PANAS-TDL: A Psychrometric Deep Learning Model for Characterizing Sentiments of Tourists Against the COVID-19 Pandemic on Twitter

Alejandro Peña¹(✉), Jorge Mesias¹, Alejandro Patiño¹, Joao Vidal Carvalho², Gregorio Gomez¹, Kevin Ibarra¹, and Santiago Bedoya¹

¹ EIA University, Envigado 055413, Colombia
{juan.pena, jorge.mesias, hector.patino, kevin.ibarra, santiago.bedoya}@eia.edu.co
² Polytechnic of Porto/CEOS.PP, S. Mamede de Infesta, Portugal
cajvidal@iscap.ipp.pt

Abstract. One of the main sectors that moves the economy of the countries worldwide is tourism and its associated services. Dynamics like globalization have led these countries to create tourism services with global standards, however, in the context of COVID-19 pandemic, these services have been affected as shown the social networks. This fact led to a change in the perception of tourists against a destination. In order to unify this change in an objective manner, we propose a Deep Learning model that integrates a PANAS scale (Positive and Negative Affect Scale) (PANAS-tDL), to characterize a tourist destination based on a series of potential factors (weather conditions, healthy, holidays, seasonality and economic factors) identified in comments obtained from a social network like Twitter. The results obtained by the PANAS-tDL model show its good performance evaluating the change of perception of tourists against four destinations affected by COVID-19, taking as reference the 11-sentiment scale defined by PANAS-t scale. Thanks to adaptation capacity, the model can be extended to evaluate the change in perception of tourists using different social networks and to evaluate different marketing strategies to promote a destination.

Keywords: PANAS (Positive and Negative Affect Schedule) • Stacked deep learning model • Twitter • Sentiment analysis • Natural language processing

1 Introduction

One of the main sectors that moves the economy of the countries is tourism and its associated services. Global dynamics have caused governments worldwide to establish favourable environments for the creation of new tourist services with high added value, however, in the context of COVID-19 pandemic, these services have been affected. In this way, social networks as Twitter, Facebook and Instagram have played a major role, since these social networks grouped comments related with these services and the
impact of COVID-19 without a unified vision, which influences wrongly the people’s
decision to visit a tourist destination [1–3].

For the solution of his problem, in the scientific literature, it can be seen three
development trends. A first development trend focuses on the analysis of aspects
related to access to tourism destinations using different data sources. In this develop-
ment trend, [4] carried out data analysis to identify behavioural patterns in tourist
according to the distance, [5] who create a model to forecast the potential factors as
weather conditions, holidays, seasonality and economic factors in tourism decision
making [5], and [6] who propose a MULTITOUR recommendation engine to recom-
manded multiple itineraries based on the tourist’s interest. Two additional papers show
how a tourist experience can be influenced by the interaction tourist to tourist [7], and a
final paper that shows how the cultural differences can help a customer have a better
experience [8]. In this development trend clearly shows the importance of the data in
the decision making, specifically to improve the experiences of the tourists in a des-
tination taking into account different potential factors. However, this development trend
does not show a unified criteria from social networks against the potential factors that
characterize a tourist destination.

A second development trend focuses on sentimental analysis for the evaluation of
destinations. In this development trend [9] apply the sentimental analysis for the
characterization of destinations in Australia, [10] presents a novel hotel selection model
driven by online textual reviews based on TripAdvisor web-page, while [11] shows the
variation of sentiments against the same tourist service. In this development trend, an
additional paper presents a model to rank tourist sites of a city based on sentiments
contained in opinions in social networks [12], while a final paper proposes a
methodology to identify the Polarity User, since many sentences may not be repre-
sentative of sentiment in opinion against a tourist attraction [13]. This development
trend clearly shows the importance of social networks for sentimental analysis,
approaching in an important way to eliminate the subjectivity in the comments against
a service or tourism destination.

The third and last development trend groups a series of papers where Deep Learning
for sentiment analysis stand out. In this development trend, [14] presents a series of
Deep Learning models to analyze hotel reviews to identify response strategies [14],
while [15] uses different tools from the big data technology based on deep learning
models to discover the tourist’s behaviours and perceptions in a tourism destination. In
this way, [16] explores distinct relationships between importance, performance and the
(a) symmetric impact of service attributes on customer satisfaction (CS) using deep
learning models equally, while [17] use deep learning models in forecasting monthly
Macau tourist arrival volumes. A final paper presents a machine learning approach for
the identification of the deceptive reviews in the hospitality sector using unique attri-
brates and sentiment orientation [18]. It is important to note the relevance that the deep
learning models have gained in the analysis of sentiments in social networks, specifi-
cally to identify behaviours and perceptions to improve services in tourist destinations.

In the scientific literature, it can be seen the absence of models that allow evaluating
the change of perception of tourists in social networks against different potential factors
or natural events that may affect a tourist destination. In order to create an objective
perception against this change of perception based on comments of tourists in a social
network as Twitter, and according to Second and Third development trend, a Stacked Deep Learning model [19] based on PANAS (Positive and Negative Affect Schedule) methodology [20] was proposed. The structure of the model has a Fully Connected Layer (FCL) defined by a Loglogistic cumulative distribution function (Softmax function), which will allow the classification of these comments in Positive Affects (PA) and Negative Affects (NA) categories, as well as in the following 11-sentiments or categories that define a PANAS-t scale: Guilt, Fear, Sadness, Hostility, Shyness, Fatigue, Surprise, Joviality, Self-assurance, Attentiveness and Serenity. According to the structure of the activation function, this scale goes from \(-1 - \text{Guilt}\) to \(1 - \text{Serenity}\) [1].

For the analysis and validation of the proposed model, a total of 93,693 comments (5-words) were obtained from the Twitter social network. In a first stage (Learning Stage), the comments were grouped in PA and NA categories (PANAS scale), as well as in the 11-sentiment categories that define the PANAS-t scale (Baseline Scenario). In a second stage (Autonomy Validation), the comments were additionally grouped taking into account four tourist destinations as Colombia, Italy, Spain and USA, and for before and during COVID-19 worldwide pandemic to analyze the change of perception of tourists against this destinations. The results show that the model reached compression rates above 80% on average for the configuration of stacked neuron layers, taking as a reference the first layer of neurons, and an auto-encoder strategy [21]. Regarding a learning stage, the model reached sensitivity and specificity indices above 85% on average against the classification of comments as PA or NA, while for the characterization of the categories defined by the PANAS-t scale (11-sentiments), the model reached IOAs above 95% on average taking as reference the Log-logistic function that defines the FCL. According to the second stage (Autonomy Validation), it is important to note that the model managed to identify the negative effects that the COVID-19 pandemic generates on four tourist destinations defined by this study in absence of a learning process, which shows, in general, the good behaviour achieved by the model in the characterization of comments on Twitter for a specific tourist destination in an objective manner.

The paper has four sections that clearly describe the structure of the proposed model against the change of perception of tourists in Twitter against a tourist destination that may be affected by a potential factor such as worldwide COVID19 pandemic. A first section describes the methodology for the construction of the proposed model taking into account the PANAS-t methodology. A second section shows the analysis and evaluation of the model’s behaviour against the change of perception, and finally, a series of conclusions and recommendations are presented as future work.

2 Methodology

Social networks have become reference tools for the analysis of people’s perception of products and services in the economy. Regarding tourism, the Twitter social network is being used more and more by the tourists to explore potential tourist destinations to visit. From this information, the tourists create their own opinions about costumes, political stability and in general, about the security of a country. However, social networks do not allow creating a unified change of perception about a tourist destination. To solve this problem, we propose the following methodology.
2.1 PANAS-x Scale

The Positive and Negative Affect Schedule (PANAS) consists of two 10-item scales to provide measures of Positive Affect (PA) and Negative Affect (NA) against a particular emotion. In this methodology, a respondent is asked to rate a particular experience (usually during last week), taking as a reference a 5-point scale per item. Each item is defined by a series of words related a lexicon. Meanwhile, the PANAS-x scale, not only rates a particular emotion in NA or PA, but also rates an emotion in 11 specific sentiments such as Guilt, Fear, Sadness, Hostility, Shyness, Fatigue, Surprise, Joviality, Self-Assurance, Attentiveness, and Serenity [1].

Goncalves et al. [1] summarize the common words used to describe each sentiment according to PANAS scale, the NA category groups words like nervous and scared, while the PA category groups words such as enthusiastic and excited. These words describe clearly the state of mind of a person against a feeling. Unlike the POMS scale (Profiles of Mood States), which establishes six different dimensions of mood swings (12-sentiments), the PANAS-x methodology had exhibited minor values of correlation among the 11-sentiments scale, what was brought about a better characterization of sentiments.

2.2 Adjusting PANAS-x for Tourism (PANAS-t - Case of Study)

According to the PANAS-x methodology, we proceed to create a database consisting of a total of 93,634 comments related with four tourist destinations (Colombia, Italy, Spain, USA), obtaining from Twitter social network throughout 2020 using a web-scraping methodology. Each comment or Tweet is defined by a total of 5-words and was classified as Negative (NA) and Positive (PA) categories according to expert criteria. The words that make up each comment was lemmatized, tokenized and standardized to achieve stability in models by adaption and learning [2]. Later, each comment was classified in 11-sentiment categories (PANAS-t scale), as well as, for before (Baseline scenario) and during the worldwide COVID-19 pandemic (Autonomy scenario). The Baseline scenario of comments is defined as follows (Table 1):

$$\alpha_s = \frac{|T_s|}{|T|}$$  \hspace{1cm} (1)

Where: $s$: Represents the sentiments or categories (PANAS - t). $T_s$: Tweets for each $s$ category. $T$: Total tweets that make up the database for before the COVID-19 pandemic (Baseline case).
For the analysis and validation of the proposed model, the comments were grouped in data for a learning phase (50% - 46.817 - First Stage), and data for validation or autonomy evaluation (50% - 46.817 - Second Stage), and were grouped taking into account four tourist destinations: Colombia, Italy, Spain and USA.

2.3 PANAS-t Deep Learning Model (PANAS-tDL)

For the analysis of change of perception based on PANAS-t methodology, a PANAS-tDL model inspired by a Stacked Deep Learning model is proposed [19, 22]:

\[ y_{sk} = \text{Softmax} \left( \frac{1}{1 + \left( \frac{S_{jn}}{c} \right)^c} \right) \]  

(2)

Where: \( y_{sk} \): Represents the Softmax function against a PANAS-t sentiment scale. The Softmax function can be expressed as follows [23]:

\[ y_{sk} = \max \left\{ S_{j_1}, S_{j_2}, \ldots, S_{j_k} \right\} \]  

(3)

Where: \( k \): Represents the number of tweets or comments. \( S_{j_k} \): Represents the fully connected layer - FCL, which can be expressed as follows:

\[ S_{j_n} = \sum_{j_{n-1}}^{n_n} w_{j_n,j_{n-1}} \cdots \left( \sum_{j_1=1}^{n_2} \left( w_{j_2,j_1} x_{j_1,i} \right) \right) \]  

(4)

Where: \( j_n \): Represents the \( j_n \) sentiment. \( w_{j_n,j_{n-1}} \): Represents the relationships among the \( j_n \) and \( j_{n-1} \) layers. \( x_{j_1,i} \): Represents the input vector or tweet. \( i \): Represents the \( i \) word for the \( k \) tweet or comment. \( n_n \): Number of neurons for the \( n \) layer.

When the \( n_n = 1 \), the Softmax activation function represents the Canonical Cumulative Distribution Function for the classification of sentiments taking as reference the PANAS-t scale (Table 2):

| Sentiment (i) | Baseline (\( \alpha_g \)) |
|---------------|--------------------------|
| Guilt         | 0.000363                 |
| Fear          | 0.003716                 |
| Sadness       | 0.019907                 |
| Hostility     | 0.068650                 |
| Shyness       | 0.155584                 |
| Fatigue       | 0.219685                 |
| Surprise      | 0.195698                 |
| Joviality     | 0.125574                 |
| Self-assurance| 0.068479                 |
| Attentiveness | 0.035564                 |
| Serenity      | 0.018561                 |

Table 1. Baseline Scenario - Fraction of tweets for each sentiment

For the analysis and validation of the proposed model, the comments were grouped in data for a learning phase (50% - 46.817 - First Stage), and data for validation or autonomy evaluation (50% - 46.817 - Second Stage), and were grouped taking into account four tourist destinations: Colombia, Italy, Spain and USA.
According to the structure that defines the PANAS-tDL model, the configuration of layers is based on an auto-encoder strategy \[21\]. In turn, The FCL configuration is based on Generalized Delta Rule \[15\].

### 2.4 Metrics

**Index of Compression.** The Index of Compression (IC) indicates the compression rates that a layer of neurons is capable of generating on the input data, as a result of an auto-encoder strategy. The IC can be defined by the Index of Agreement as follows (IOA):

\[
\rho_{xy} = \frac{\sigma_{xy}}{\sigma_x \cdot \sigma_y}
\]  \hspace{1cm} (5)

Where: \(\rho_{xy}\): Index of Compression or Index of Agreement (IOA). \(\sigma_x\): Standard deviation for the input vector \(x_{j_1,i}\). \(\sigma_y\): Standard deviation for the output vector \(x_{j_1,i}\). \(\sigma_{xy}\): Covariance between the input \((x_{j_1,i})\) and output vectors \((x_{j_1,i,o})\).

**Confusion Matrix.** The confusion matrix is known as the matrix error, and is used to evaluate a model against the classification of data in two categories (PA, NA) (Table 3):

| Lower Limit \((s_j)\) | Upper Limit \((s_j)\) | Sentiment | \(y_{j_k}\) |
|-----------------------|-----------------------|-----------|-------------|
| \(-\infty\)          | \(-1\)                | Guilt     | 0.00669     |
| \(-1\)               | \(-0.78\)             | Fear      | 0.01984     |
| \(-0.78\)            | \(-0.56\)             | Sadness   | 0.05732     |
| \(-0.56\)            | \(-0.34\)             | Hostility | 0.154446    |
| \(-0.34\)            | 0.12                   | Shyness   | 0.35434     |
| 0.12                 | 0.1                   | Fatigue   | 0.62245     |
| 0.1                  | 0.32                  | Surprise  | 0.83201     |
| 0.32                 | 0.54                  | Joviality | 0.93702     |
| 0.54                 | 0.76                  | Self-Assurance | 0.97811 |
| 0.76                 | 0.98                  | Attentiveness | 0.99260 |
| 0.98                 | \(\infty\)            | Serenity  | 0.99912     |
Table 3. Confusion matrix

| Predicted values | Actual values |
|------------------|---------------|
| PA               | PA            |
|                  | TP            |
|                  | FP            |
| NA               | FN            |
|                  | TN            |

Where: PA: Number of positive records. NA: Number of negative records. TP: Number of true positive records. FP: Number of false positive records. FN: Number of false negative records. TN: Number of true positive records.

\[
TPR = \frac{TP}{TP + FN}
\]  

Where: TPR: True positive rate or sensitivity.

\[
TNR = \frac{TN}{TN + FP}
\]

Where: TNR: True negative rate or specificity.

Radar Chart. The radar matrix is known the chart of multidimensional classification and allows to evaluate the model against the number of sentiments correctly classified according to PANAS-t scale. This chart has a PA zone (left side) and a NA zone (right side), while the axis is defined by 11- sentiment defined by the FCL (−1 − Guilt to 1 − Serenity).

Relative evaluation: Let \( S \) the set of tweets for a particular event of risk (e.g. COVID-19, natural disasters, political events, etc.) and \( S_s \) the subset of these tweets related to \( s \) sentiment. \( \beta_s \): represents the relative occurrence of sentiment \( s \) for event \( S \). The \( \beta_s \) can be expressed as follows [1]:

\[
\beta_s = \frac{|S_s|}{S}
\]

Dimensional Sentiment: Let \( s \) categories that define the PANAS-t scale, the Score Function \( P(s) \) can be expressed as follows:

\[
P(S) = \frac{(\alpha_s - \beta_s)}{\alpha_s} \text{ if } \beta_s \leq \alpha_s
\]

\[
P(S) = -\frac{(\beta_s - \alpha_s)}{\beta_s} \text{ if } \beta_s \geq \alpha_s
\]
The values for \( P(s) \) is defined by the interval \([-1,1]\) for each \( s \) sentiment. \( P(S) = 0 \) means that the event has no increase or decrease for the \( s \) sentiment in comparison with the \( T_s \) database. A \( P(S) \geq 0 \) represents an increase for a \( s \) sentiment, while a \( P(S) \leq 0 \) represent a decrease for a \( s \) sentiment.

**Skewness Index.** The Skewness Index (SI) is a measure of the asymmetry of a probability distribution of a real-valued random variable about its mean. The SI index can be expressed:

\[
SI = E \left[ \left( \frac{X - \mu}{\sigma} \right)^3 \right]
\]

Where: For Cumulative Distribution Function, the SI can be zero (CDFs - Centred), Negative (CDFs - Heavy tails) and Positive (CDFs - Long tails) \[24\].

### 2.5 Experimental Validation

For the analysis and validation of the PANAS-tDL model, two stages were considered. In a first stage, each tweet (comments), record or input vector \((x_{i,j})\) was defined for a total of five (5) words and their multiples. Each tweet was classified as a Negative (NA) and Positive (PA) comment, as well as, classified according to the words that define a sentimental category in the PANAS-t scale (11-sentiment). In general, the database of comments (DC) was segmented in comments for learning process (Learning stage - 50%), and validation comments (Autonomy validation - 50%). Regarding the first stage is expected that the model reaches values above 75\% on average against the PA and NA classification taking as reference the Confusion Matrix (Eqs. 9 & 10), as well as, values above 90\% on average for cumulative distribution function (CDF) integrated into FCL (e.g. Learning Stage, Autonomy Validation). In the first stage, the structure of the model was evaluated according to the structure of layers, taking as reference the first layer of neurons \((n_j)\). Here, the model is expected to reach compression rates (IC) close to 90\% as a result of an auto-encoder learning strategy.

In a second stage (Autonomy Stage), the model was evaluated in the absence of a learning process based on the Relative evaluation metric (Eq. 8). Here, the comments were grouped in four worldwide tourist destinations: Colombia, Spain, Italy and the USA. The comments also were grouped for before and during COVID-19 pandemic. Here, the proposed model is expected to evolve into the negative zone (NA) of the Radar Chart due mainly to the impact of the COVID19 pandemic \( (P(s) \geq 0) \). Regarding the structure and shape of the activation function that defines the FCL, the proposed model is expected to evolve toward CDFs more slender with log tail structures \( (SI(s) \geq 0) \), with Skewness Indexes higher that the SIs that defines the Baseline scenario for each tourist destination. This evolution will allow evaluating the impact of COVID-19 has had in terms of comments or perceptions from tourists against a destination.
3 Analysis and Discussion of Results

In the Fig. 1 it can be seen the normalized values for the configuration of the structure for the PANAS-tDL model (Number of Layers, Number of Neurons per Layer, Compression Index (IC Index), Limit of Compression). In Table 4 it can be seen the last value achieved by the IC index, which was above 85%. Despite the number of layers and the number of neurons for the first layer was increased, the IC index did not change approximately from 8-layers and for 800-neurons as show the IC curve (Green line).

![PANAS-tDL model structure](image)

**Fig. 1.** PANAS-tDL model structure

| n   | N Layers | NO Fist Layer | CI    |
|-----|----------|---------------|-------|
| 0.1 | 0.1      | 0.010         | 0.2591|
| 0.2 | 0.3      | 0.037         | 0.3373|
| 0.3 | 0.3      | 0.037         | 0.3546|
| 0.4 | 0.5      | 0.185         | 0.3888|
| 0.5 | 0.6      | 0.480         | 0.5906|
| 0.6 | 0.9      | 0.495         | 0.7416|
| 0.8 | 1.0      | 0.925         | 0.8738|
| 1.0 | 1.0      | 1             | 0.8793|

Table 5 shows the results reached by the model against the classification of comments as PA and NA sentiments in the Frist Stage, taking the Confusion Matrix as reference. The results show that the PANAS-tDL model reached classification percentages above 85% on average for the sensitivity (Eq. 6) and for specificity (Eq. 7), which shows *a priori* the good behavior of the model according to the *Softmax* activation function for a $n_r = 1$ (Eq. 2).
Figure 2 shows the good behaviour achieved by the proposed PANAS-tDL model during the learning stage about the CDF (Orange Line - $SI = 0.290816$). In general, the model reached an Index of Agreement (IOA) close to 98% on average taking as reference the Baseline scenario represented by the Log-logistic CDF structure that defines the FCL (Blue line $SI = 0.589903$). Meanwhile, Fig. 3 shows the characterization of the sentiments in each category that define the PANAS-t scale. The radar chart shows the slight trend of the PANAS-tDL model to classify PA comments in a better way, due to a lower value reached against the SI index. This behaviour was mainly due to the complexity involved in the classification of sentiments in the limit between PA and NA, as shown in the confusion matrix.

Table 5. Confusion matrix - learning stage

| Learning Stage | PA  | NA   | Indices | TPR  | TNR  |
|----------------|-----|------|---------|------|------|
| PA             | 19113 | 2792 | TPR     | 0.872540 |
| NA             | 2230  | 18550| TNR     | 0.892685 |

Figure 4 shows the CDF given by the PANAS-tDL (Orange line – $SI = 0.750858$), taking as reference the CDF that represent the Baseline scenario for the validation of the proposed model (Blue Line $SI = 0.617066462$). It can be seen that the model reach an IOA above to 95% in the characterization of sentiments in absence of a learning process, despite the IOA value was located slightly below the IOA achieved by the model in the learning stage. However, this fact guarantees the good behaviour of the model in the characterization of sentiments in the absence of a learning process. According to CDF (Orange line), the proposed model has a slight trend to classify in a better way NA comments as shown a higher SI value reached. This behaviour was extended from the learning stage.
Figure 5 show the CDF for the comments grouped under the label of Colombia for before and the current impact of COVID-19. Here, it can be seen that the CDF (currently - COVID-19) showed characteristics similar to slender CDFs (Orange line $SI = 0.92693$). Regarding the Baseline scenario for Colombia (Blue line - $SI = 0.4707791$), the CDFs given by the model showed long-tail structures with a SI value much higher, which indicates the presence of a large number of NA comments regarding this tourism destination. This behaviour can be observed in the radar chart (Fig. 6), where the currently comments for Italy were located toward the negative zone (Right side Orange line), standing out in the comments sentiments like Fear, Sadness and Hostility, which clearly shows the impact of COVID-19 on this tourism destination [22, 25].
Table 6 shows the values reached by the proposed model for $P(s)$. Here, you can see how the perception of tourists evolved into NA comments for Italy destination (change perception), taking as reference the Eqs. 9 & 10. This fact corroborates once again the good performance of the PANAS-tDL in absence of a learning process, constituting as a tool for the objective evaluation of sentiments based on comments in Twitter social network.

Fig. 5. CDF PANAS-tDL model - Impact COVID-19 (Colombia)

Fig. 6. Radar Chart - Impact COVID-19 (Italy)
4 Conclusions and Future Work

The proposed model allowed to evaluate the change of perception against different worldwide tourist destinations, taking as reference a set of comments placed by users in Twitter. This change of perception was characterized on 11 sentience categories defined by the PANAS-t scale, where the proposed model clearly showed the impact that the COVID-19 pandemic has had on different tourist destinations from the point of view of a social network.

The Radar Chart shows, in general, the gap among the Baseline Scenario (Blue line) and the characterization carried out by the model against two stages defined by this study (Orange line) (Fig. 3). This fact was mainly due to the complexity that involves the classification process against neutral sentiments as Fatigue and Surprise. However, the model can be able to identify in a better way the change of perception of comments (PA to NA) in the absence of a learning process.

For its capacity of adaptation, the proposed model can be extended for the characterization of worldwide tourist destinations using different social networks, and to characterize these destinations based on NA or PA events, or against potential factors as weather conditions, holidays, seasonality and economic factors. Here, the change of perception can be used to evaluate different marketing strategies to promote services, facilities and amenities in this same tourist destinations.

As future work, the authors propose the creation of a specific methodology for the analysis and characterization of tourist destinations integrating different comments from social networks specialized in tourism. In this sense, to achieve a better characterization, the authors also propose the use of neuron layers using radial basis structures, to achieve an affinity between comments and characteristics of a tourist destination.

Acknowledgements. This work is financed by portuguese national funds through FCT - Fundação para a Ciência e Tecnologia, under the project UIDB/05422/2020.
References

1. Gonçalves, P., Benevenuto, F., Cha, M.: PANAS-t: a psychometric scale for measuring sentiments on twitter, CoRR, vol. abs/1308.1857 (2013)
2. Tellez, E.S., Miranda-Jíménez, S., Graff, M., Moctezuma, D., Siordia, O.S., Villaseñor, E.A.: A case study of Spanish text transformations for twitter sentiment analysis. Expert Syst. Appl. 81, 457–471 (2017)
3. Rocha, A., Reis, J., Peter, M., Bogdanovic, Z., Abreu, A., Carvalho, J., Franchi, L., Victor, J.: Marketing, tourism and technologies [marketing, turismo e tecnologias]. In: RISTI - Revista Iberica de Sistemas e Tecnologias de Informacao, vol. 2019, no. E24, pp. xii–xii (2019). cited By 0
4. Xue, L., Zhang, Y.: The effect of distance on tourist behavior: a study based on social media data. Ann. Tour. Res. 82, 102916 (2020)
5. Li, C., Ge, P., Liu, Z., Zheng, W.: Forecasting tourist arrivals using denoising and potential factors. Ann. Tour. Res. 83, 102943 (2020)
6. Sarkar, J.L., Majumder, A., Panigrahi, C.R., Roy, S.: Multitour: a multiple itinerary tourists recommendation engine. Electron. Commer. Res. Appl. 40, 100943 (2020)
7. Lin, H., Zhang, M., Gursoy, D., Fu, X.: Impact of tourist-to-tourist interaction on tourism experience: the mediating role of cohesion and intimacy. Ann. Tour. Res. 76, 153–167 (2019)
8. Jia, S.S.: Motivation and satisfaction of Chinese and U.S. tourists in restaurants: a cross-cultural text mining of online reviews. Tour. Manage. 78, 104071 (2020)
9. Liu, Y., Huang, K., Bao, J., Chen, K.: Listen to the voices from home: analysis of Chinese tourists’ sentiments regarding Australian destinations. Tour. Manage. 71, 337–347 (2019)
10. Nie, R., Tian, Z., Wang, J., Chin, K.S.: Hotel selection driven by online textual reviews: applying a semantic partitioned sentiment dictionary and evidence theory. Int. J. Hosp. Manag. 88, 102495 (2020)
11. Sharma, A., Park, S., Nicolau, J.L.: Testing loss aversion and diminishing sensitivity in review sentiment. Tour. Manage. 77, 104020 (2020)
12. Bueno, I., Carrasco, R.A., Ureña, R., Herrera-Viedma, E.: Application of an opinion consensus aggregation model based on OWA operators to the recommendation of tourist sites. Procedia Comput. Sci. 162, pp. 539–546 (2019). 7th International Conference on Information Technology and Quantitative Management (ITIQM 2019): Information technology and quantitative management based on Artificial Intelligence
13. Valdivia, A., Hrabova, E., Chaturvedi, I., Luzón, M.V., Troiano, L., Cambria, E., Herrera, F.: Inconsistencies on tripadvisor reviews: a unified index between users and sentiment analysis methods. Neurocomputing 353, 3–16 (2019). Recent Advancements in Hybrid Artificial Intelligence Systems
14. Chang, Y.-C., Ku, C.-H., Chen, C.-H.: Using deep learning and visual analytics to explore hotel reviews and responses. Tour. Manage. 80, 104129 (2020)
15. Zhang, K., Chen, Y., Li, C.: Discovering the tourists’ behaviors and perceptions in a tourism destination by analyzing photos’ visual content with a computer deep learning model: the case of Beijing. Tour. Manage. 75, 595–608 (2019)
16. Hu, F., Li, H., Liu, Y., Teichert, T.: Optimizing service offerings using asymmetric impact-sentiment-performance analysis. Int. J. Hosp. Manage. 89, 102557 (2020)
17. Law, R., Li, G., Fong, D.K.C., Han, X.: Tourism demand forecasting: a deeplearning approach. Ann. Tour. Res. 75, 410–423 (2019)
18. Martinez-Torres, M., Toral, S.: A machine learning approach for the identification of the deceptive reviews in the hospitality sector using unique attributes and sentiment orientation. Tour. Manage. 75, 393–403 (2019)

19. Fischer, T., Krauss, C.: Deep learning with long short-term memory networks for financial market predictions. Eur. J. Oper. Res. 270(2), 654–669 (2018)

20. Heubeck, B.G., Wilkinson, R.: Is all fit that glitters gold? comparisons of two, three and bifactor models for Watson, Clark & Tellegen’s 20-item state and trait panas. Pers. Individ. Differ. 144, 132–140 (2019)

21. Charte, D., Charte, F., [del Jesus], M.J., Herrera, F.: An analysis on the use of autoencoders for representation learning: fundamentals, learning task case studies, explainability and challenges. Neurocomputing 404, 93–107 (2020)

22. González-Ruiz, J.D., Peña, A., Duque, E.A., Patiño, A., Chiclana, F., Gónora, M.: Stochastic logistic fuzzy maps for the construction of integrated multirates scenarios in the financing of infrastructure projects. Appl. Soft Comput. 85, 105818 (2019)

23. Borja-Robalino, R., Monléon-Getino, A., Rodellar, J.: Deep learning algorithm for detecting floating marine macro litter in aerial images [estandarización de métricas de rendimiento para clasificadores machine y deep learning]. In: RISTI - Revista Iberica de Sistemas e Tecnologias de Informacao, vol. 2020, no. E30, pp. 184–196, 2020. Cited By 0

24. Peña, A., Bonet, I., Lochmuller, C., Patiño, H.A., Chiclana, F., Góngora, M.: A fuzzy credibility model to estimate the operational value at risk using internal and external data of risk events. Knowl. Based Syst. 159, 98–109 (2018)

25. Peña, A., Bonet, I., Lochmuller, C., Chiclana, F., Góngora, M.: Flexible inverse adaptive fuzzy inference model to identify the evolution of operational value at risk for improving operational risk management. Appl. Soft Comput. 65, 614–631 (2018)