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The Design of a Bayesian Network Model for Increasing the Number of Graded Tourism Establishments

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Abstract

Research has been conducted on the grading of tourism establishments but little research has been conducted on the implementation of Artificial Intelligence (AI) to increase the number of graded tourism establishments. The objective of this study was to identify variables influencing tourism grading and to use them to construct a Bayesian Model for increasing the number of tourism establishments. Data was collected using an online survey questionnaire developed using the Survey Monkey tool. A total of 87 responses were received from 60 non-graded and 27 graded tourism establishments. The results indicate six factors affecting tourism grading, namely cost of grading, grading benefits, simplicity/complexity of grading application process, government funding, training of prospective grading applicants and computer literacy. The results further indicate grading cost and grading benefits as the most important factors for increasing the number of tourism establishments. The study implies that using this model will assist grading professionals to make informed decisions on initiatives aimed at increasing the number of graded tourism establishments. The study is among the first on implementation of AI to increase tourism grading establishments.

Keywords: Tourism grading, Bayesian networks, tourism establishments, computational intelligence, tourism establishments

Introduction

Tourism is the world's largest and fastest growing sector in world, and a significant contributor to global Gross Domestic Product (GDP) and jobs (Haarhoff & De Klerk, 2019). In 2019, tourism contributed $ 8.9 trillion to GDP and 330 million jobs globally (World Travel & Economic Council, 2020). Many countries have begun to realise the importance of tourism towards economic development (Thano & Kote, 2015), which has led to more tourism destinations and products being available for tourists worldwide (Strydom, Mangope & Henema, 2019), as well as increased competition among countries and local tourism businesses. This collaborates the findings of Page (1999), that tourism is robust, competitive and service-intensive. Therefore, tourism businesses need to deliver high quality services in order to gain competitive advantage (Supanan & Sornsaruht, 2019).

In South Africa, tourism is regarded vital towards economic growth (Muzekenyi, Nheta & Tshipala, 2019), and contributed a total of R 125 billion into the GDP in 2019 (South African Tourism, 2019). Negatively, South Africa's earnings from international tourism declined from R 108 billion in 2018 to R 125 billion in 2019 (Statistics South Africa, 2019), while international trips to South Africa declined from 10.4 million in 2018 to 10.2 million in 2019, which may signal increased competition and a negative shift in South Africa as a preferred tourist destination (South African Tourism, 2019). Therefore, in order to gain competitive advantage, South Africa needs to improve tourism service quality levels and the number of quality products available for tourists. Improving accommodation service quality and infrastructure will increase tourist loyalty (Viet, 2019), and can be achieved by increasing the number of graded tourism establishments.

Grading is a quality assurance system for classifying tourism establishments based on the quality of facilities and services they provide (World Tourism Organization, 2015). It ensures the provision of quality tourism services and facilities; increased customer base, as well as a competitive advantage over competitors (Du Plessis & Saayman, 2011). Therefore, graded tourism establishments are likely to have a competitive advantage over non-graded tourism establishments. Despite the grading benefits, there remains a low number of graded tourism establishments in South Africa, with 5098 out of 30 000 known tourism establishments being graded (TGCSA, 2017). In the Free State province of South Africa, a total of 152 out of 744 known tourism establishments are graded (TGCSA, 2017). Henama (2013) discovered that the majority of tourism establishments' owners in the Free State do not consider grading to be beneficial.

This article aims to investigate the variables and the degree to which each variable influences the grading of tourism establishments in the Free State. A Bayesian network model for increasing graded tourism establishment is also constructed using the identified variables. The model will provide grading practitioners with predictive intelligence and information on factors influencing tourism grading. This will allow them to make informed decisions on initiatives towards increasing the number of graded tourism establishments in the Free State. This article is divided into four sections. The first section reviews the literature on factors influencing tourism grading and the use of Artificial Intelligence (AI) within the tourism sector. The second section discusses the research methodology used to answer the research questions. The section further analyses the results of 87 responses from graded and non-graded tourism establishments. The third section discusses the tools and AI methods used to construct the Bayesian model for increasing graded tourism establishments. The last section discusses the findings of the research study, focusing on its implications as well as the benefits of using the model to the tourism sector.

Literature review

Tourism establishment "grading" systems, sometimes referred to as "classification" or "rating" systems, are used in almost all countries worldwide (Sufi & Singh, 2018). The World Tourism Organisation (UNWTO) which is the United Nations' agency responsible for promotion of tourism (Healey & Carvao, 2016), defines a tourism grading as classifying tourism establishments according to their physical and service characteristics (Narangajavana & Hu, 2008). However, a universal and standardised grading system which is used by all countries worldwide remains unavailable (Tefera & Govender, 2015), as a result, countries use their own grading systems determined by a government or private institution. In fact, there are over 100 grading systems available worldwide (Felix & Clever, 2014), with unique processes, challenges, benefits and perceptions around each grading system.

The grading system used in the European Union (EU) countries is voluntary and based on a star grading system between 1-5 stars (Foris, 2014). This star grading system is similar to the one used by India (Suffi & Singh 2016), South Africa (TGCSA, 2019) and Kenya (Fredrick, 2019). The star grading notation is the most commonly used globally (Fredrick, 2019), however, a diamond notation rating system exists, and is used in the United States of America, and also uses the scale of 1-5 (Minazzi, 2010). Tourism grading is commonly performed by a government organisation of a respective country. In India, grading is performed by Hotel and Restaurant Accreditation Committee, which is an agency of the Indian Ministry of Tourism (Sufi & Singh, 2016), while in Kenya it is performed by the Hotels and Restaurants Authority (HRA). This the same as in South Africa, for which grading is mandated to the TGCSA under the Tourism Act 72 of 1993 (TGCSA, 2019a). This law provides clear regulations to TGCSA grading administrators on how to operationalise the grading scheme (Department of Tourism, 2014)

Makindi, Makindi & Obwoyere (2014) found a positive relationship between grading with hotel earnings in Kenya. Grading was also found to increase service quality and customer loyalty in India (Sufi, 2019). In addition, a study conducted in South Africa by Du Plessis & Saayman (2011), also found that grading improves service quality and assists tourism establishments to gain a competitive edge over competitors. Despite the known grading benefits, the number of graded tourism establishments Kenya, India and South Africa remains low. In Kenya, only 23 782 rooms are graded out of an estimated 40 000 (Fredrick, 2019), while only 952 tourism establishments are graded in India, out of thousands available, although the exact total number is not known by the Indian Ministry of Tourism (Sufi, 2019). This is also the case in South Africa, where only 5098 tourism establishments are graded out of a total of 30 000 known tourism establishments in South Africa (TGCSA, 2017).

In South Africa, the majority of tourism establishments are graded at 4-star, with the least being graded at 1 star (TGCSA, 2017). Tourism establishments with 5-star grading level are guaranteed to provide luxurious facilities and quality of services, and therefore attract wealthy tourists with high buying power, contributing positively to job creation and economic growth. Among the nine provinces of South Africa, the Western Cape has the most number of graded establishments with 1691, while the Northern Cape has the least with 141 (TGCSA, 2017). The Free State has the second least number of graded establishments at 152 out of a total of 744 known tourism establishments. The majority of tourism establishments in the Free State are graded at 3 stars, with the least being at 1-star, followed by 2 stars. Grading at 1-star and 2-star remain low, despite being the least stringent and less costly. According to Henama (2013), most tourism establishments in the Free State perceive grading to be non-beneficial. Increasing the number of graded tourism establishments in the Free State will positively impact on the number of visitors, economic growth and job creation. Table 1 provides a summary of the research findings and objectives past research studies conducted on tourism grading and prediction of tourism demand and tourist arrivals using AI methods. Six studies on tourism grading were reviewed to understand the factors influencing tourism grading. Also, four research studies on prediction of tourism demand and arrivals using AI methods were studied understand the various implementations of AI within the tourism sector.

Table 1: Summary of research studies on grading tourism establishments

Topic	Research objective and method	Research findings	Research location	Authors
A Critical Evaluation of Hotel Classification System of India	Research objective: To investigate reasons for the large number of hotels not opting for grading. The research data was collected from a total of 205 managers from graded and non-graded hotels in North India using a structured questionnaire. The data was analysed using SPSS software to reasons for non-grading.	The study found the following: • The cost of grading is high as graded hotels were required to pay higher salaries to staff. • The grading application fee was high, and also the application processes was difficult as it required massive documentation to be compiled and submitted. • That government funding is inadequate.	India	Sufi (2019)
An analysis of hotel rating and its implication on financial turnover of rated hotels in kenya	Research objective: The objective of the study was to investigate the financial implications of grading of hotels The research data was collected from 50 hotels in Kenya using face to face interviews.	The study found the following: • The study found tourism grading increases revenue and customer service for tourism grading establishments. • Natively, grading membership were found to be expensive while the grading application process was difficult. • That government subsidy is inadequate.	Kenya	Kiplagat, Makindi& Obwoyere (2014)
Relationship between hotel grading system, service quality improvement and hotel performance changes	Research objective: To examine the correlation between the hotel rating/grading system, service quality improvement and hotel performance changes in Thailand. The research data was collected from hotel managers using a survey and analysed using descriptive statistics.	The study found the following: • Cost of grading is expensive, particularly for small and medium enterprises. • The grading application process was complex. • There is a positive relationship between service quality improvement, hotel performance and grading.	Thailand	Narangajavana and Hu (2017)
Perception of grading in South Africa	Research objective: To understand the perception of the tourism sector regarding the importance and value of grading in South Africa. Data were collected over two calendar months using a quantitative questionnaire administered to tourism establishment owners and managers, tourism associations, tourists, TGCSA grading assessors, travel-related service business owners, SAT representatives and provincial tourism associations.	Reasons for grading: • Increase in client base; • Increase in service quality. • Unsatisfactory benefits; Reasons for non-grading: • Expensive grading; • Subjective grading; • No change in client base; • Unattainable criteria; and • No changes in occupancy rate.	South Africa	TGCSA (2017)
Grading and price in the accommodation sector of South Africa	Research objective: To investigate the correlation between tourism grading and price in tourism accommodation establishments. Data was collected over five months from 2 457 tourism accommodation establishment owners, belonging to three main associations in the tourism accommodation market: Federated Hospitality	The research study found the following: • A positive relationship between between grading and price among various types of tourism accommodation establishments in South Africa. Grading was being used by accommodation establishments for the primary purpose of providing quality customer service and value	South Africa	Du Plessis and Saayman (2010)

Topic	Research objective and method	Research findings	Research location	Authors
	Association of South Africa, the TGCSA and South African Tourism Service Accommodation. Correlation analysis was used to determine the relationship between tourism accommodation grading and pricing.	for money, as well as to obtain a competitive advantage.		
Tourism grading as a marketing instrument in B&B establishments in the Durban metropolitan region: An entrepreneurial approach	Research objective: To evaluate how grading is assisting entrepreneurs in performing the marketing function of Bed and Breakfast (B&Bs) establishments. A qualitative questionnaire was administered to B&B owners belonging to KwaZulu-Natal B&B associations. The perceptions and opinions of these owners regarding the TGCSA grading system were examined.	The B&B establishments were graded for the following reasons: • Improved marketing; • Increased profit and client base; and • Improved the standard of services and facilities. The majority of non-graded B&B owners indicated the following reasons for not being graded: • The high cost of grading; • Non-satisfactory benefits; • Complex grading application process.	Durban, South Africa	Tanner (2003)
The machine learning model for occupancy rates and demand forecasting in the hospitality industry	Research objective: To design a model for forecasting occupancy rate and demand in the tourism hospitality sector using machine learning algorithms. Radial basis function networks, multi-layer perception, kernel ridge regression and ridge regression were used as the machine learning algorithms. Historical reservation and occupation data from 1 July 2008 to 30 June 2019 (2 191 days) was used.	The ridge regression model outperformed the other three competing forecasting models. The model incorporated the quality of customer service as well as the star grading of the accommodation establishment.	Columbia	Caicedo-Torres and Payares (2017)
Using a Bayesian network and AHP method as marketing approach tools in defining tourists' preferences	Research objective: To identify variables influencing tourist destination preferences. Bayesian networks and AHP tools were used to develop a marketing approach to define tourists' preferences.	The following variables influenced tourist destination preference: • Occupation, age, the personality of tourist; • Travel type; • Tour motivation for tourist; • Preferred activities for tourist; • Price of destination; and • Distance to destination.	Phuket, Thailand	Blagojević et al. (2012)
Modelling and forecasting the demand for Hong Kong tourism	Research objective: To compare the tourism forecasting performance of VAR with that of the combination of BVAR. Historical tourism demand data of Hong Kong included the following variables: • Tourist arrivals; • the income of origin country; • Exchange rate; and • Price index.	The BVAR model outperformed VAR models about forecasting tourism demand because the BVAR model could incorporate qualitative variables such as war and the oil crisis.	Hong Kong, China	Wong et al. (2007)
Forecasting tourist arrivals in South Africa	Research objective: To forecast tourism arrivals into South Africa from Great Britain, the Netherlands, the USA, Germany and France. ARIMA, the naïve model and Holt-Winters forecasting models were used to forecast the	Seasonal ARIMA models delivered the most accurate forecasting of arrivals over three-time horizons, namely 3, 6 and 12 months.	South Africa	Saayman and Saayman (2010)

Topic	Research objective and method	Research findings	Research location	Authors
	international arrivals. Historical data on international tourist arrivals in South Africa between 1994 and 2007 obtained from Stats SA was used			

Factors influencing the grading of tourism establishments

Literature indicates six variables which influence the grading of tourism establishments. The variables are the cost of grading, grading benefits, simplicity/complexity of grading application process, training prospective grading applicants on grading application process, government funding and computer literacy level. Table 2 provides a summary of variables influencing the grading of tourism establishments.

Table 2: Variables influencing the grading of tourism establishments

Variable	Description	Reference
Cost of grading	The monetary value which tourism establishment owners have to pay for grading their establishment influences whether their establishments will be graded or not.	TGCSA (2017) Narangajavana and Hu (2017) Du Plessis and Saayman (2010) Kiplagat, Makindi& Obwoyere (2014) Sufi (2019)
Grading benefits	The grading benefits which tourism establishments receive influence on whether their establishments will be graded or not.	TGCSA (2017) Tanner (2003) Narangajavana and Hu (2017) Du Plessis and Saayman (2010) Kiplagat, Makindi& Obwoyere (2014) Sufi (2019)
Simplicity/ complexity of the grading application process	The complexity level of the grading application process influences whether tourism establishment owners will have their establishments graded or not.	TGCSA (2017) Tanner (2003) Narangajavana and Hu (2017) Du Plessis and Saayman (2010) Kiplagat, Makindi& Obwoyere (2014) Sufi (2019)
Training of prospective grading applicants on the grading process	Training of prospective grading applicants will influence the perceived complexity level of the grading application process, thereby influencing whether tourism establishment owners will have their establishments graded or not.	TGCSA (2017) Tanner (2003) Narangajavana and Hu (2017) Du Plessis and Saayman (2010) Kiplagat, Makindi& Obwoyere (2014) Sufi (2019)
Government Funding	Government funding influences the grading benefits and grading cost, thereby influencing whether tourism establishment owners will have their establishments graded or not.	TGCSA (2017) Tanner (2003) Kiplagat, Makindi& Obwoyere (2014) Sufi (2019)
Computer literacy of grading applicant	The computer literacy level of grading applicants influences the perceived complexity level of the grading application process, thereby influencing whether tourism establishment owners will have their establishments graded or not.	TGCSA grading experts

Research methodology

The quantitative research method was used in this study. A literature study was first conducted to identify variables influencing grading of tourism establishments. Telephonic interviews were conducted with grading professionals from TGCSA to verify the identified variables. The verified variables were then utilised to develop an online survey questionnaire using the Survey

Monkey tool. The online survey questionnaire was then sent to a total of 737 tourism establishments in the Free State, comprising of 145 graded and 592 non-graded. A total of 87 responses were received, 60 were non-graded and 27 were graded. The data received was first analysed using descriptive statistical methods. The Free State was ideal for obtaining a holistic understanding of factors influencing tourism grading. This is due to its various types of tourism establishments located in diverse human settlement types, including cities, small towns, townships, rural and townships (Municipal Demarcation Board, 2018). To achieve the objectives for this research study, the following questions were posed:

- What are the factors influencing the grading of tourism establishments?
- What are the most important variables influencing the grading of tourism establishments?
- What is the relationship between tourism grading variables and the increase in the number of graded tourism establishments?

The identified variables were used to build a Bayesian Model for increasing the number of graded tourism establishments. The model was constructed using the Sensitivity Analysis, modelling, Inference and More (SAMIAM) tool (Automated Reasoning Group, 2010).

Artificial intelligence (AI) methods

AI methods allow for effective analyses of hidden patterns of data and information using various AI algorithms, such as Bayesian model, artificial neural network (ANN) and naïve Bayes (Aziz, Ahmad & Ismail, 2013). Bayesian networks were used to construct the model for increasing the number of graded tourism establishments.

Bayesian networks

Bayesian networks use directed acyclic graphs (DAG) to represent uncertain knowledge and relationship among a set of events (Olga, 2018). Bayesian networks methods can model complex problems (Lee, Song, Cho & Park, 2010). Bayesian networks models are constructed by combing a set of related variables to form a DAG (Darwiche, 2009). Each variable exists of two or more outcomes, which are assigned a probability value. Probability values for outcomes of a particular variable equal to 1. The probability values are then used to construct conditional probability tables (CPTs). CPTs are knowledge bases which hold answers to all queries regarding a specific model. Bayesian networks have been used forecasting of tourism demand, predicting tourists' product loyalty and for tourism recommender systems. Table 3 provides a list of focus areas in which Bayesian has been used within the tourism domain.

Table 3: Application of Bayesian networks within the tourism domain

Focus area	Research outcomes	Limitations	Reference
Forecasting of tourism demand	The study found that Bayesian global vector autoregressive (BGVAR) performs better than the autoregressive model.	The limitations of this study included using a small sample of data due to data availability limitations. The study also used data for only one weather season. Using data for all four weather seasons may provide different results.	Assaf et al. (2018)
Tourism trip recommender systems	The research used customer flights data to construct a Bayesian Network model for recommending tourism trip to tourists.	Although the data for constructing the model included key demographic attributes such as birthdate and gender, it did not include attributes such as tourism preferences and budget. Including	Ucar and Karahoca (2015)

		such attributes may enhance the performance of the model.	
Predicting tourists' loyalty	The study found integrating Bayesian networks with linear structural relation model produces effective tourist loyalty prediction results.	Although the study included key attributes such as customer service and perceptions to predict customer loyalty, the variable price was not included.	Hsu, Shih, Huang and Lin (2009)

Justification for selecting Bayesian networks for this study

The Bayesian networks allow for effective representation and processing of complex data (Marcot, Pourret & Naim, 2008). Moreover, Bayesian networks handle incomplete data effectively (Heckerman, 2006). ANN is a competing AI method, however it not suitable for this study as it requires a large amount of data. It is against this that Bayesian networks were selected for this study. Table 4 provides a comparison between the advantages and disadvantages of Bayesian networks and ANN.

Table 4: Advantages and disadvantages of Bayesian networks

Ai method	Advantages	Disadvantages
Bayesian network	Effectively handles incomplete data	Sometimes slower than traditional linear methods
	Flexible compared to traditional linear methods	Quality of results depends on the quality of the model
	Accurately models small and large data	Requires many numerical parameters
	Has the ability to examine and model complex problems	Missing or incomplete data may result in problems regarding model parameterisation

Bayesian model for increasing the number of graded tourism establishments

Figure 1 shows the Bayesian network research model for increasing the number of graded tourism establishments. The data for constructing the model was obtained through literature study and the questionnaire responses from tourism establishments located in the Free State. Analysis of obtained data indicated a total of six variables as influencing tourism grading, namely cost of grading, grading benefits, simplicity/complexity of grading application process, training of prospective grading applicants on grading application process, stringent grading process and government funding. A Bayesian network model is graphic (Darwiche, 2009). Therefore, the model was constructed using Microsoft Word tool. Round shapes were used to depict each variable, while arrows were used to indicate the relationships among the variables. The relationship among the variables was tested using two Bayesian network statistics, namely prior marginals and posterior marginals.

The results for prior marginals and posterior marginals show that variables Trained (T), Computer Literate (CL) and Government Funding (GF) are first-level variables with direct influence indirect influence on graded tourism establishments (Increased Grading (IG)). The results further show that variables Computer Literacy (CL) and Trained (T) have a direct influence on whether a grading applicant will find the grading application process easy or difficult (Grading Complexity). Additionally, first-level variable Government Funding (GF) has a direct influence on the satisfactory level of grading benefits (Benefits) and affordability of grading cost (Grading Cost). The results further prove that variables Grading Complexity (G), Benefits (B) and Grading Cost (GC) are second-level attributes with direct influence on the number of grading. This is evident in that a change in either of these variables results in a significant change on variable Increased Grading (IG). The results indicate that the three variables are the most important variables for increasing the number of graded tourism establishments.

Therefore, because all six identified variables influence tourism grading, a dependent variable named Increased Grading (IG) was derived when constructing the model. The variable represents the likelihood that graded tourism establishments will increase or decrease given a change in one or more of the six identified variables influencing tourism grading.

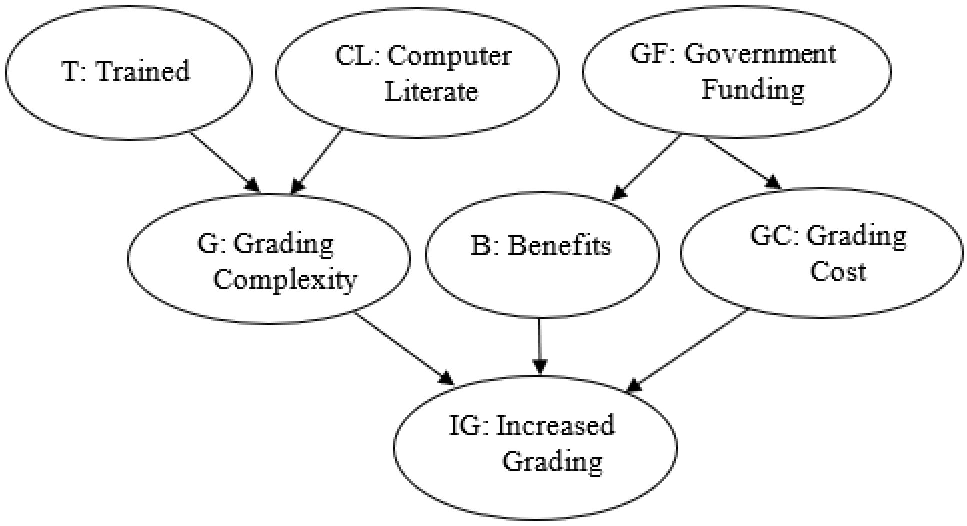

Figure 1: Bayesian network model

Results

Primary data was collected using an online survey questionnaire developed using the Survey Monkey tool. A total of 87 responses were received from 60 non-graded and 27 graded tourism establishments. The data was then downloaded using the Survey Monkey tool and response values converted from text to numeric values to derive quantitative statistics. A Microsoft Excel spreadsheet was used to analyse the data to identify variables influencing grading of tourism establishments.

The demographics data for both graded and non-graded tourism establishments which participated in this research study are shown in Table 5. The majority of tourism graded and non-graded establishments which participated in this study are guesthouses, followed by Bed & Breakfast (B&Bs) and guesthouses. It is critical to increasing the number of graded B&Bs and guesthouses to improve the quality of tourism products and services available and provided to tourists. This is because B&Bs and guesthouse exist in vast numbers due to the low barrier of entry, thus majority are informal, small and have limited funding. There are fewer chances of small businesses surviving 42 months in South Africa (Von Broembsen, 2005), therefore increasing graded B&Bs and guesthouses will also increase their chances of survival.

The majority of respondents from graded and non-graded tourism establishments were owners, followed by managers. This increased the credibility of the data collected. In terms of size, the majority of respondents were from graded and non-graded tourism establishments with 1-10 rooms. The response from graded tourism establishments indicates that small establishments such as B&Bs and guesthouses regard grading as important. This is a positive indicator, as the majority of these small tourism establishments are generally owner-managed with limited funding. Therefore, grading increases ensures the provision of quality services and facilities, while also occupancy rate and profitability (Narangajavana and Hu, 2017). The response from non-graded tourism establishments may indicate a significant number of small businesses who are not graded. This may be due to owners and tourism establishments considering grading to be not beneficial or cost to be high. It may also be that these establishments provide budget services for clientele that is not looking for luxury facilities or a high standard of service.

Lastly, the demographic results indicate that the majority of graded and non-graded tourism establishments who participated in this study were establishments which had been operational for 5 or fewer years. Response received from graded tourism establishment indicate that there are tourism establishments who integrate grading in their operations early on in their existence. This may be establishments who value the provision of quality services and facilities, and who may be catering for a clientele that is willing to pay extra for top luxury and quality. The response of non-graded tourism establishments indicates that other establishments may only consider grading later on in their existence. This may be due to their limited funds which may allow them only to invest in their day-to-day business operations.

Table 5: Demographic data for non-graded tourism establishments

		Non-graded establishments		Graded establishments	
Demographic type	**Indicator / scale**	**Frequency**	**Percent (%)**	**Frequency**	**Percent (%)**
Type of establishment	Hotel	8	13.3	3	11.1
	Country house	4	6.6	2	7.4
	Guesthouse	19	31.6	11	40.7
	B&B	14	23.3	5	18.5
	Backpacker and hostel	2	3.3	1	3.7
	Caravan and camping	1	1.6	1	3.7
	Lodge	7	11.6	2	7.4
	Self-catering	3	5	1	3.7
	Game lodge	2	3.3	1	3.7
	Total	**60**	**100%**	**27**	**100%**
Designation of respondent	Owner	35	58.3	16	59.3
	Manager	20	33.3	6	22.2
	Other	5	8.3	5	18.5
	Total	**60**	**100%**	**27**	**100%**
Size of establishment	1-10	21	35	11	40.7
	11-20	15	25	5	18.5
	21-30	11	18.3	4	14.8
	31-40	5	8.3	3	11.1
	41-50	3	5	4	14.9
	51-60	5	8.3	0	0
	Total	**60**	**100%**	**27**	**100%**
Years of operation	5 years or less	19	31.7	9	30
	6-10 years	14	23.3	7	26
	11-15 years	7	11.7	4	21
	16-20 years	12	20	6	16
	More than 20 years	8	13.3	1	7
	Total	**60**	**100%**	**27**	**100%**

Modelling the increasing tourism grading computational intelligence framework

Figure 1 depicts a computational Bayesian network model for increasing the number of graded tourism establishments developed using the SAMIAM tool (Automated Reasoning Group, 2010). The model represents a computational intelligence framework for increasing the number of graded tourism establishments. The constructed framework can be used to predict whether the number of graded tourism establishments will increase or decrease based on a change in one or more variables of the model. Prior and posterior marginal experiments were computed on the framework to investigate the relationship among variables influencing tourism grading, as well as the degree to which each variable influence tourism grading. Posterior marginals are marginal distributions which are given some evidence. In contrast, prior marginals are marginal distributions constructed given no evidence (Darwiche, 2009).

Prior marginals
Figure 2 shows the prior marginals computed for each variable of the Bayesian model for increasing the number of graded tourism establishments. Each variable of the model exists of two possible outcomes for which have been assigned a probability value using data obtained from non-graded and graded tourism establishments through a questionnaire. The total probability value for each outcome of a particular variable equals 1. The computed prior marginal results for the constructed model indicate that the current state of variables of the model are unfavourable, and will most likely result in a decrease in graded tourism establishments. The computed prior values for each variable indicate the following probability values: The likelihood that a grading applicant has undergone training on the grading application process is 25%, while the likelihood that a grading applicant has *not* undergone training on the grading application process is 75%. The results also indicate that the likelihood that a grading applicant is computer literate is 60%, while the likelihood that a grading applicant is *not* computer literate is 40%. In terms of grading complexity, the results show that the likelihood that a grading applicant will find the overall grading application process difficult is 56.50%, while the likelihood that a grading applicant will *not* find the grading application process difficult is 43.50%. Furthermore, the results indicate that the likelihood that government funding to the TGCSA is adequate is 40%, while the likelihood that government funding to the TGCSA is *not* adequate is 60%. The results also show that the likelihood that grading benefits will be regarded as satisfactory by tourism establishments is 48%, while the likelihood that grading benefits will *not* be regarded as satisfactory by tourism establishments is 52%. In addition, the results indicate that likelihood that grading will be considered expensive is 52%, while the likelihood that grading will not be considered expensive is 48%. Lastly, the results show that the likelihood that the number of graded tourism accommodation establishments will increase is 46.35%, while the likelihood that the number of graded tourism accommodation establishments will *not* increase is 54.65%.

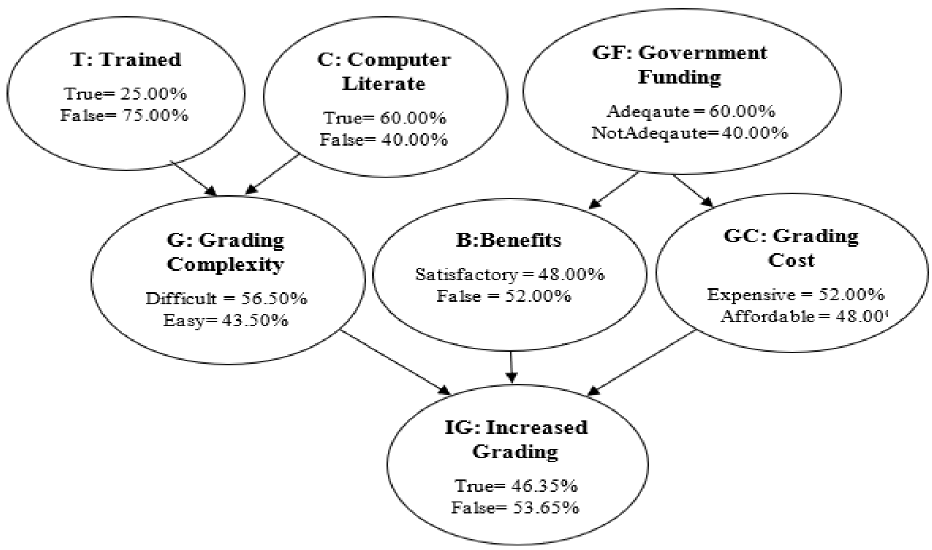

Figure 2: Prior marginals for Bayesian model

Posterior marginals

Table 6 shows the posterior marginals computed using one variable and a combination of variables as evidence variable/s. An evidence variable is a variable whose value is known. The posterior marginal results prove that each of the six variables influences tourism grading, namely Trained (T), Compute Literate (CL), Government Funding (GF), Grading Complexity (G), Benefits (B) and Grading Cost (GC). This is evident in that a change in each one of the variable, despite others remaining unchanged, results in a change in the likelihood that the number of graded tourism establishment will increase or decrease. Furthermore, the posterior results further indicate the relationships among variables and the degree to which each variable influences tourism grading.

The posterior results show that providing training to a grading applicant (Training = True) will result in the likelihood that graded establishments will increase rises by 2.25%, from 46.35% to 48.60%. Inversely, when training has been *not* being provided to a grading applicant (Training = False), the likelihood that graded establishments will not increase rises by 0.75%, from 53.65% to 54.40%. The percentage change in Table 6, show that training of grading applicants has the second least influence on tourism grading.

Furthermore, when a grading applicant is computer literate (Computer Literate = True), the likelihood that graded establishments will increase rises by 0.75%, from 46.35% to 46.75%. Inversely, a grading applicant is *not* computer literate (Computer Literate = False), the likelihood that graded establishments will not increase rises by 0.6%, 53.65 to 54.25%. The percentage change in Table 4 shows the computer literacy level of grading applicants has the least influence on tourism grading.

Additionally, the posterior marginal results show that when grading application is easy (Grading Complexity = Easy), the likelihood that graded establishments will increase rises by 5.65%, from 46.35% to 52%. Inversely, when grading application process is difficult (Grading Complexity = Difficult), the likelihood that graded establishments will not increase rises by 4.35%, from 53.65% to 54.25%. The percentage change in Table 6 shows that the complexity level of the grading application process has the second most influence on tourism grading.

Furthermore, the posterior marginal results indicate that adequate government funding in (Government Funding) Complexity = Easy) will result in the likelihood that graded establishments will increase rises by 3.6%, from 46.35% to 49.95%. Inversely, when government funding is not adequate (Government Funding= Not adequate), the likelihood that graded establishments will not increase rises by 2.4 %, 53.65 to 56.05%. The percentage change in Table 5 shows that government funding is the third most important factors for increasing graded tourism establishments.

The posterior marginal results further indicate show that grading benefits and grading cost are the most important factors towards increasing graded tourism establishments. A non-parallel change in either of the two variables will result in an identical influence on tourism grading. When grading the cost of grading is affordable (Grading Cost= Affordable) the likelihood that graded establishments will increase rises by 8%, from 46.35% to 61.03%. The same is true for when grading benefits are satisfactory (Benefits= Satisfactory). Inversely, when grading cost is expensive (Grading Cost = Expensive), the likelihood that graded establishments will not increase rises by 6.38%, from 53.65% to 61.03 %.

Discussion

The prior marginal experimental results show a total of six variables which influence grading, namely cost of grading, grading benefits, simplicity/complexity of grading application process, training of prospective grading applicants on grading application process, stringent grading process and government funding. The results indicate that the current state of these variables is unfavourable, and will most likely result in a decrease in the number of graded tourism establishments. This is evident in that the prior marginal results indicate a 46.35% likelihood that the number of graded establishments will increase, while there is 54.65% likelihood that graded establishments will decrease. Therefore, practical initiatives aimed at improving the state of these variables and the number of graded tourism establishments need to be implemented by tourism professionals, government and other sector stakeholders.

Table 6: Posterior marginal results: the influence of each variable

Variable	Experiment	Increased Grading (IG) (Before/Prior)	Increased Grading (IG) (After/Posterior)	Change
Trained (T)	T = **True**	**True** = 46.35%	**True** = 48.60%	+2.25%
	T = **False**	**False** = 53.65%	**False** = 54.40%	+0.75%
Computer Literate (CL)	CL = **True**	**True** = 46.35%	**True** = 46.75%	+0.4%
	CL = **False**	**False** = 53.65%	**False** = 54.75%	+1.1%
Grading Complexity (G)	G = **Easy**	**True** = 46.35%	**True** = 52.00%	+5.65%
	G = **Difficult**	**False** = 53.65%	**False** = 58.00%	+4.38%
Government Funding (GF)	GF = **Adequate**	**True** = 46.35%	**True** = 49.95%	+ 3.6%
	GF = **Not Adequate**	**False** = 53.65%	**False** = 56.05%	+2.4%
Benefits (B)	B = **Satisfactory**	**True** = 46.35%	**True** = 54.35%	+8%
	B = **Not Satisfactory**	**False** = 54.65%	**False** = 61.03%	+6.38%
Grading Cost (GC)	GC = **Affordable**	**True** = 46.35%	**True** = 54.35%	+8%
	GC = **Expensive**	**False** = 54.65%	**False** = 61.03%	+6.38%

The prior marginal further indicates that currently, the cost of grading is most likely to be regarded as expensive, and grading benefits are most likely to be regarded as unsatisfactory. This is consistent with the research findings made by Sufi (2019), were grading cost was found to be expensive. According to the posterior marginal, grading cost and grading benefits are the most important variables towards increasing graded tourism establishments. This is consistent with the research findings made by TGCSA (2007), were grading cost and grading benefits were predominately indicated as factors influencing grading. Also, the posterior marginals indicate that both variables grading cost and grading benefits are influenced by government funding. This supports the findings made by Kiplagat, Masinda & Obwoyere (2014), which show that government funding is critical towards affordability of the grading cost by tourism businesses, as well as the perceived grading benefits. Therefore, initiatives aimed at making the grading cost affordable need to be implemented. These can include additional subsidies by the government towards grading cost. Furthermore, additional non-financial benefits such as skills training, marketing and booking systems could also be provided by grading organisations and made available to graded establishments to increase benefits.

The prior marginal further indicates that currently, grading applicants are less likely to have undergone training on the grading application process. Furthermore, the results indicate that grading applicants are less likely to be computer literate. This negatively impacts on the grading applicant's ability to successfully and accurately complete a grading application, and ultimately on the number of graded tourism establishments. This is because a grading applicant who is struggling to complete a grading application will most likely abandon the process. Also, the prior marginal results are consistent with those made by Tanner (2003), where the majority of tourism establishments indicated that the grading application process is difficult, and should be simplified. Posterior Marginal results indicate that simplifying the grading application process will result in a 52% likelihood that the number of graded establishments will increase. The results further indicate that the simplicity of the grading application process is the second most influential factor towards increasing the number of graded tourism establishments. Therefore, initiatives the government and grading organisations need to regularly implement training initiatives on grading application process. The training programmes will provide information to prospective grading applicants on components being graded, allowing them to better prepare their establishments for a particular grading level.

Therefore, it is recommended that initiatives be implemented simultaneously to simplify the grading application process, provide satisfactory benefits and ensure affordable grading cost, as posterior marginal results indicate that it will result in a 70% chance that graded tourism establishments will increase. However, where it is not possible to implement all initiatives simultaneously due to various reasons, initiatives towards improving grading cost and benefits should be the first priority. This is because the results prove that both factors are the most important factors for increasing the number of graded tourism funds. Thus, adequate funding needs to be availed to achieve this. The second priority should be on initiatives aimed at simplifying the grading application should be second priority.

Conclusion

Grading enables tourism establishments to provide quality services and facilities, and ultimately to gain a competitive advantage over competitors (Du Plessis & Saayman, 2011). However, the number of graded tourism establishments in South Africa remains low, with only 16% graded (TGCSA, 2017). Therefore, the main purpose of this article was to develop a Bayesian Model for increasing the number of tourism establishments.

The research results indicated six variables which influence the number of graded tourism establishments, namely cost of grading, grading benefits, simplicity/complexity of grading application process, training of prospective grading applicants on grading application process, stringent grading process and government funding. Furthermore, the results showed that grading cost and grading benefits are the most important factors for increasing tourism establishments. The third most important variable is simplicity/complexity of the grading application process, with the fourth most important being government funding. The fifth most important variable is training of prospective grading applicants, with the computer literacy level of grading applicants being the least important variable.

The identified variables were used to construct a Bayesian network model for increasing the number of graded tourism establishments. The model when followed, could significantly increase the number of graded tourism establishments. This study contributes new knowledge on the factors influencing, and the degree to which each factor influence of tourism grading. Also, the study provides tourism grading practitioners at South African Tourism, the TGCSA and the South African Department of Tourism with a computational framework for increasing the number of graded establishments in South Africa. The intelligence computational framework enables tourism grading practitioners to make informed decisions on which initiatives and programmes to implement towards increasing the number of graded tourism establishments.

Limitations of this study included the inability to collect performance data such as occupancy rate and profitability. This data could have assisted to profile tourism establishments based on affordability. Research data was only collected in the Free State, thus studies conducted in other provinces may yield different results. Also, qualitative data was not collected on the reasons for perceptions on factors influencing tourism grading. This data could have assisted better understanding components involved in each factor, for example, what benefits are most important to tourism establishments. Therefore, opportunities for future studies could include conducting a similar study in all provinces to better generalise the research results. Different AI and computational intelligence methods such as support vector networks, multi-layer perceptron and ANN can be used to construct a similar model, and be compared with the constructed model in this study. A study to investigate the effectiveness of this model could also be conducted. Lastly, a study to investigate the impact of the model on tourist arrivals could also be developed.

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