FACTORS RELATING BEHAVIOURAL PATTERNS ON FILM VIEWERS IN EAST MALAYSIA

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Abstract

Market studies in the field and issues of social sciences, such as on the behavioural patterns on film viewers have not been explored extensively. In the advent wave of competitive global businesses, these behavioural patterns by film viewers have to be studied and analysed with contemporary perspectives, hence determining the choice of films shown. This study thus would help existing and budding film producers and directors to understand the behavioural patterns of film viewers. In addition, it can strategically guide the film makers to lure the cinema fans back to viewing films be it in the cinemas or at home. This paper thus expounds the concept of mathematical modelling in the methodology of social sciences using the multinomial logistic regression (MLR) technique. This technique is executed to determine the significant factors on these behavioural patterns, namely focussing on the data filtering and cleaning, factor analysis, data transformation, model-building development, multicollinearity remedials and the removal of insignificant factors. The various variables used would include the viewing frequency, encouragement, motivation, perception, gratification and genre. The best model (M1.0.2) is obtained based on the deviance goodness-of-fit statistics via the modified eight selection criteria (M8SC) that thus relates the frequency of film viewers with significant factors, namely motivation from interest, family and boredom. This study hence would give an insight to the sustainable factors contributing to the sustainability of the Malaysian film industry.

Keywords: mathematical modelling, behavioural patterns, multinomial logistic regression (MLR), model-building, sustainability factors, film industry.

1 INTRODUCTION

Malaysia’s leading film agency, Nasional Film Development Corporation Malaysia (FINAS) has defined that Malaysian films are films that are produced in Malaysia, or in any other places, but produced by Malaysians, or by companies registered in Malaysia with majority of its shareholders are Malaysians. With its two main objectives i.e. to develop the film industry to an international level, and to boost the growth of the local film industry as a destination centre for films in this region. Bernama (2014) had stated that more local film producers are encouraged to produce films which portray the social and cultural aspects of the people, while Mahadi (2010), suggested that more Islamic perspectives should be depicted in films. The management of the film development agency in Malaysia needs to set clear publishing guidelines and not confined to focussing on strategies based on increasing cinema tickets collection and number of films produced.

The Department for Culture, Media and Sports (DCMS) had stated that one of the 13 sectors comprising the creative industries is the film industry (DCMS, 1998). According to DeFillippi & Arthur (1998), film making and production were very closely related to the new economic millennium whereby natural-based projects and large management scale involving the exploitation of ideas from creative individuals and counterparts. However, current research had shown that countries in Asia and less-developed countries had emerged as major film producers. India is an example whereby a less-developed country has become the world’s largest film producer (UNESCO, 2006; UNCTAD, 2008), with a production of about one thousand films annually which is more than by Hollywood itself. This phenomenon can also be seen in South Asia where the film industry of Korea is amongst the most successful film industry and contributes to the country's economic growth. The success of the Korean film industry is partly due to the support from their government. Hence, the government's role and support are of prime importance in ensuring the success of the film industry (Rampal, 2005).

2 LITERATURE REVIEW

According to Pardoe (2005), it was difficult in the decision-making processes of deciding the award winners, especially in the main Oscar winning awards- Best Picture, Best Director, Best Male Actor and Best Female Actress which had been nominated annually. He believed that Oscar awards panel of judges had not exploited the full use of the statistical report, and hence the award winning results were not always empirical. He thus had suggested the methods on how to choose the potential candidates from each category of the academy awards (Pardoe, 2005). Discrete choice models were used to compare the Bayesian method with the maximum likelihood estimator. His research had answered the difference in opinions on the Oscar award winning results, and thus had placed the award winners in a better position of their acting career. In addition, it had also given a positive message on role of mathematics to those involve in the media and the film industry.

Akira (2012) had a surprise finding in his research on forecasting the success or failure of a blockbuster box office film using a mathematical model. His research in the '*The "Hit" Phenemonon : a Mathematical Model of Human Interactions as a Stochastic Process'* had used the effects of advertisements and verbal communication to form a model that had successfully been able to predict how the outcome of each film which was shown at silver screen. The conventional model which was exponential in nature was only able to predict the sale of tickets in viewing films by cinema goers after being linearized using logarithmic transformation, and factors representing film qualities such as, advertising budget, main role of leading actors, strength of verbal combination, actors role, script quality and others.The expected outcome can be seen in the increased interest in watching films through the funds used for film advertising and verbal communication through the WebPages and links.

Mustafa (2002) had also studied the trends of going to the movies and hence investigated the factors which influenced the Egyptian audiences choice of motion pictures. He had identified whether watching movies were still popular to general Egyptian public and had discovered whether there were other ways of viewing a movie. The research findings had benefited the Egyptian film production and distribution companies in reaching their audiences and motivate them to go and see the film.

Dyna (2012) had done an exploratory research using a qualitative approach to capture the complexity of factors that influence the selection decision making process of films in theatres and in the cinema context. A qualitative approach was adopted using the focus group discussion where at least five factors were identified, namely: marketing communication (i.e. advertising and publicity), neutral information source (i.e. film reviews and word of mouth), film characteristics (i.e. genre, director, remake production, country of origin, actor, adaptation works, production house, title), content (for example, story, objectionable content and technology) and ease (like screening schedule and title).

3 METHODOLOGY

3.1 Data Collection

Data samples were collected using questionnaires that is, focussing on the viewers in East Malaysia (Sabah and Sarawak). The questionnaires comprised of two parts with 117 items. Part 1 of 23 items represented the demographic profiles of respondents, while part 2 represented the film viewers perceptions and factors to watch films. Significant demographic factors would include region, state, location, age, gender, ethnicity, religion, frequency, education and salary. In this study, there were 1,337 respondents, comprised of 647 males and 688 females, and aged between 7 to 68 years.

3.2 Modelling Technique Using Multinomial Logistic Regression (MLR)

According to Devore (2012), multiple regression is an extension of the simple linear regression consisting of two or more independent variables $(W_1, W_2, W_3, ..., W_k)$ relating to the dependent variable (Y), while Agresti (2007) stated that with dichotomous categorical data, the binary logistic regression is more appropriate,

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giving a general equation as in equation (1) : $Y = \ln\left(\frac{P_i}{1-P_i}\right) = \Omega_0 + \Omega_1 W_{1i} + \Omega_2 W_{2i} + \ldots + \Omega_k W_{ki} + u_i$ ……(1.0) for I=1,2, …, n with $P_i = \frac{e^{\Omega_0+\Omega_1 W_{1i}+\Omega_2 W_{2i}+\ldots+\Omega_k W_{ki}+u_i}}{1+e^{\Omega_0+\Omega_1 W_{1i}+\Omega_2 W_{2i}+\ldots+\Omega_k W_{ki}+u_i}}$. Equation (1.0) shows that *Y* is the dependent variable, W_j as the j-th independent variable, Ω_0 is the constant regression coefficient, Ω_j is the j-th regression coefficient of independent variable W_j, u_j is the random residuals and *k* is the number of independent variables where *j =1, 2, …, k.* All these variables were categorical or qualitative; hence, each independent variable would be accompanied by a corresponding dummy variable denoting the factors affecting the behavioural patterns of the film viewers (Noraini *et al*., 2014). According to Hosmer & Lemeshow (2000), the multinomial logistic regression (MLR) model would involve the dependent variable to be in a nominal scale where it is parameterized to form two logistic regression equations based on the maximum likelihood estimation.

3.3 Data Cleaning and Filtering

Modelling processes were developed encompassing data sampling, data filtering and rescaling, variable selection using factor analysis, variable transformation into dummies and finally model-building procedures so as to obtain the best model. Data cleaning and filtering would involve two stages, i.e. filtering through column by column and row by row methods. Information which had no numerical values, data with similar categories and unexplained data, such as data with negative values would have to be removed. This will avoid errors during model building and consequently, the misinterpretation of its outcome.

3.4 Factor Analysis and Statistical Tests

According to Huck (2012), factor analysis is a statistical procedure performed to reduce the number of variables in a data set besides relating their relationships. While according to Hair *et al.* (1995), factor analysis is a statistical method which is part of the multivariate analysis. Its main objective is to identify the basic structure in a data matrices; thus the correlations between the variables known as factors. However, Zainodin *et al*.(2011) has considered factors as variables. There were 117 variables that could be used as independent variables in this study.

The number of possible models without interactions can be calculated using the following formula: $N = \sum_{j=1}^{q} C_j^q$ … (2.0) where '*q*' is the number of independent variables and *j=1,2,…,q*. In this paper, q=5, hence, the total models without interactions are: $N = C_1^5 + C_2^5 + C_3^5 + C_4^5 + C_5^5 = 31$ models … (3.0). Gujarati & Porter (2009) had implicated that the number of observations (n) has to be greater than the number of parameters (NP) so as to satisfy the regression assumptions. Zainodin *et al.* (2014) had shown the formula used to calculate the number of parameters, hence implying the appropriateness of a regression model.

3.5 Model-Building

Zainodin *et al.* (2011) had shown the four phases in model-building while the multicollinearity remedial techniques and coefficient test on variables with absolute correlation coefficients more than 0.95 (i.e.$|r|$≥0.95) had been carried out as in Noraini & Zainodin (2013). However, in this study, the near perfect multicollinearity existed and its removal procedures would be illustrated. The coefficient test of the multinomial logistic models was carried out to remove any insignificant factors that have p-values greater than 0.05 (Zainodin *et al*., 2014). The likelihood ratio test is based on the model fitting criteria of the -2 log likelihood of the reduced model and the p-value of the Chi-square test. The removals of insignificant factors were carried out until the factors that remain have p-values less than 0.05.The best model was then chosen from the selected models that remained based on the deviance statistics of the Modified Eight Selection Criteria (M8SC). The model which had the minimum and satisfied most the selection criteria would be the best.

4 RESULTS AND DISCUSSIONS

Initially, the data filtering and screening were performed, with 38 items had been removed by the column method leaving a total of 79 items. Using the row method, 305 respondents with 21 items had remained

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based on location. Factor analysis based on the principal components in a varimax rotation of 0.3 was then carried out, resulting in seven components with eigen values greater than one were chosen.

The first component containing six factors was chosen for analysis, and was represented by the symbols Y, A, B, C, D and E as shown in Table 1. In this paper, the factor on frequency in film viewing was chosen as the dependent variable (Y_i), while the other five factors were the independent qualitative variables. The chosen variables were frequency in viewing film (dependent variable) while encouragement, motivation, perception, gratification and genre respectively were the independent variables. Each qualitative factor had its own respective transformed dummy variable. These selected variables were also similar to other past researches on film viewing patterns.

Table 1: Summary and Symbols of Research Factors

Factor	Description	Category	Variable Type
Y: Frequency in Viewing Films	Frequency of One time or less in a month	Y1	Qualitative
	Frequency of 2 times in a month	Y2	
	Frequency of 3-4 times in a month	Y3	
	Frequency of 5 times or more in a month	Y4	
A: Encouragement [Y_I =f(W_1)]	A_1 : Encouragement- Interest A_2 : Encouragement-Family A_3: Encouragement -Friends A_4: Encouragement -Boredom A_5: Encouragement -Routine	1=Not Important 2=Less Important 3=Slightly Important 4=Important 5=Very Important	Qualitative
B: Motivation [Y_i =f(W_2)]	B_1:Motivation-Theme B_2:Motivation-Director B_3 :Motivation-Actor/Actress B_4:Motivation-Reviews/Promotion B_5 :Motivation-Human Influence	1 =Not Important 2 =Less Important 3=Slightly Important 4 =Important 5 =Very Important	Qualitative
C: Perception [Y_i =f(W_3)]	C_1:Perception-Ticket Price C_2:Perception-Location C_3:Perception-Clean C_4:Perception-Showing Times C_5:Perception-Foreign Film	1=Not Suitable 2 =Less Suitable 3=Slightly Suitable 4 = Suitable 5 =Very Suitable	Qualitative
D: Gratification [Y_i =f(W_4)]	D_1:Gratification-Emotion/Soul D_2:Gratification-Entertainment D_3:Gratification-Inspiration D_4:Gratification-Information D_5:Gratification-Cultural/Historical D_6:Gratification-Relationship	1 =Not Important 2 =Less Important 3=Slightly Important 4 =Important 5 =Very Important	Qualitative
E: Film Genre [Y_i =f(W_5)]	E_1:Genre-Action E_2: Genre-Comedy E_3: Genre-Romantic E_4: Genre-Drama E_5: Genre-Animation E_6: Genre-Science Fiction E_7: Genre-Horror E_8: Genre-Thriller	1 =Not Suitable 2 =Less Suitable 3=Slightly Suitable 4 = Suitable 5 = Very Suitable	Qualitative

Referring to equation (3.0), since there were five independent qualitative/categorical variables $(W_1, W_2, W_3, W_4, W_5)$, hence the total numbers of models without interactions were 31 models. Taking model M6:[$f(W_1, W_2)$] for illustration purposes:

$$M6: Y_5 = \Omega_0 + \delta_1 A_1 + \delta_2 A_2 + \delta_3 A_3 + \delta_4 A_4 + \delta_5 A_5 + \lambda_1 B_1 + \lambda_2 B_2 + \lambda_3 B_3 + \lambda_4 B_4 + \lambda_5 B_5 + u_j \text{ …....(4.0)}$$

where *Y* as the dependent factor on frequency in viewing film, A_j are the j^{th} independent variables of factors on 'Encouragement' with *j=1,2,…,5*, and B_j are the j^{th} independent variables of factors on 'Motivation' with *j=1,2,…,5.* The j^{th} regression coefficients were given by $\delta_j, \lambda_j, \tau_j$ for the independent variables, A_j and B_j

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respectively. The random error was given by ‘u_j’, and ‘k_j’ is the total number of independent categorical variables with respect to each factor for *j =1, 2, …, k.*

The presence of perfect and near-perfect multicollinearity (NPM) in the models could be identified when the variance of the each item according to category were calculated. Perfect multicollinearity existed when the variance was large and approached the value of 1, while the near-perfect multicollinearity existed when the variance was minimum and as near 0. In this work, B_1 was removed since it had the highest variance. Model M6.0.0 then became model M6.1.0 after a multicollinearity source factor (B_1) being removed.

Next, the coefficient test was performed on all the models that after had undergone the multicollinearity remedial test. Using model M6.1.0 for illustration purposes on the coefficient test of the likelihood ratio, Table 2 showed that factor B_5 has the highest p-value of 0.576. Hence, factor B_5 was removed from model M6.1.0 and the model was then rerun to become model M6.1.1.

Table 2: Coefficient Test of Likelihood Ratio in Model M6.1.0

Model M6.1.0	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	p-value
Intercept	446.870	27.774	3	0.000
A1	428.043	8.947	3	0.030
A2	429.857	10.761	3	0.013
A3	422.123	3.027	3	0.387
A4	427.226	8.129	3	0.043
A5	427.728	8.632	3	0.035
B2	421.216	2.120	3	0.548
B3	424.774	5.678	3	0.128
B4	421.396	2.300	3	0.512
B5	421.081	1.985	3	0.576

Table 3 showed that factor B_2 in model M6.1.1 has the highest p-value of 0.552. Hence, factor B_2 was removed and model M6.1.1 was then rerun to then become model M6.1.2.

Table 3: Coefficient Test of Likelihood Ratio in Model M6.1.1

Model M6.1.1	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	p-value
Intercept	375.355	26.860	3	0.000
A1	357.819	9.324	3	0.025
A2	358.826	10.331	3	0.016
A3	352.174	3.679	3	0.298
A4	356.449	7.954	3	0.047
A5	356.752	8.257	3	0.041
B2	350.593	2.098	3	0.552
B3	353.831	5.336	3	0.149
B4	351.504	3.009	3	0.390

Table 4 showed that factor A_3 in model M6.1.1 has the highest p-value of 0.299. Hence, factor A_3 was removed and model M6.1.2 was then rerun to become model M6.1.3.

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Table 4: Coefficient Test of Likelihood Ratio in Model M6.1.2

Model M6.1.2	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	p-value
Intercept	319.861	26.647	3	0.000
A1	302.459	9.244	3	0.026
A2	306.316	13.102	3	0.004
A3	296.889	3.674	3	0.299
A4	301.076	7.862	3	0.049
A5	301.391	8.177	3	0.042
B3	353.831	5.336	3	0.149
B4	351.504	3.009	3	0.390

Subsequent six removals of insignificant variables (B_5, B_2, A_3, B_4, B_3 and A_5) had been carried out on model M6.1. Referring to model labelling (Zainodin *et al.,* 2011; Noraini & Zainodin, 2013), model M6.1 thus became M6.1.6 which indicated there was one multicollinearity source variable (B_1) being removed and six insignificant variables had been removed. The elimination process can be given as: M6.1.0=> M6.1.0=> M6.1.0=> M6.1.1=>M6.1.2=>M6.1.3=>M6.1.4=>M6.1.5=>M6.1.6. It can be seen in Table 5 that the significant factors that remained in the model had all the p-values less than 0.05. These modelling procedures are illustrated in detail (Zainodin *et al.,* 2011; Noraini & Zainodin, 2013). Remedial and model-building phases were performed so that the models that remained were free from multicollinearity and insignificant factors.

Table 5: Coefficient Test of Model M6.1.6

Model M6.1.6	*Model Fitting Criteria*	*Likelihood Ratio Tests*		
	-2 Log Likelihood of Reduced Model	*Chi-Square*	*df*	p
Intercept	103.419	27.945	3	.000
A1	91.160	15.686	3	.001
A2	87.003	11.530	3	.009
A4	92.429	16.955	3	.001

All the possible 31 models had undergone the statistical tests in the methodology section. Finally the best model was chosen based the modified eight selection criteria (M8SC) (Ramanathan, 2002) and is given by model M1.0.1 in equation (5.0).

$$\mathrm{M1.0.2} = \Omega_0 + \delta_1 A_1 + \delta_2 A_2 + \delta_4 A_4 \quad \text{...(5.0)}$$

Substituting the values of the regression coefficients, equation (5.0) then becomes:

$$\text{M1.0.2:} \quad \begin{array}{l} Y1 = 2.972 + 0.177A_1 + 10.873A_2 + 0.352A_4 \\ Y2 = 2.295 + 0.203A_1 + 9.129A_2 + 1.011A_4 \\ Y3 = 1.763 + 0.528A_1 + 11.978A_2 + 1.140A_4 \end{array} \quad \text{..(6.0)}$$

Substituting the original representation of the research factors into equation (6.0), the best model M1.0.2 is implicated by:

Y_1 – Frequency of film viewing 1 time or less in a month;
Y_2 – Frequency of film viewing 2 times in a month;
Y_3 – Frequency of film viewing 3-4 times in a month;
A_1 – encouragement due to interest;
A_2 – encouragement by the family and
A_4 – encouragement due to boredom.

Equation (6.0) implies that the frequency in the viewing films by the movie fans are significantly affected by these behavioural factors in the best model of M1.0.2. These relevant factors are those that are concerned with interest, family and boredom. Interest in the film genre besides the influence from family to watch family movies as recreational activities are contributing to the increase in the frequency in film viewing. In addition, boredom is found to be a getaway cause to watch films and thus acts as social and psychological pastime to some. These factors are found to be simplistic factors compared to Noraini *et al.* (2014) where multiple regression technique was employed on Malaysian audiences. It was found out that he director's motivation, perception on the film's location, gratification and inspiration from film-viewing besides relationships involved in the script, gave significant positive impacts on film viewers in East Malaysia. These differences can be said due to the geographical location, demographic factors, income levels, facilities available, cultural influence and infrastructure development. The best model (M1.0.2) implies that the frequency in the film viewing was based on the behavioural factors are those that are concerned with encouragement from interest, family and due to boredom. All these factors are contributing positively to the increase in the frequency in film viewing.

5 CONCLUSIONS

This paper introduces the concept and procedures in mathematical modelling using the multinomial logistic regression technique so as to identify significant factors that affect the sustainability of the Malaysian film industry. Significant factors are as represented in the best model of M1.0.2:

$$\mathrm{Y1} = 2.972 + 0.177\,\mathrm{Encouragement(Interest)} + 10.873(\mathrm{Encouragement(Family)} + 0.352\,\mathrm{Encouragement(Boredom)}$$

$$\mathrm{Y2} = 2.295 + 0.203\,\mathrm{Encouragement(Interest)} + 9.129(\mathrm{Encouragement(Family)} + 1.011\,\mathrm{Encouragement(Boredom)}$$

$$\mathrm{Y3} = 1.763 + 0.528\,\mathrm{Encouragement(Interest)} + 11.978(\mathrm{Encouragement(Family)} + 1.140\,\mathrm{Encouragement(Boredom)}$$

These factors give positive and direct contribution to the increase in the frequency in film viewing of the East Malaysian audiences. It can be concluded that interest on films genres of various themes, family recreational and getaway social activities would certainly boost the Malaysian film industry while providing various choices in film viewing. While it is only appropriate that all genres and themes of films being produced herewith must be compliant to FINAS perspectives, the factors affecting the behavioural patterns should not be neglected since these would ensure the Malaysian film industry's survival and view ability appeals.

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