# Online reservation systems in e-Business: Analyzing decision making in e-Tourism

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**Abstract:** *Tourism is one of the fastest growing industries worldwide and in general, the Internet continues to gain importance in the tourism sector. The study focuses on exploration of knowledge of online booking systems and on the views of local students-users concerning the booking rate based on these online systems. Another perspective of this project is to investigate the decision-making process (emotion-focused) that they follow in order to choose a tourist destination via online booking systems. For the purposes of this study, three scales were administered E-WOM and Accommodation Scale, Emotion-Based Decision-Making Scale and Trait Emotional Intelligence Scale. Then, survey data were collected, preprocessed and analyzed based on Data Mining techniques evaluating the results. More specifically, classification and association algorithms were utilized to manage to describe hidden patterns. E-Tourism will continue to be oriented towards the consumers and the technology that surrounds them, providing dynamic communication in electronic business.*

**Keywords:** *Online Booking Systems, Hotel Selection Factors, e-Tourism, Expert System*

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## 1 INTRODUCTION

The electronic commerce is defined as the activity of sale and marketing for products and services through an electronic system such as, for example, the Internet. It involves the electronic data transfer, the distribution management, e-marketing (online marketing), online transactions, electronic data changes, the automated inventory of used management

systems, and automated data collection. E-Tourism (electronic tourism) is a part of electronic commerce and unites one of the fastest development technologies, such as the telecommunications and information technology, hospitality industry and the management / marketing / strategic planning.

The aim of this research is to study student's views on the use of electronic booking tools and to investigate the decision-making process in travel planning via these electronic tools. The online booking platforms in the tourism sector are constantly increasing, as mentioned above. This method of booking benefits both tourists and hotel owners. Several researches have been made about identifying and satisfying the services provided by these modern booking systems on the part of travelers. Few have been made for this group of students with their peculiarities as a group. The aim is therefore to identify these views that determine their choices and the decision-making process they follow in travel planning through electronic tools. Also, the areas that are examined through current project (Western Greece and Ionian Islands) is considered as an ideal research population. that has been tourism all year round.

## 2   LITERATURE REVIEW

### 2.1. Use of Word of Mouth in Travel Planning

Word of mouth (WOM) communication refers to interpersonal communication among consumers concerning their personal experiences with a firm or a product. Previous studies illustrate the significance of WOM for consumers' purchase decisions especially within a service context. Because service products are intangible and cannot be easily described, consumers tend to rely on word of mouth from an experienced source to lower perceived risk and uncertainty. Word-of-mouth information search is greater in circumstances when a consumer is unfamiliar with a service provider, which is often the case for travel-related decisions. WOM has long been recognized as one of the important external information sources for travel planning. As the use of the Internet for travel planning becomes ever more prevalent, travel decision making processes are expected to become increasingly influenced by e-WOM.

Consumer reviews and ratings are the most accessible and prevalent form of e-WOM. Consumer reviews serve two distinct roles: First, they provide information about products and services; and, second, they serve as recommendations. Consumer reviews are perceived as particularly influential because they are written from a consumer's perspective and, thus, provide an opportunity for indirect experience (Sigala & Christou, 2002, 2014). They are also perceived as more credible than information provided by marketers. Online consumer reviews appear to play an increasing role in consumer decision making processes (Gretzel et al., 2012). Importantly, almost half of those whose purchasing decision was influenced by consumer reviews said that consumers' opinions actually caused them to change their mind about what they purchased. Clearly, online consumer-generated information is taking on an important role in online travelers' decision making (Stack et al., 2004).

### 2.2. Emotional Based Decision-Making Framework

Most theories of human reasoning and decision-making fall between two different positions. The first one argues that we make decisions in a way similar to that of solving problems in formal logic. According to this view, when faced with a problem, we form a list of all different options and their possible outcomes, and then we use logic in its best sense to perform a cost/benefit analysis that will provide us with the best possible choice. The second view considers reasoning and decision-making to be associative. That is, when confronted with a situation that requires a decision, we compare it to similar situations that have been encountered in the past and tend to act accordingly. Emotion-Based Decision Making that models important aspects of emotional processing, and integrates these with other models of perception, motivation, behavior, and motor control. A particular emphasis is placed on using some of the mechanisms of emotions as building blocks for the acquisition of emotional memories that serve as biasing signals during the process of making decisions and selecting actions such as the choice of a traveling destination via booking services (Christou, 2005; Christou & Nella, 2012). Although the two positions in decision-making framework vary in description and terminology seem to represent two streams: the first one - the logical thought based in rules and particular steps - and the second one - is more intuitive emotion-based form of reasoning. Additionally, most of the theories highlight that there is interaction between these two positions. Social behavior is determined by both reflective and impulsive processes which formulate behavioral decisions based on one hand on knowledge about facts and values (problem decision-making) and on the other hand on the impulsive system which elicits behavior through associations and motivational orientations (Chaudhry et al, 2012).

### 2.3. Emotional Intelligence of Travelers

Emotional intelligence, a type of social and personal intelligence, is important in managing interpersonal relationships and interactions, especially in the business sphere. Businesses that involve frequent customer contact and interaction, such as those in the field of tourism, can benefit from the application of multiple intelligences. The notion of emotional intelligence its applications to business is a vital theme in order to suggest an application to tourism, a sector based largely on the interaction between people. Emotional intelligence can be an effective tool and a benefit to tourist services, to reflection the tour operator's role as cultural mediator between tourists and host community, and to explore how emotional intelligence can help in this tourist/host relationship. From the literature review, emotional intelligence can be cultivated through education and training and can contribute to various areas of one's personal and professional life (Gkintoni et al., 2016). According to Salovey and Mayer, emotional intelligence allows the appropriate use of emotions enhancing thinking, problem-solving and adaptability to everyday life, promoting creative thinking and motivation. Another theorist of emotional intelligence, Goleman highlights that emotional intelligence is considered as a mixed form of intelligence that consists of cognitive ability and personality aspects. Goleman

indicates two dimensions: personal competencies – self-awareness, self-regulation, motivation and social competencies – empathy, social skills. Thereafter, theorists such as Law, Wong and Song refer that emotional intelligence is separate from personality and also is a notable predictor of job performance ratings (employee creativity). Creativity as a as a basic ingredient of emotional intelligence is beneficial in tourist services and is considered to be a key point for better promotion of tourist products to recipients who can emotionally moving through expert electronic applications (Chatzigeorgiou, 2017).

## 2.4. E-WOM and Accommodation Scale (E-WOM)

An online questionnaire was created using the E-WOM Accommodation Scale and was sent to the study sample by email and social networks. The questionnaire was primarily composed of closed-ended questions measured using a 7-point Likert-type scale. The sample was selected along purposive lines with a focus on identifying travelers who had recently read ORs when searching for information on accommodations while planning their holidays. This scale is analyzed in the following dimensions:

- Information timeliness refers to information that is up to date, current, and represents the state of the art of a product/service. In comparison to traditional WOM, ORs are available 24 hours a day. The most recent ORs are displayed first on COPs, so consumers can easily access the latest reviews published on specific accommodations.
- Information understandability refers to readability, interpretability, and ease of understanding, as well as language, semantic, and lexical expressions used by reviewers (Murphy, 2019).
- Information relevance refers to the extent to which a review is applicable and helpful for a task at hand and depends on different customer needs in specific situations ORs are relevant if they provide the kind of information a customer is looking for.
- Information accuracy is defined as the correctness in the mapping of stored information to the appropriate state in the real world that the information represents. The accuracy of information depends on travelers' perceptions that information is accurate, correct, believable, and credible.
- Value-added information is the extent to which information is beneficial and provides advantages from their use. ORs may empower a traveler's capacity to make informed decisions by providing information that is generally not easy to access through traditional marketing communications Chenini & Touaiti, 2018).
- Information completeness is defined as the extent to which information is of sufficient breadth, depth, and scope for the task at hand. Accordingly, a customer may judge a review as complete based on the degree to which information from ORs is comprehensive and exhaustive for booking accommodation.
- Information quantity is the extent to which the quantity or volume of available data is appropriate for a specific task Information quantity represents the number of ORs per accommodation; it is a peripheral cue to information

processing since it is a short cut that consumers may use to make a decision.

Product Ranking refers to a typology of categorical or numerical information based on travelers' overall (average) evaluation of accommodations in a destination. The ranking or numbers of stars represents the average customer's evaluation of accommodation and summarizes the proportion of positive, neutral, and negative reviews.

## 2.5. Emotion-Based Decision-Making Scale (EBDMS)

The Emotion-Based Decision-Making Scale (EBDMS) attempts to measure a person's tendency to rely upon emotions and "gut reactions" in making decisions. It has 10 items that use a 5-point Likert response scale. Five items are reverse-coded. Four items of the scale indicate the influence of feeling in decision-making process e.g. "I listen to my heart rather than my brain when making decisions". Likewise, four, three and two items were used to assess the role of emotions or feelings in performance evaluations, decision implementation and resource allocation process, respectively.

Figure 1. E-WOM Research Model
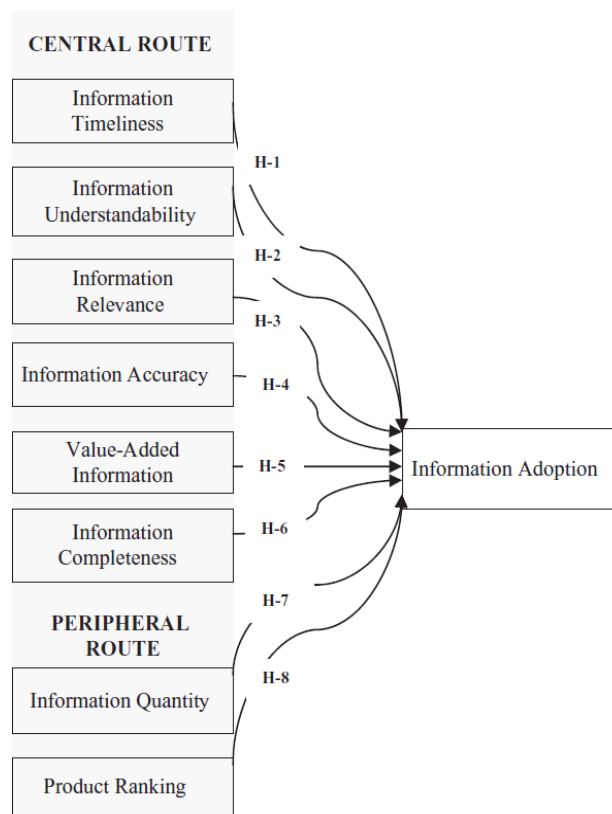


## 2.6. Trait Emotional Intelligence (EI)

For recording, tracing and evaluation concerning the emotional intelligence was used the standardized scale Trait Emotional Intelligence (TEIQue) which examines the Trait model of EI as proposed by K.V. Petrides (Petrides et al, 2006; Gkintoni, 2015). The Trait Emotional Intelligence Questionnaire is a self-report questionnaire that has been developed to cover the trait EI sampling domain comprehensively. Questionnaire measures of EI have been proliferating over the past few years, and it is important to

mention three advantages of the TEIQue over them to justify the focus of this research. First, the TEIQue is based on a psychological theory that integrates the construct into mainstream models of differential psychology. Second, the TEIQue provides comprehensive coverage of the 15 facets of the trait EI sampling domain. Several independent studies have demonstrated the ability of the TEIQue to predict criteria (outcomes) significantly better than other questionnaires. Third, the full TEIQue has excellent psychometric properties. Finally, the TEIQue has been used in numerous studies wherein the assessment of affective aspects of personality was required. These include research in the areas of neuroscience, relationship satisfaction, psychopathology, addictions, reaction time, general health, and behavioral genetics. The TEIQue provides an operationalization for the model of Petrides and colleagues that conceptualizes EI in terms of personality. The test encompasses 15 subscales organized under four factors:

- Well being: The Well-being factor comprises three different traits: Happiness, Optimism and Self-esteem. They measure how people judge their general level of life satisfaction.
- Self control: The Self-control factor describes how far people think they can control their impulses or are controlled by them. It comprises three different traits: Impulse Control, Stress Management and Emotional Regulation.
- Emotionality: The Emotionality factor comprises four different traits: Empathy, Emotion Perception, Emotion Expression and Relationships. Together they indicate how aware you may be of your own emotions and feelings, as well as those of other people.
- Sociability: The Sociability factor describes how comfortable people feel in different social contexts, from parties and social gatherings to formal business meetings.

Figure 2. Trait Emotional Intelligence Questionnaire (TEIQ)



## 3    METHODOLOGY

In this paper were applied Machine Learning and Data Mining methods in order to evaluate the booking behavior of Greek tourists using Emotion-Based Decision-Making Scale (EBDMS), the E-WOM and Accommodation Scale (E-WOM) and Emotional Intelligence Quotient (TEIQue) The methodology, that was adopted, consists of three concrete phases. During the first phase electronic questionnaires were created and posted through the website http://www.cicos.gr. Subsequently, data were collected and preprocessed from the questionnaires. The data set for analysis was consisted of demographics elements of responders, such as the gender, the birth-place, the place of present residence, educational background of both the respondents and their parents, professional occupation of parents and also of subscales of the EBDMS, E-WOM and TEIQue tests. During the third phase, the data set was analyzed based on Data Mining techniques and evaluate the results. More specifically, we utilized classification algorithms so as to manage to describe the hidden patterns underlying in the data. Decision trees are a powerful way in order to represent and facilitate statements analysis (psychological) principally, comprising successive decisions and variable results in a designated period.

### 3.1. Booking Behaviour Personal Traits of Greek Tourists during Economic Recession

Global financial community, it has been entered in a new and unknown economic phase. The huge crisis of the financial system, which has been arises in the developed countries results a risk of insolvency and has led to unstable economies and create millions of unemployed worldwide. Today, national economies are closely dependable each other. In addition, commercial and financial information is moving at breakneck speed through the Internet and mobile networks. It is true that unfavorable economic circumstances have a repercussion in the sector of travel industry which there is a need to be adjusted in an economic environment full of uncertainty, in order to address even the most demanding and needs of travelers. A useful element that travels industry, it is necessary to take into account is the different personality traits of travelers that interfere with their booking behavior and determine their decision-making towards their choice when they have to select a travel destination.

As far as the repercussion of personality traits in booking behavior, recent advances in personality psychology can help us predict tourist motivation. Traits are defined as enduring and stable patterns of behavior, attitudes, emotions, that vary between individuals. Traditionally, researchers were interested in understanding how individuals differ, and so they put a great deal of effort into discovering how to measure, map, and define personality traits. An effort was made through trait theory in order to define personality traits. Trait theory suggests that personality is made up of a set of quantitative measurable characteristics or units known as traits. Traits are pre-dispositional attribute and are relatively stable. Every personality has a unique combination of traits and given its stability, people with a given combination of traits can be expected to behave consistently across situations and over time. The development of trait theory is attributed

to the pioneering works of psychologists such as, Gordon Alport, Henry Odbert Raymond Cattell and Hans Eysenck.

## 3.2. Data Mining Techniques

Data Mining is an emerging knowledge discovery process of extracting previously unknown, actionable information from very large scientific and commercial databases. It is imposed by the explosive growth of such databases (Petrides & Furnham, 2006). Usually, a data mining process extracts rules by processing high dimensional categorical and/or numerical data. Classification, clustering and association are the most well-known data mining tasks. Classification is one of the most popular data mining tasks. Classification aims at extracting knowledge which can be used to classify data into predefined classes, described by a set of attributes (Revilla Hernández et al., 2016). The extracted knowledge can be represented using various schemas. Decision trees, "if-then" rules and neural networks are the most popular such schemas. A lot of algorithms have been proposed in the literature for extracting classification rules from large relational databases, such as symbolic learning algorithms including decision trees algorithms (e.g. C4.5) and rule based algorithms (e.g. CN2), connectionist learning algorithms (e.g. back{propagation networks), instance-based algorithms (e.g. PEBLS) and hybrid algorithms. Association rules can be used to represent frequent patterns in data, in the form of dependencies among concepts attributes. In this paper, we consider the special case, that is known as the market basket problem, where concepts-attributes represent products and the initial database is a set of customer purchases (transactions).

## 4    RESULTS AND DISCUSSION

### 4.1. Classification Trees

Classification methods aim to identify the classes from some descriptive traits. They find utility in a wide range of human activities and particularly in automated decision making. Decision trees are a very effective method of supervised learning. It aims is the partition of a dataset into groups as homogeneous as possible in terms of the variable to be predicted. It takes as input a set of classified data, and outputs a tree that resembles to an orientation diagram where each end node (leaf) is a decision (a class) and each non- final node (internal) represents a test. Each leaf represents the decision of belonging to a class of data verifying all tests path from the root to the leaf. The tree is simpler, and technically it seems easy to use. In fact, it is more interesting to get a tree that is adapted to the probabilities of variables to be tested. Mostly balanced tree will be a good result. If a sub-tree can only lead to a unique solution, then all sub-tree can be reduced to the simple conclusion, this simplifies the process and does not change the final result. Ross Quinlan worked on this kind of decision trees.

Decision trees are built in "ctree (Conditional Inference Trees)" by using a set of training data or data sets. At each node of the tree, "ctee" chooses one attribute of the data that most effectively splits its set of samples into subsets enriched in one class or the other. Its criterion is the normalized information gain (difference in entropy) that results from choosing an attribute for splitting the data. The attribute with the highest normalized information gain is chosen to make the decision. During the construction of the decision tree, it is possible to manage data for which some attributes have an unknown value by evaluating the gain or the gain ratio for such an attribute considering only the records for which this attribute is defined. Using a decision tree, it is possible to classify the records that have unknown values by estimating the probabilities of different outcomes. Ctree builds decision trees from a set of training data in the same way as ID3 or C4.5, using the concept of information entropy.

The training data is a set  of already classified samples. Each sample    consists of a p-dimensional vector , where the  represent attribute values or features of the sample, as well as the class in which  falls. At each node of the tree, "ctree" chooses the attribute of the data that most effectively splits its set of samples into subsets enriched in one class or the other. The splitting criterion is the normalized information gain (difference in entropy). The attribute with the highest normalized information gain is chosen to make the decision. The "ctree" algorithm then recurs on the smaller sublists. In order to specify the best result, it was necessary to fit the data to the model in a proper way. This task was carried away by changing and testing the controls of "ctree".

The parameters in the control function that were altered are:

- mincriterion: The value of the test statistic (for testtype == "Teststatistic"), or 1 - p-value (for other values of testtype) that must be exceeded in order to implement a split.
- minsplit: The minimum sum of weights in a node in order to be considered for splitting.
- mtry: The number of input variables randomly sampled as candidates at each node for random forest like algorithms.
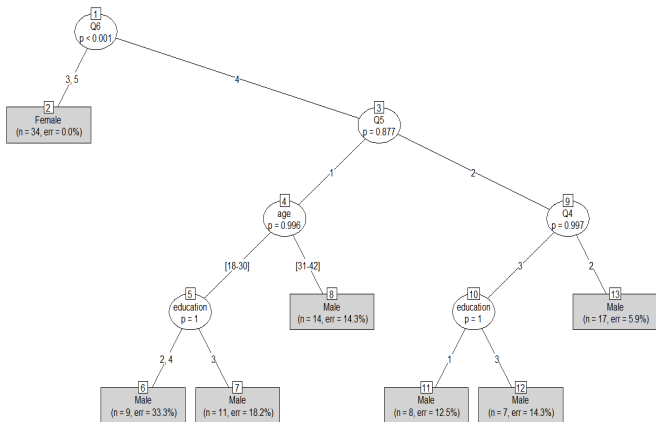- maxdepth: The maximum depth of the tree.



Figure 3. Tree 1
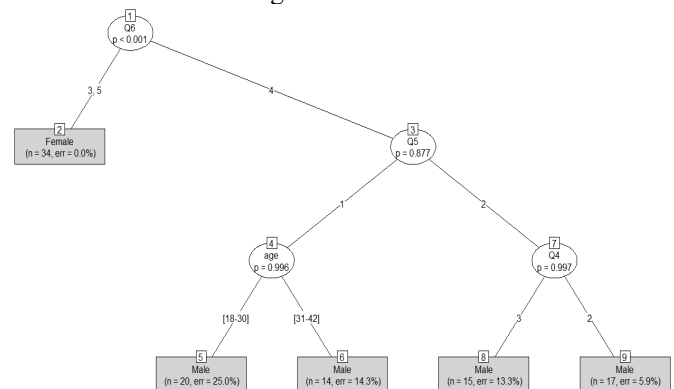
Note:
- *Depended variable: sex*
- *Independed variables:*
  - *'mincriterion' value: 0.0005*
  - *'minsplit' value: 10L*
  - *'mtry' value: Inf (Infinite)*
  - *'maxdepht' value: Inf (Infinite)*

### 4.2 Association Rule Learning

Association rule learning is a rule-based machine learning method for discovering interesting relations between variables in large databases. It is intended to identify strong rules discovered in databases using some measures of

interestingness (Zafiropoulos et al., 2015). They are usually required to satisfy a user-specified minimum support and a user-specified minimum confidence at the same time.

Figure 4. Tree 2



Note:
- *Depended variable: sex*
- *Independed variables: Rest*
  - *'mincriterion' value: 0.0005*
  - *'minsplit' value: 10L*
  - *'mtry' value: Inf (Infinite)*
  - *'maxdepht' value: Inf (Infinite)*

Apriori uses a "bottom up" approach, where frequent subsets are extended one item at a time, and groups of candidates are tested against the data. The algorithm terminates when no further successful extensions are found. Apriori uses breadth-first search and a tree structure to count candidate item sets efficiently. It generates candidate item sets of length k from item sets of length k − 1. Then it prunes the candidates which have an infrequent sub pattern. According to the downward closure lemma, the candidate set contains all frequent k-length item sets. After that, it scans the transaction database to determine frequent item sets among the candidates.

Figure 5. Graph diagram of 169 rules
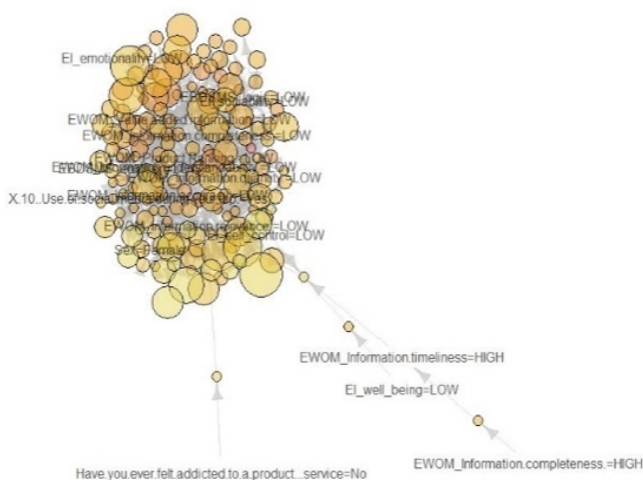


Association rules present association or correlation between item sets. An association rule has the form of A "B, where A and B are two disjoint item sets.

The Goal: studies whether the occurrence of one feature is related to the occurrence of others.
Three most widely used measures for selecting interesting rules are:

- Support is the percentage of cases in the data that contains both A and B,
- Confidence is the percentage of cases containing A that also contain B, and
- Lift is the ratio of confidence to the percentage of cases containing B.

## 4.3. Visualizing Extracted Rules

Visualization has a long history of making large data sets better accessible using techniques like selecting and zooming. In this paper we use the R-extension package "arulesViz" which implements several known and novel visualization techniques to explore association rules. Below, we represent the extracted rules in a variety of ways with different techniques (Christou, 2003; Maimon & Rokach, 2010).

Graph-based visualization offers a very clear representation of rules, but they tend to easily become cluttered and thus are only viable for very small sets of rules.

Figure 6. Parallel coordinates plot for 169 rules
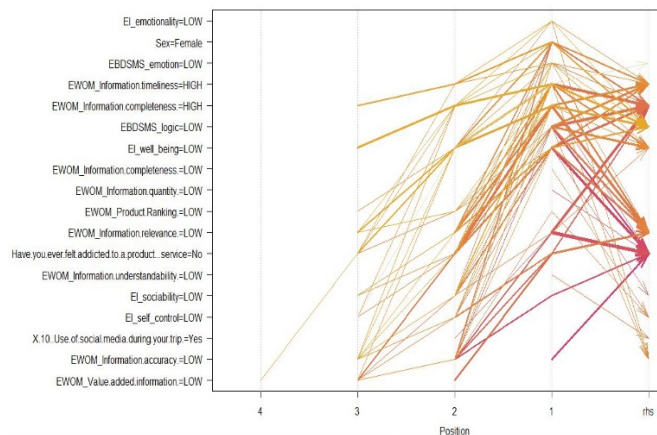


Parallel coordinates plots are designed to visualize multidimensional data where each dimension is displayed separately on the x-axis and the y-axis is shared. Each data point is represented by a line connecting the values for each dimension

## 5  CONCLUSION

This paper showed how the development of the Internet has significantly changed the market conditions of tourist organizations providing new tools for tourist marketing and management. It allows interaction between tourist organizations and users and as a result changes the entire process of development, management and marketing in tourism. By reviewing literature, one can notice that research in the field of e-Tourism still has many unanswered questions and that numerous questions are yet to be raised (Mensah & Mensah, 2018). As up to date, e-Tourism will continue to be oriented towards the consumers and the technology that

surrounds them, providing dynamic communication with tourist organizations. Through on-line booking systems, consumers have become very powerful and more able to determine the elements of tourist products especially students who are tourists of lower budget. Also, they have become more sophisticated and experienced, and thus have become harder to satisfy. Innovations in technology will help in interaction, personalization and networking therefore it is necessary to design strategies that will take advantage of the opportunity's ICT has to offer and turn them in favor of tourist organizations. There are many opportunities for further research in this field, because the complex nature of human behavior, the constant changes in the environment and the various e-technologies create many chances to tourist companies for innovative activities and use of new and still unrecognized opportunities (Nair & George, 2016). Given the mass of participants in tourist transactions, it is relatively easy and possible to collect a large number of data with the help of current technology.

Even repeated studies can be meaningful, because of the rapid changes in modern economy can induce new results. Technology offers many opportunities about which a lot has been written in this paper, but technology itself cannot provide answers to all questions if they are not asked. As the potential customers today are exposed to a (too) large number of options thanks to fast growing access to information, so are the service providers sometimes lost in the possibilities of the technology that extend the budget to various sides (Volgger et al., 2017). Although they all care to monitor the profitability of investments in each information channel, profit maximization is still missing in the numerous examples, and corrective measures are taken too late. It is evident that it is crucial to understand your customers, as well as to act in accordance with that knowledge (Misirlis et al., 2018). Knowing the cause and the consequence is, in simple terms, what should be achieved. In this direction many issues can and should be raised that question the relationship of the customers, their characteristics, the way they 'came' to the hotel (information search, booking and paying for accommodation) as well as various factors that led to their decision.

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