

Technographic segmentation using neural network at the Rainforest World Music Festival

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Abstract

Market segmentation is a marketing strategy practice that divides consumers into groups with varying needs and interests. This helps marketers to understand the subgroups' needs and to tailor their marketing efforts and product offerings to meet those needs. Event marketers are no exception. Although the most frequently used technique in identifying market segment, cluster analysis, yields unstable results and cannot handle large data sets, neural networks can overcome these problems. This study proposes the development of technographic segmentation of visitors attending a music festival based on their smartphone usage and a combination of psychographic and behavioral factors. This system classifies consumers based on motivations, use patterns, and attitudes towards technology. It uses cluster analysis to identify segments, and to demonstrate the applicability of using neural network for segmentation process.

Keywords:

Market Segmentation, Cluster Analysis, Artificial Neural Network

1 Introduction

The term market segmentation was first introduced by Smith (1956) to describe the process of dividing a large market into smaller segments based on consumers' needs, characteristics, and behaviours (Kotler & Armstrong, 2010). Since then, multiple techniques for segmentation have been proposed (Dolnicar & Leisch, 2004a; Liao, Chu, & Hsiao, 2012). In the events and tourism industries, researchers use several techniques to segment the visitors. These include conventional methods such as cluster analysis (Dolnicar, Grun, Leisch, & Schmidt, 2014; Y. H. Kim, Duncan, & Jai, 2016; C.-K. Lee, Lee, & Wicks, 2004; Müller & Hamm, 2014; Thompson & Schofield, 2009; Tuma, Decker, & Scholz, 2011), latent class analysis (Hamka, Bouwman, De Reuver, & Kroesen, 2014), and factor analysis (Cha, McCleary, & Uysal, 1995; Formica & Uysal, 1998). The evolution of technology has led to a rapid growth in the applications of soft computing technologies, which has introduced new segmentation techniques that involve fuzzy logic (D'Urso, Disegna, Massari, & Osti, 2016; Werro, Stormer, & Meier, 2006), self-organising map (Kiang, Hu, & Fisher, 2004), and Bayesian probabilities (Allenby & Rossi, 1998) that can also be used in segmenting visitors.

The literature identifies the non-hierarchical and hierarchical methods as the most popular cluster analysis algorithms (Dolnicar, 2003; Jain, 2010), and many researchers have acknowledged that cluster analysis could give the best segmentation results (Díaz, Gómez, Molina, & Santos, 2018; Dolnicar, 2003; Srihadi, Sukandar, & Soehadi, 2016). Non-hierarchical *k*-means is the most suitable clustering algorithm because it aims to group the observations around a centre (Prayag, Disegna, Cohen, & Yan, 2015). Additionally, it can provide high accuracy when the starting point and number of clusters are provided (Kuo, Ho, & Hu, 2002). However, the disadvantages include that the number of clusters needs to be determined in advance (Kuo et al., 2002), there is no single optimal solution for tap on the best clusters, and the stability of the results is not guaranteed (Arimond & Elfessi, 2001; Dolnicar, 2003). To date, the problem related to the number of clusters has not been solved even though researchers have proposed a number of heuristics (Dolnicar, 2002a).

The basic idea of cluster analysis is to merge individuals that belong to a particular segment that display similar behaviours. Nevertheless, the outcome may result in many possible solutions when repeating the results to evaluate their reliability. The researchers (Dolnicar, 2003; Ernst & Dolnicar, 2018) added that the stability issue has received little attention because in 67% of tourism segmentation studies, the investigation is not completed. According to Dolnicar, Grun, Leisch, and Schmidt (2014) and Ernst and Dolnicar (2018), assigning individuals to particular segments may produce instability and a random solution when respondents are added and the analysis is repeated. This has motivated researchers to overcome these limitations and to produce a stable cluster solution.

To contribute to the research on cluster analysis in market segmentation, this study has two objectives:

(1) To use technographic segmentation to develop a segmentation profile of visitors attending a cultural event;

(2) To demonstrate the applicability of neural networks in the segmentation process by using a two-stage algorithm for clustering based on Ward's method cluster analysis and neural network.

2 Literature Review

2.1 Market Segmentation in Tourism and Events

For the purposes of planning and managing demand-oriented policies, market segmentation is one of the most powerful tools available to tourism and events professionals. Smith (1956) defined market segmentation as a technique that involves subdividing a market into a smaller homogeneous group. There is no right or wrong way to segment a market. The concept of market segmentation relies on the assumption that consumers vary, which leads to a variety of demands (Dibb & Simkin, 2016). Nevertheless, identifying one to two segments that are relevant to the market is necessary to focus marketing resources, and the less important segments can be withdrawn from the market. Generally, market segmentation allows marketers to target the groups of customers that are more economically significant (Thompson & Schofield, 2009). Tourism and events are a natural extension of market segmentation analysis, as this analysis allows marketers to allocate resources more effectively in attracting different and unique groups of travelers and attendees (Kau & Lim, 2005).

The number and type of techniques used to conduct market segmentation have grown swiftly, since the introduction of market segmentation in the late 1950s (Dolnicar & Leisch, 2004; Liao, Chu, & Hsiao, 2012). Pesonen (2013) and Prayag, Disegna, Cohen, and Yan (2015) conducted valuable researches on market segmentation in tourism. They identified two major approaches for segmenting individuals: a priori segmentation occurs when a group is identified using pre-determined variables or classifications that are expected to yield heterogeneity among consumers. For example, in tourist segmentation, a priori segmentation could be based on cohorts or generations (e.g., baby boomers vs. millennials) or classifications based on the types of tourist.

Using this approach, Ignatov and Smith (2006) predefined three Canadian culinary tourist segments, which is the *food tourists*, *wine tourists*, and *food and wine tourists* based on motivations, and sociodemographic variables. Formica and Uysal (1996) examined the existing profiles of Umbria Jazz Festival visitors in Italy and obtained three segments according to motivational, sociodemographic and event behaviour characteristics. However, in earlier studies carried out by LaPage (1969) and Stynes and Mahoney (1980), the researchers failed to identify the right consumers using behavioural variables. Therefore, although a priori segmentation is valuable when the

segments are known, it requires further examination and more segments could exist than the predetermined segments due to the variations in behavior.

A posteriori segmentation refers to identifying segments through quantitative data analysis (Brida, Disegna, & Scuderi, 2014). Cluster analysis remains the most frequently used method and remains popular (Dolnicar, 2002; Jain, 2010; Y. H. Kim, Duncan, & Jai, 2016; M. Wedel & W. Kamakura, 2012). Generally, clustering methods are divided into three categories; non-overlapping algorithms, where each object is partly derived from a single segment (Tuma, Decker, & Scholz, 2011); overlapping algorithms, where objects might belong to more than one cluster (Wedel & Kamakura, 2002; M. Wedel & W. Kamakura, 2012); and fuzzy algorithms where each object is assigned by a degree of membership to a segment (Tuma et al., 2011). The hierarchical and non-hierarchical methods are two common approaches classified as non-overlapping algorithms. These methods have been used in marketing and tourism researches (Báez & Devesa, 2014; Dolnicar, 2002, 2003; Dolnicar & Leisch, 2004; Ernst & Dolnicar, 2018; Tuma et al., 2011).

The main objective of using the hierarchical methods is mainly reproducing the analysis to join the “closest” clusters to one or more observations, or to divide the “furthest” clusters. The most popular algorithm used in hierarchical clustering in tourism and events is Ward’s method (Dolnicar, 2003; Kruger & Saayman, 2016, 2017; Masiero & Nicolau, 2012). Yet the hierarchical method also faces challenges, including an inability to handle large amounts of data; a lack of flexibility, as classifications cannot be modified once individuals are assigned to a particular group, and sensitivity of the results to outliers (Kuo, Ho, & Hu, 2002). Moreover, hierarchical methods may believe objects or respondents to be clustered when this does not reflect the market reality (Wedel & Kamakura, 2002; M. Wedel & W. A. Kamakura, 2012).

Among non-hierarchical methods, *k*-means method is widely applied in the context of marketing studies focused on tourism, events and festivals (Amaro, Duarte, & Henriques, 2016; Arimond & Elfessi, 2001; Báez & Devesa, 2014; Dolnicar, 2002; Tuma et al., 2011). The main function of *k*-means is to group the observations around a centre to find a segment of the set of units in a certain number of clusters (Prayag et al., 2015). However, several drawbacks to the method remain unsolved. In a marketing study to determine the total stock that should be maintained and the profit margin for every item using the *k*-means method (Kusrini, 2015), it can be concluded that this method is not efficient when the data increase to several hundred data sets (Ernst & Dolnicar, 2018; Zhao, Deng, & Ngo, 2018). This causes instability when an individual is assigned to a different group when numbers of respondents are increased. Although many internal validity indexes have been developed such as the Silhouette and Dunn indexes which allow researchers to evaluate and select the suitable number of clusters (Handl, Knowles, & Kell, 2005), none has been widely accepted or applied efficiently in the tourism and events field (Brida, Disegna, & Scuderi, 2013).

2.2 Artificial Neural Network in Market Segmentation

Various techniques have been found in recent years in breaking down markets into meaningful segments. An artificial neural network (ANN) is a type of computing simulation of the biological neural network of the human brain. It is said that ANN is a reliable method in the field of recognising patterns and non-linear functions, as it is characterised by excellent interaction and connections between each of its elements (Kuo et al., 2002; Law, 1998). Perceptron, the most basic ANN (Boone & Roehm, 2002) was first mathematically described by McCulloch and Pitts (1943). An ANN consists of three connected layers: the input layer, hidden neuron layer, and output (Padil, Bakhary, & Hao, 2017). The concepts of implementing the ANN model can be considered in two stages, namely the training stage; and the testing stage (Padil et al., 2017).

Studies have applied ANN to segment Austrian tourists (Mazanec, 1992), West Australian senior tourists (J. Kim, Wei, & Ruys, 2003), and to conduct tourist market segmentation using linear and non-linear techniques (Bloom, 2004). One of the advantages of ANN is that no priori assumptions are made about the relationship being modelled (Fish, Barnes, & Aiken, 1995), the model is robust and the same network can be used in future for classifying new buyers (Venugopal & Baets, 1994). It has also been proven that a neural network can overcome the clustering results of multivariate techniques (Bloom, 2005; Prayag et al., 2015). Bloom (2005), J. Kim et al. (2003), Palmer, José Montaña, and Sesé (2006) and Venugopal and Baets (1994) revealed that ANN can analyse non-linearity (Mostafa, 2009). This suggests that ANN is a promising technique to overcome the limitations of cluster analysis mentioned above, which makes it ideal for the current study.

ANN segmentation begins with the training stage, when the network is trained to understand and trace the patterns of the structurally different changes based on a measured response. Through this training process, the network can recognise the relationship pattern between input and output and store the information in connection strength (Padil et al., 2017). After the training completes, subsequently, during the testing stage, the network is tested with other inputs which have not been used in the training and validation process. These two stages are considered a complete ANN and can be applied in damage detection (Padil et al., 2017). The field of perceptron and ANN was almost abandoned in the 1960s (Fish et al., 1995), but researchers realised that to solve the classification, pattern recognition, nonlinear feature detection, and nonlinear forecasting problems, ANN is the most suitable methodology (White, 1989).

2.3 Segmentation of Visitors to Cultural Events

This study focuses on the segmentation analysis of cultural events which has been the object of many studies. Tkaczynski and Rundle-Thiele (2011) reported that based on 120 articles, variety of techniques have been applied. Although studies using cluster analysis combined with other methods for two-stage analysis have been limited, the type of events examined has been broad. The commonality in these works achieving the objective of identifying the extent to which each segment is attracted by cultural events or local tourist attractions or tourists' technology usage behaviours.

Motivations that encourage visitors to attend international cultural-historical events are different from the motivations that attract people to attend community and rural festival. Formica and Uysal (1998), using cluster analysis to examine 23 motive items, generated two distinct segments: *enthusiast and moderates*. C. Lee and Lee (2001) obtained three segments from cluster analysis with a *high, medium, and low* level of cultural orientation and classified them using a 34-item list of motivations to attend a cultural festival. Prentice and Andersen (2003) labelled clusters of visitors who attended the Edinburg Festival based on three consumption styles by interviewing respondents: *serious consumers of international culture, British drama-going socializers, Scottish performing arts attenders, Scottish experience tourists, gallery-goers, incidental festival-goers, and accidental festival-goers*. C.-K. Lee, Lee, and Wicks (2004) reported four clusters of visitors to the Kyongju World Expo, South Korea, *seeking culture and family seekers, multi-purpose seekers, escape seekers, and event seekers* after examining 34 motivation items using cluster analysis. Chang (2006) revealed that motivation is the most important factor that attracts tourists to the aboriginal cultural festival in Taiwan, with visitors into *aboriginal cultural learner, change routine life travellers, and active culture explorers* with 26 items in five motivation dimensions examined using cluster analysis. Li, Huang, and Cai (2009) explored six motivational factors and generated five distinct clusters regarding the perception of the festival and attendees' intention to revisit it: *family travellers, event enthusiasts, loyal festival goers, escapers, social gathering lovers*. Finally, Brida et al. (2014) conducted a survey in three different cities in Italy during the Christmas period and generated three segments: *businesspeople, Christmas fans, and general tourists*.

The purpose of this study is to address the research gap by exploring the psychographic and behavioural segmentation of visitors to a cultural festival, and to classify the market into groups based on technographic segmentation using an ANN to overcome the limitations of cluster analysis.

3 Methodology

3.1 Population and Sampling

The target population of this study was people who used a smartphone while attending a music festival. The unit of analysis was attendees of the Rainforest World Music Festival held in the state of Sarawak on the 13th to 15th July 2018. Known as the largest music festival in Malaysia, this event received the Songlines Best International Festivals award from 2010 until 2015. *Songlines* is a UK based world music magazine. The festival showcased everything from traditional music to fusion and contemporary music with 37 performers from Malaysia, Spain, and Serbia and crowds of more than 20,000 people.

One thousand copies of a questionnaire were distributed to visitors using the convenience sampling approach. A total of 586 questionnaires were collected, but 64 were removed due to incomplete and missing data. Thus, 522 usable questionnaires,

representing a 52.2% response rate were collected during the three-day event. All 522 questionnaires were then analysed.

Table 1 describes the socio-demographic profile of the respondents who participated in this study. Most respondents were male (54%) and aged between 21-30 years while 79% of respondents attended the event with their friends and only 21% attended alone. In terms of smartphone usage, the majority of them, 53% are using a pre-paid mobile plan, and 47% were post-paid users. More than three-quarters, 76% were using only one smartphone, 20% used two smartphones, and 4% used three smartphones.

Table 1: A socio-demographic profile of respondents

	Item	n	%
<i>Gender</i>	Female	238	45.6
	Male	284	54.4
	Total	522	100.0
<i>Education</i>	SPM/A-Level	168	32.2
	Diploma	140	26.8
	Degree	158	30.3
	Master/PhD	56	10.7
	Total	522	100.0
<i>Age</i>	Below 20	127	24.3
	21 - 30	257	49.2
	31 - 40	115	22.0
	41 - 50	19	3.6
	Above 51	4	0.8
	Total	522	100.0
<i>Income</i>	Less than RM 1500	250	47.9
	RM1501 - 3000	139	26.6
	RM3001 - 4500	57	10.9
	Above RM 4500	76	14.6
	Total	522	100.0
<i>Traveling Partner</i>	Single	110	21.1
	My partner	86	16.5
	My family	59	11.3
	Group of friends	267	51.1
	Total	522	100.0
<i>Mobile Plan</i>	Post-paid	247	47.3
	Pre-paid	275	52.7
	Total	522	100.0

	1	398	76.2
<i>No. of</i>	2	102	19.5
<i>Smartphone</i>	3	22	4.2
	<i>Total</i>	522	100.0

3.2 Data collection procedures

A set of variables on motivations, attitudes, and usage patterns was generated from research on the use of technologies such as the Internet, smartphones, computers, and social media. The questionnaire was pre-tested for face validity with two experts, one academia and one from the industry. Later, the bilingual (Malay and English) questionnaire was pilot tested at a small cultural festival to refine the list of items. The validity of dimensionality and inter correlation was evaluated by exploratory factor analysis. The researcher invited lecturers with doctoral degrees in the areas of event marketing and tourism to obtain industry-related feedback and suggestions regarding amendments of instruments developed. Once respondents completed and returned the questionnaires, they received a postcard from *Tourism Malaysia* and a packet of candy as a token of appreciation.

Table 2 shows the results of the Cronbach’s alpha test conducted to assess the internal consistency of the items.

Table 2: Reliability Analysis of the Variables

Variables	Dimensions	Cronbach’s alpha
Motivation	<i>Perceived usefulness</i>	0.831
	<i>Excitement</i>	0.669
	<i>Ease of use</i>	0.708
	<i>Socialisation</i>	0.889
Attitude	<i>Emotions</i>	0.809
	<i>Actions</i>	0.886
	<i>Beliefs</i>	0.829
Usage pattern	<i>Frequency</i>	0.880
	<i>Total</i>	0.952

The Kaiser-Meyer-Olkin measure of sampling adequacy indicates whether the correlations between variables can be explained by other variables in the data set (Pallant, 2013; Sarstedt & Mooi, 2014). Kaiser (1974) suggested that the threshold value should be above 0.5; however, a value of 0.8 and higher can be labelled as perfect. The most common and reliable criterion is the use of eigenvalues in extracting factors. Therefore, in this research, all items with a factor loading above 0.5 were included, whereas all items with a factor loading lower than 0.5 were removed. After items with a factor loading less than 0.5 were eliminated, the remaining items were factor analysed again using varimax rotation. Thirty-nine items were removed and 37 remained.

Table 3 shows the results of factor analysis, using the Kaiser-Meyer-Olkin (KMO) and varimax rotation procedures, of 76 variable items to delineate underlying dimensions of the variables associated with the Rainforest World Music Festival.

Table 3: Results of Kaiser-Meyer-Olkin (KMO) and Bartlett’s Tests

Test	Measure	Result
KMO	Sampling Adequacy	0.542
	Approx. χ^2	9374.783
Bartlett’s Test of	Sphericity (Malhotra, Birks, Palmer, & Koenig-Lewis, 2003)	2850
	Sphericity (sig.)	.000

4 Findings

4.1 Multivariate cluster analysis

This statistical analysis research involved two phases. In the first phase, cluster analysis was applied to obtain the best number of cluster results to be considered in the neural network as the output. In the second phase, a neural network was applied to evaluate the differences between the actual and prediction results on segmentation.

The implementation of a neural network involved three stages: training, testing, and validating the data. During the first phase, the researcher applied Ward’s hierarchical cluster technique (Hair, Black, Babin, Anderson, & Tatham, 2006) as previous studies recommended that this method is suitable for separation techniques (Everitt, 1993; Hair et al., 2006; Morey, Blashfield, & Skinner, 1983) using SPSS software. This approach has been widely applied by many researchers to segment visitors attending events and festivals (Kruger & Saayman, 2016, 2017; J. J. Lee & Kyle, 2014).

To explore the natural structure of the data, the researcher applied Ward’s method with Euclidean distances to avoid any priori view of which data points should fall into which segment. The clustering began with 76 features. The lowest significant discriminators were removed, and then testing was conducted for 38, 37, and 36 features across three to five clusters. Based on the results, four clusters across 37 variables yielded the greatest classification among groups. Table 4 presents the multivariate clustering result based on smartphone usage patterns during the music festival.

Table 4: Multivariate cluster result

Variables	Segment 1	Segment 2	Segment 3	Segment 4
Motivations	3.76	3.51	3.11	3.45
Attitudes	2.8	3.27	3.27	3.27
Usage Pattern	2.37	2.32	3.08	1.61

4.1.1 The feed-forward back propagation neural network architecture

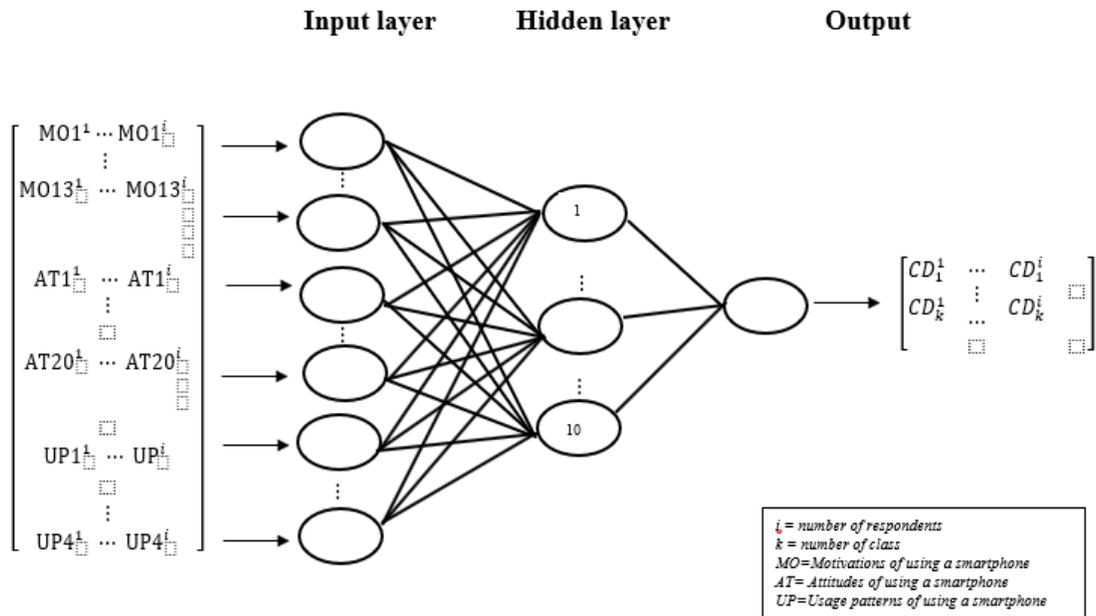


Figure 1: Multilayer perceptron ANN architecture

Figure 1 illustrates that the predictions of each segment classification from the neural network is comparative to the actual values. Thus, the forecasting output from a neural network is accurate with an acceptable margin of error. The low mean percentage error illustrates that the deviations between the estimated values analysed by the neural network and the actual values are very small.

Figure 2 illustrates the testing results of the neural network specifically the predictions of the number of classes compared to the actual results obtained using Ward's method. The segments were classified into four categories. Thirty-seven pieces of input data were analysed with 10 hidden neurons and single output. Based on the bar chart in Figure 2, the error function is presented. The Mean Squared Error (MSE) analysis was carried out on the results as shown in Figure 2. The Levenberg-Marquardt algorithm was used during the training and testing stage and the ANN training performance reached 0.20367 at the end of 7 epochs. Therefore, this result indicates that ANN is reliable in predicting the segmentations of visitors attending cultural events.

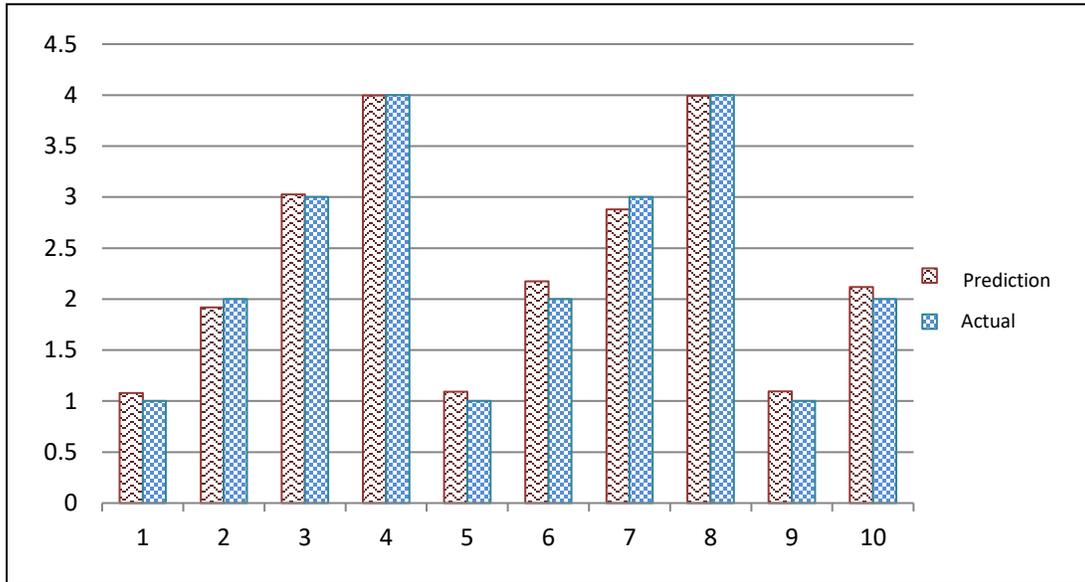


Figure 2: Actual and prediction results

4.1.2 Characteristics of Music Festival Visitors

The analysis reveals four distinct market segments. The main psychographic and behavioural characteristics based on motivations, attitudes and usage pattern on smartphone are as follows:

The fuse blower. This is the average users who refuse to conduct any online transactions, stream content and make purchases on the paid apps. While this group achieves the second highest scores on motivations and attitudes, they score low on usage patterns. They have a moderate knowledge of the technology use.

The plug puller. These individuals consider the benefits of and have the expertise to technology, but they are hesitant to share any information on any kind of social networking sites. Although this group has high motivations and awareness of the basic benefits of using a smartphone, they have the lowest score on both attitudes and usage patterns. They also believe that if they conduct online transactions, post photos or updates about themselves, they lose their privacy.

The alarm hitter. These people are ranked the most highly motivated, with the highest attitude and usage pattern scores. This group is quick to stream live content and update their statuses on social networking sites. They do not think about the consequences of updating information before they decide to post. Alarm hitters are well versed in the current use of technology and forget that technology might be harmful to them.

The technology ticker. These festival attendees love letting their friends know about their current activities and share them on social networking sites. Members of this group

do not believe that technology is a way to relieve boredom; therefore, this group scores the lowest on motivations. They can survive, even if they are disconnected from technology. This group believes advertising and promotions will not influence their purchasing decisions.

5 Conclusion

This study has investigated the use of a neural network in segmenting the market of people attending to a cultural festival by measuring the motivations, attitudes, and usage patterns of smartphone users. The results indicate that it is possible to apply an artificial neural network to predict market segmentation. This is in line with the previous study on estimating the room occupancy rates compared to the actual room occupancy rates in Hong Kong using the artificial neural network (Law, 1998), and J. Kim et al. (2003) identified neural network as one of the techniques to be employed for the segmentation of senior tourists in Australia. Both findings revealed that the performance of neural network is outperformed compared to other commonly used forecasting approach such as multiple regression.

Generally, the results of this study indicate that neural networks can be applied for segmentation purposes. The neural network is superior to the traditional statistical methods in forecasting and predictions can recognise the higher-level features, such as intra-correlation or serial correlation, of a training set. Furthermore, the neural network yields an outstanding performance on standard statistical models in forecasting with a small size training data set and random noise from the data (J. Kim et al., 2003). Neural network models involve a larger number of parameters, which include the traditional statistical methods, where the introduction of non-linear terms and interactions might increase the degrees of freedom to some extent. Furthermore, neural network models are more flexible in analysing incomplete or missing data. In summary, this preliminary result seems to encourage further investigation of using neural networks in segmentation research.

Our study indicates that neural networks can be applied not only in the engineering and computer science fields but also in the social sciences, particularly in market segmentation. The ANN technique appears to efficiently segment the types of consumer markets that retailers (Boone & Roehm, 2002; Wray, Palmer, & Bejou, 1994), tourism vendors (J. Kim et al., 2003; Mazanec, 1992), and online vendors (K.-j. Kim & Ahn, 2008) are likely to encounter. Practitioners and policy makers can apply neural networks as an alternative to improve the traditional statistical methods and forecasting models for future planning activities.

6 Limitations and directions for future research

The initial objective is to test the reliability of neural networks in forecasting related to the events industry in Malaysia. Currently, cultural events in Malaysia are facing the challenges related to the changing of the global tourist market due to the technological

advancement, competition from neighbouring countries, and the political issues that arose during 2014 due to flights MH370 which disappeared, and MH17 which crashed. Future research is possibly to be conducted on other festivals in Malaysia. Additionally, another potential area for future research is identifying the classification number of each segment using an ANN by identifying the error (s) that occurred in this research. Error analysis should be calculated in order to determine how accurate and precise a measurement is between predictions and actual value.

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