, and Solutions*, IGI Global.

Further reading

Halper, F. (2016), "Best Practices Report | Data Science and Big Data: enterprise paths to success", available at: https://tdwi.org/research/2016/12/best-practices-report-data-science-and-big-data.aspx (accessed 15 November 2007).

Helm, S. (2007), "The role of corporate reputation in determining investor satisfaction and loyalty", *Corporate Reputation Review*, Vol. 10 No. 1, pp. 22-37.

Mármol, F.G. and Pérez, G.M. (2016), "Towards pre-standardization of trust and reputation models for distributed and heterogeneous systems", *Computer Standards & Interfaces*, Vol. 32 No. 4, pp. 185-196.

Schermann, M., Krcmar, H., Hemsen, H., Markl, V., Buchmüller, C., Bitter, T. and Hoeren, T. (2014), "Big Data – an interdisciplinary opportunity for information systems research", *Business & Information Systems Engineering*, Vol. 6 No. 5, pp. 261-266.

Yang, J., Liu, Z., Jia, C., Lin, K. and Cheng, Z. (2014), "New data publishing framework in the big data environments", *Proceedings of the International Conference on P2P, Parallel, Grid, Cloud and Internet Computing, IEEE*, pp. 363-366.

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