Deep LSTM for Generating Brand Personalities Using Social Media: A Case Study from Higher Education Institutions

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Abstract: This paper introduces a novel technique to generate brand personalities for organizations from social media text data using a deep bi-directional Long Short-Term Memory (BiLSTM) neural network model in combination with an accepted brand personality scale model. Brand Personality has evolved into an indispensable element in modern business organizations. Currently brand personality of an organization is generated using traditional techniques such as stakeholder interviews, questionnaires, which are time and resource intensive and limited in efficacy. However, the rise of the internet and social media have provided a platform for stakeholders to frequently and freely express their opinions and experiences related to organizations. Such social media data while now successfully being used for customer analytics have not yet been fully investigated and used to understand brand personalities. Our research investigated how this data can be effectively leveraged by organizations to generate and monitor their brand in near real time. Our technique has been successfully demonstrated on Higher Education Institutes, as Higher Education is an industry that is increasingly being exposed to business competition over the last few decades.

Key words: Big data, brand personality, deep learning, neural networks, social media, word embedding.

1. Introduction

The concept of Brand Personality appears as a powerful tool in business and marketing literature [1]. It has ascended to the status of providing distinctive institutional-identities in the business world since mid 1990s, and holds a prominent position in corporate marketing and strategic management due to its ability to create business and shareholder value [2].

Higher Education sector stands out as an industry increasingly being exposed to business competition over the last few decades [3]. As reported in Balmer [2], in this competitive environment many Higher Education Institutes (HEIs) are struggling to maintain their brand image, keep up with official evaluations and rankings, constantly implementing improvements to attract high achieving students and staff and to retain their already enrolled students.

Although there is agreement that understanding institutional brand personality and clearly developing and communicating that brand is of great value to organizations/HEIs, capturing the stakeholder opinions, thoughts and experiences of an organization, to generate this brand personality remains a challenge [4].

Traditional techniques, most widely used to date for the extraction of this brand personality, are brand personality scales together with questionnaires, interviews and surveys [5]–[7]. Some recent attempts have been made to incorporate more contemporary methods of data collection such as online product reviews and social media [8]–[12]. Brand personality scales have been demonstrated to be a reliable, effective and generalizable scale for evaluating brand personality [13].

While the traditional methods have been effective, they require time, resources, money and experts in domain knowledge to design, execute and analyze. The time and resource consuming nature of these processes confines the frequency at which the brand personality can be generated and observed for an organization. Moreover, the quantity of data (sample size) that can be collected and processed is very limited and further confines the accuracy and effectiveness of the generated brand personality.

However with the recent emergence of social media, stakeholders have begun to express themselves more frequently , in-depth and in-detail via social media platforms [14]. Such user generated data are rich in stakeholder opinions, emotions and experiences that are freely expressed and updated often.

Consequently, researchers and commercial organizations are now increasingly using this social media data to inform customer analytics, human resources, recruitment etc. [15]. According to Alahakoon [15], organizations that adopt these new big data sources and technologies will be able to make real-time business decisions and thrive, while those that are unable to embrace and make use of this shift will find themselves at a competitive disadvantage. However, social media data has not yet been fully investigated in generating brand personality for organizations. In fact, as per Dhar [16] and Alahakoon [15], organizations' ability to harness the opportunities presented by Big Data is still in it's infancy.

The key difficulty is that social media data constitutes not only of structured data, but semi-structured as well as a large volume of unstructured text. Transferring opinions, ideas and emotions expressed in text into a structured form that can be evaluated, quantified and reported is a highly challenging process that is still under research.

In this paper we report our work using a deep machine learning LSTM (Long Short-Term Memory) to generate, capture and quantify such patterns and generate brand personalities for organizations using social media data. We use an accepted brand personality scale model as our basis together with text mining and Natural Language Processing (NLP) techniques to pre-process and transform raw text data to a form that can be fed into the deep learning model. We demonstrate our technique using Higher Education Institutes.

The rest of the paper is structured as follows. The background section introduces and reports the existing theories, models and technologies related to Brand Personality and LSTM; the two main components that have been used for this study. Methodology section presents the proposed technique, while experimental results section demonstrates the proposed approach on a case study from HEIs. Finally, the paper will conclude with a discussion of the findings and implications of this study with concluding remarks.

2. Background

2.1. Brand Personality

The term Brand Personality, was first introduced by Martineau in 1958 [17] and refers to a set of human characteristics or stakeholder perceptions associated with a brand [13]. Brand personality scales found throughout marketing literature have been demonstrated to be a reliable, effective and generalizable scale for evaluating brand personality [13].

Since 1997, most of the marketing literature has adopted Likert scale surveys [18], which are based on the Aaker's scale to estimate brand personality [13].

In 2016, Rauschnabel [4] introduced the University Brand Personality Scale (UBPS) to represent the human-like mental associations stakeholders have with and about a particular university. The UBPS consists of six dimensions developed using a series of qualitative and quantitative studies. The six dimensions of the UBPS consists of Prestige, Sincerity, Appeal, Lively, Conscientiousness and Cosmopolitan. This brand personality scale has been successfully applied to generate brand personalities for universities using data collected from stakeholder interviews [4].

Throughout literature a range of methods have been used as explained in the introduction, to practically apply these brand personality scales for the extraction of the brand impression among customers with modest success or effectiveness.

2.2. LSTM

Deep learning is a Neural Network (NN) architecture that allows computational models consisting of multiple layers of processing to learn data representations (such as sequences) with multiple levels of abstractions. A composition of multiple such transformations allows even highly complex patterns to be learned. Hence, for classification tasks, higher layers of representation amplify aspects of the input that are important for categorization [19]. This technique has dramatically improved the state-of-the-art in many domains that require sequence and pattern recognition such as speech recognition and hand writing recognition [19].

There are several Deep Learning architectures such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN).

Long Short-Term Memory (LSTM) is a RNN architecture introduced by Hochreiter [20] that has yielded successful results in sequential data modelling with recent studies [21]–[25]. Hence, this architecture was selected as the most effective method to learn and classify brand personalities from text data in our research. For our experiment we used a Bidirectional Long Short-Term Memory (BiLSTM) which uses a forward pass NN and a backward pass NN to learn sequences in both directions.

2.3. Honeycomb Social Media Framework

The present big data environment is home to a rich and diverse ecology of social media sites, which vary in terms of their scope and functionality [26]. Therefore, before using any automation technique on social media data, first a decision has to be made on which functionalities of the social media should be considered to engage with for the task at hand. In order to compare and contrast the functionalities and implications of different social media activities in online communities, the honeycomb social media framework [26] was applied.

According to [14] the social media honeycomb model provides an analytical lens for firms' specific ‘community needs’, and can educate the design or use of an appropriate social media platform.

This framework introduces a honeycomb of seven functional building blocks: identity, conversations, sharing, presence, relationships, reputation, and groups. The blocks allow to unpack and examine different facets of the social media user experience, and their implications for organizations. The building blocks help to understand how different levels of social media functionality can be configured [26]. According to this framework each social media platform is driven by primary, secondary and tertiary building blocks, which provide the foundation for important social media design decisions [14]. After an intensive investigation into the functionality and data of the selected social media sites, the honeycomb framework was applied to identify the areas of the online communities to utilize for the extraction of the dataset.

3. Methodology

The Fig. 1 illustrates the steps of the *Deep LSTM* technique proposed in this paper. The first step is selecting appropriate data sources to generate the brand personality of the organization of interest.

3.1. Selection of Data Sources

As the social media data sources to be used for experimenting our technique, several relevant public online discussion forums were selected. These social media platforms are rich in stakeholders' opinions, expectations and experiences related to many industries and hence a highly valuable source for insight generation related to organizations that remains underutilized. In order to demonstrate this approach we selected the higher education (HE) sector of Australia [3], [27]. We selected three of the most widely used forums;

- Whirlpool (http://forums.whirlpool.net.au/)
- ATAR Notes (https://atarnotes.com/forum/)
- Board of Studies (http://www.boredofstudies.org/)

These forums were selected, as they are the current most widely used public discussion forums in Australia with the largest selection of posts and discussions related to various aspects of Australian HEI. Hence, they hold millions of posts from various customer/stakeholder groups discussing resources and processes related to universities in Australia. They share requirements, opinions and experiences on courses and universities, discuss university facilities, well-functioning and defective processes they have come across, etc.

In order to identify the areas in the selected online communities to engage with for maximum impact, the Honeycomb framework proposed by Kietzmann *et al*. was used [26]. This framework was selected as it is the currently most widely accepted framework for social media.

The application of the Honeycomb framework disclosed that in terms of public online discussion forums, "Conversation" and "Groups" are the building blocks or areas to engage with this social media for impact. Public online communities are a type of social media environment designed to mainly enhance conversations. Hence, our dataset was extracted from conversations in HE groups from the public online communities.

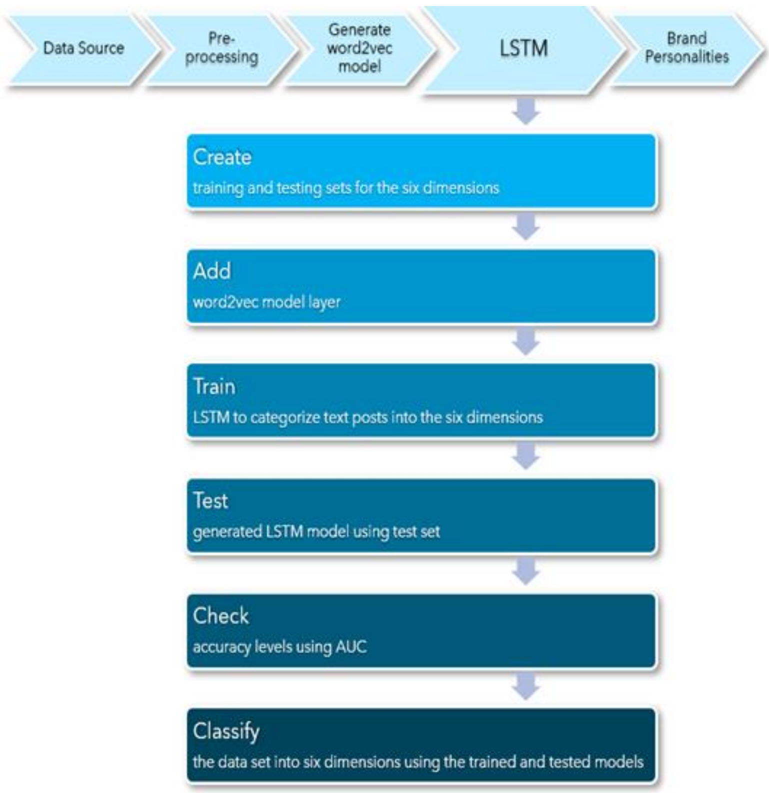

Fig. 1. Deep LSTM Technique for the extraction of brand personality from social media.

These forums are rich in stakeholders' impressions, related to varied universities in Australia. Stakeholders freely share their personal requirements, opinions and experiences related to courses and universities, discuss about the facilities and processes (well-functioning and defective) they have come across, etc during their interactions with the universities. The extracted data set used for this study consists of over 1.2 million social media posts on Australian universities.

3.2. Generating Brand Personalities: The Deep BiLSTM Technique

As illustrated in Fig. 1, after selecting the data sources, pre-processing of the text data was done using NLP techniques. This included data cleaning, removing of noise and merging of data from the three sources.

Next step was generating a word2vec model for the dataset. Distributed representations of words in a vector space have proven to help learning algorithms achieve better performance in NLP tasks by grouping similar words [28]. Furthermore, word representations computed using NN possess the capacity to encode many linguistic patterns into the learned vectors [28].

Word2vec is a NN based algorithm introduced by Mikolov *et al*., supported by Google, which has been succesfully used for learning Word Embeddings or vector representations of words and discover the semantic relationships between words in a text document [29].

The algorithm consists of two learning models, Continuous Bag of Words (CBOW) and Skip-gram, and the meaning of words is given by the words that frequently appear close-by [28]. This technology can be used to reveal the embedding meanings in words and describe the vector expression of sentence based on a trained word2vec model [30].

Hence, for our approach the word2vec word embedding NN was trained for the dataset (Fig. 1) and a word2vec model was generated (Which would be fed into the LSTM NN later). Once these steps were completed, the LSTM process is executed. In the LSTM process, first (Fig. 1) a training set and a testing set were created for each of the six brand dimensions presented in the UBPS (a negative and positive set for each dimension) using the data set. A random set of 20,000 posts were used for each of the training sets (For every dimension) and a random sample of 50 posts were used for each of the testing sets (25 posts for the positive sample and 25 posts for the negative sample for each dimension).

The positive samples consisted of posts that were identified manually through skilled human observation (i.e. by careful reading of the post) to represent the brand dimension under consideration. Likewise, negative samples were generated by hand picking posts that clearly had no relationship to the considered brand dimension. This was individually performed for each of the six brand dimensions.

Thereafter, the trained word2vec model was fed into the LSTM NN as an intermediary layer to provide extra knowledge (depth) for the training process. Subsequently, Deep BiLSTM models were generated for each of the six brand dimensions. The validation sets were randomly created (through automation) for 5 epochs or iterations and the testing phase was repeated for 10 runs to maximize accuracy.

As the next step, the trained Deep BiLSTM models were tested using the testing sets and accuracy levels were obtained. Finally, after checking the acceptability of accuracy levels, the trained and tested Deep BiLSTM models were used to classify the text dataset into the six dimensions, and the strength of each dimension was measured to generate the brand personality for the organization (Fig. 1).

4. Experimental Results

Values for Area Under the Curve (AUC) were calculated for training of all UBPS dimensions using *Deep LSTM*. Table 1 presents the average AUC obtained for each of the six dimensions during the training process of the *Deep LSTM*.

AUC refers to the area under the Receiver Operating Characteristic (ROC) curve. AUC is used as a performance measure for machine learning algorithms and is highly accepted as an indicator of accuracy. A higher AUC number indicates a higher accuracy with the maximum number being 1.0 indicating an accuracy of 100 percent [31].

Table 1. The AUC for Training of the Six Brand Dimensions

Brand dimension	Average AUC
Prestige	0.984882829
appeal	0.936647972
sincerity	0.983898515
lively	0.979387417
conscientiousness	0.987680669
cosmopolitan	0.987671367

Table 2. Average Testing Set Predictions for NN Models Trained for the Six Brand Dimensions

Brand Dimension	Average prediction: test sample	
	Positive sample	Negative sample
Prestige	0.805096746	0.121755627
appeal	0.913727908	0.002702125
sincerity	0.890718808	0.074712933
lively	0.782405805	0.030281347
conscientiousness	0.843108274	0.009791983
cosmopolitan	0.606904834	0.042598566

Table 2 present the accuracy levels generated during the Testing phase. It can be observed that the Deep BiLSTM has obtained high accuracy levels for each of the six dimensions with the AUC approaching 1 for the positive sample and 0 for the negative sample.

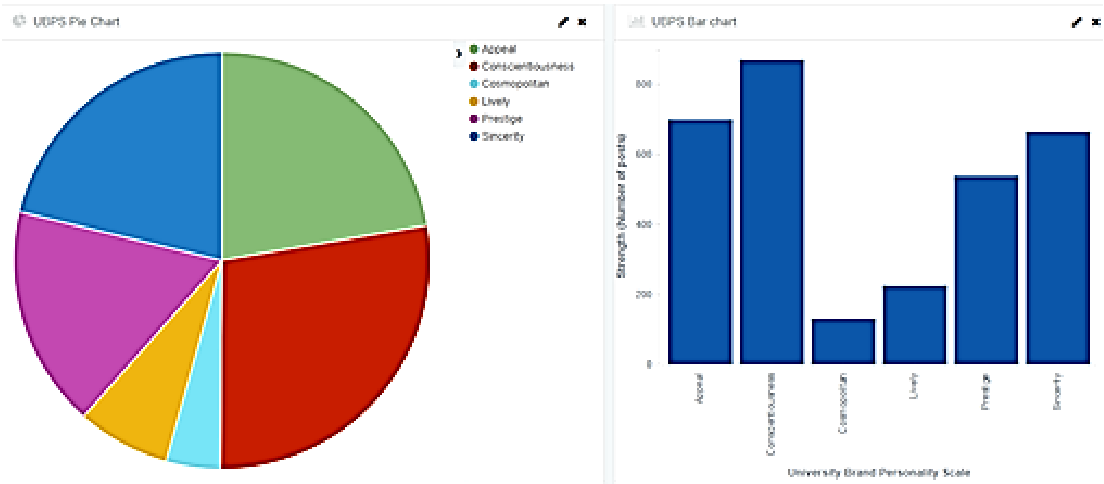

Fig. 2. Generated Brand Personality for La Trobe University: Demonstrating the strength of the six dimensions in the Brand Personality scale (2012-2016).

Fig. 2 demonstrate the final generated Brand Personality for La Trobe University Australia from public forum data for the period 2012-2016. The graphical view in Fig. 2 demonstrate the strength of La Trobe university in stakeholders' eyes for the six brand dimensions; *Appeal, Conscientiousness, Cosmopolitan, Lively, Prestige* and *Sincerity*.

Fig. 3 demonstrate a comparison of the generated Brand Personality for La Trobe University against the same of three competitor universities in Victoria, for the period 2012 to 2016. This illustrate how the introduced technique can successfully be used for real-time benchmarking against competitors by monitoring the organizations Brand Personality together with competitor organizations.

The visualizations were generated using the Kibana Visualization tool, that support visualization of real time analytics dashboards on top of large volumes of high velocity data.

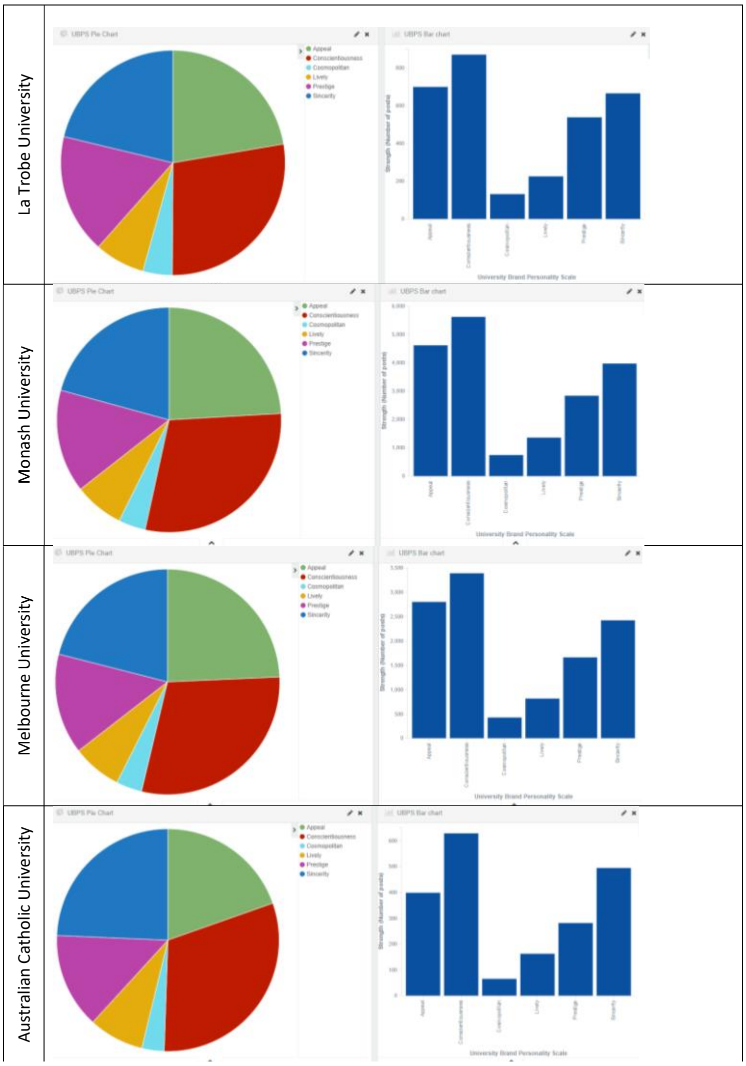

Fig. 3. Generated Brand Personality (consisting of six dimensions) for La Trobe University and three other competitor universities in Victoria, Australia (2012-2016).

5. Discussion and Conclusion

This research presents a novel technique the authors call *Deep LSTM*; a deep-learning based technique that can generate brand personalities for organizations in near real time using social media data in text form. The technique is based on accepted brand personality scales from marketing literature and combines a word embedding model with a Bi-directional LSTM NN to categorize social media posts into brand dimensions and generate Brand Personalities for organizations. The technique was successfully demonstrated on an Australian Higher Education Institute using a social media dataset of over 1.2 million posts which demonstrate that the technique is highly effective for generating Brand Personalities.

As exemplified, with the rising significance of social media, organizations are increasingly depending on social media management techniques to analyze social media content and to professionalize their social media engagement [32].

Public online discussion forums are packed with public opinions and sentiments which are liberally being expressed. Since online discussion forums are a type of social media where identity of users is less visible, users' necessity for personal impression management is much less than in a network like facebook, twitter or linkedin where identity is more significant. Therefore, users are more free to share their opinions and experiences without having to readjust their conversations to safeguard their self-image. This adds onto the authenticity of the data for extraction of Brand Personality of organizations they converse about.

The results demonstrate that social media data in the form of public online discussion forums, are highly effective for generating and monitoring brand personality of organizations and is currently heavily underutilized. As this data is freely expressed, freely available (cost free to be extracted and used by any organization) and updated often, it enables an organization to listen to voices and emotions of stakeholders, in other words monitor it's brand performance. The *Deep LSTM* makes all this possible while requiring a significantly less amount of resources compared to traditional methods.

Furthermore, this data consists of millions of discussions allowing a much larger sample to be used which is near impossible with the traditional survey based methods of extracting brand personality.

The *Deep LSTM* technique presented in this paper was observed to generate high accuracy levels during the training (Table 1) as well as the testing (Table 2) phases. These exceptionally high accuracy levels in learning can be assumed to be the result of the use of a word embedding model as an extra layer into the learning of the BiLSTM generating a deep BiLSTM. However, it was observed that the dimension *Cosmopolitan* showed a significantly lower accuracy value compared to other dimensions during the testing phase (an AUC of of 0.606) for the positive testing sample (Table 2). When investigating into this we discovered that in the initial lists of terms used for definition/identification of each brand dimension (using the brand personality scale presented in [4]), *Cosmopolitan* had the lowest number of terms. Therefore, a possible cause of this lower accuracy level could be that the number of terms defining this category (dimension Cosmopolitan) is few, and it may not have captured the category comprehensively.

While traditional methods for extraction of brand personality such as interviews and questionnaires have been accepted and successful for decades, it is evident, that these techniques are subject to limitations. These traditional techniques can be very restrictive in a competitive business environment, specially with the increasing challenges faced by contemporary organizations. One of the inherent limitations of survey-based methods is flexibility. Constructing and conducting surveys can be extremely time-consuming and labour-intensive, thus limiting the sample size to hundreds or several thousand at most. In addition, it is expensive to assess brand personality frequently.

The introduced technique can provide contemporary organizations the much needed, technology driven, timely insights necessary to be proactive to the needs of their stakeholders/customers and obtain a competitive advantage.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

PW conducted the research, implementations, analysis and wrote the paper; DA supervised the research

and writing of the paper; DD Co-supervised the research and writing of the paper; SK provided technical support for the implementations; all authors had approved the final version.

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References

[1] Clifton, R., & Simmons, J. (2003). Brands and branding. *London Econ. Profile Books. Google Sch.*, (pp. 13-14).

[2] Balmer, J. M. T. (2017). *Explicating Corporate Brands and Their Management: Reflections and Directions from 1995*. London: Palgrave Macmillan.

[3] Khanna, M., Jacob, I., & Yadav, N. (2014). Identifying and analyzing touchpoints for building a higher education brand. *J. Mark. High. Educ.*, *24(1)*, 122–143.

[4] Rauschnabel, P. A., Krey, N., Babin, B. J., & Ivens, B. S. (2016). Brand management in higher education: The university brand personality scale. *J. Bus. Res.*, *69(8)*, 3077–3086.

[5] Matzler, K., Strobl, A., Stokburger-Sauer, N., Bobovnicky, A., & Bauer, F. (2016). Brand personality and culture: The role of cultural differences on the impact of brand personality perceptions on tourists' visit intentions. *Tour. Manag.*, *52*, 507–520.

[6] So, K. K. F., King, C., Hudson, S., & Meng, F. (2017). The missing link in building customer brand identification: The role of brand attractiveness. *Tour. Manag.*, *59*, 640–651.

[7] Gordon, R., Zainuddin, N., & Magee, C. (2016). Unlocking the potential of branding in social marketing services: Utilising brand personality and brand personality appeal. *J. Serv. Mark.*, *30(1)*, 48–62.

[8] Saboo, A. R., Kumar, V., & Ramani, G. (2016). Evaluating the impact of social media activities on human brand sales. *Int. J. Res. Mark.*, *33(3)*, 524–541.

[9] Gensler, S., Völckner, F., Egger, M., Fischbach, K., & Schoder, D. (2015). Listen to your customers: Insights into brand image using online consumer-generated product reviews. *Int. J. Electron. Commer.*, *20(1)*, 112–141.

[10] Unnisa, M., Ameen, A., & Raziuddin, S. (2016). Opinion mining on Twitter data using unsupervised learning technique. *Int. J. Comput. Appl.*, *148(12)*, 12–19.

[11] Hudson, S., Huang, L., Roth, M. S., & Madden, T. J. (2016). The influence of social media interactions on consumer-brand relationships: A three-country study of brand perceptions and marketing behaviors. *Int. J. Res. Mark.*, *33(1)*, 27–41.

[12] Callarisa, L., García, J. S., Cardiff, J., & Roshchina, A. (2012). Harnessing social media platforms to measure customer-based hotel brand equity. *Tour. Manag. Perspect.*, *4*, 73–79.

[13] Xu, A., *et al.* (2016). Predicting perceived brand personality with social media. *Proceedings of the Tenth Int. AAAI Conf. Web Soc. Media* (pp. 436–445).

[14] Kietzmann, J. H., Silvestre, B. S., McCarthy, I. P., & Pitt, L. F. (2012). Unpacking the social media phenomenon: towards a research agenda. *J. Public Aff.*, *12(2)*, 109–119.

[15] Alahakoon, D., & Wijenayake, P. (2018). *Leveraging Big Data for Organizational Performance Management and Control*.

[16] Dhar, S., & Mazumdar, S. (2014). Challenges and best practices for enterprise adoption of big data technologies. *Proceedings of the 2014 IEEE International Technology Management Conference* (pp. 1–4).

[17] Martineau, P. (1958). *The Personality of the Retail Store*.

[18] Likert, R. (1932). A technique for the measurement of attitudes. *Arch. Psychol*.

[19] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521(7553)*, 436.

[20] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Comput., 9(8)*, 1735–1780.

[21] Graves, A., Mohamed, A., & Hinton, G. (2013). Speech recognition with deep recurrent neural networks. *Proceedings of the 2013 IEEE International Conference on Acoustics, Speech and Signal Processing* (pp. 6645–6649).

[22] Shi, B., Bai, X., & Yao, C. (2017). An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition. *IEEE Trans. Pattern Anal. Mach. Intell.*, *39(11)*, 2298–2304.

[23] Liu, W., Wang, Z., Liu, X., Zeng, N., Liu, Y., & Alsaadi, F. E. (2017). A survey of deep neural network architectures and their applications. *Neurocomputing*, *234*, 11–26.

[24] Sak, H., & Senior, A. W. (2017). Processing acoustic sequences using long short-term memory (LSTM) neural networks that include recurrent projection layers. Google Patents.

[25] Breuel, T. M. (2017). High performance text recognition using a hybrid convolutional-lstm implementation. *Proceedings of the 2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR): Vol. 1*. (pp. 11–16).

[26] Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Bus. Horiz.*, *54(3)*, 241–251.

[27] Duesterhaus, A., & Duesterhaus, M. (2014). Attributes of successful university brands in the USA. *J. Brand Strateg.*, *3(2)*, 169–183.

[28] Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *Advances in Neural Information Processing Systems*, 3111–3119.

[29] Le, Q., & Mikolov, T. (2014). Distributed representations of sentences and documents. *Proceedings of the International Conference on Machine Learning* (pp. 1188–1196).

[30] Xia, C., He, T., Li, W., Qin, Z., & Zou, Z. (2019). Similarity analysis of law documents based on word2vec. *Proceedings of the 2019 IEEE 19th International Conference on Software Quality, Reliability and Security Companion (QRS-C)* (pp. 354–357).

[31] Bradley, A. P. (1997). The use of the area under the ROC curve in the evaluation of machine learning algorithms. *Pattern Recognit.*, *30(7)*, 1145–1159.

[32] Benthaus, J., Risius, M., & Beck, R. (2016). Social media management strategies for organizational impression management and their effect on public perception. *J. Strateg. Inf. Syst.*, *25(2)*, 127–139.

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