



Artificial intelligence

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Artificial Intelligence: A Systematic Review of Methods and Applications in Hospitality and Tourism

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Abstract

Purpose

Several review articles have been published within the Artificial Intelligence (AI) literature that have explored a range of applications within the tourism and hospitality sectors. However, how efficiently the applied AI methods and algorithms have performed with respect to the type of applications and the multimodal sets of data domains has not yet been reviewed. Therefore, this paper aims to review and analyse the established AI methods in hospitality/tourism, ranging from data modelling for demand forecasting, tourism destination, and behavior pattern to enhanced customer service and experience.

Design/methodology/approach

The approach was to systematically review the relationship between AI methods and hospitality/tourism through a comprehensive literature review of papers published between 2010-2021. 146 articles were identified and then critically analysed through content analysis into themes including “AI methods” and “AI applications”.

Findings

The review discovered new knowledge in identifying AI methods concerning the settings and available multimodal datasets in hospitality and tourism. Moreover, AI applications fostering the tourism/hospitality industries were identified. It also proposes novel personalised AI modelling development for smart tourism platforms to precisely predict tourism choice behaviour patterns.

Practical Implications

41 This review paper offers researchers and practitioners a broad understanding of the proper
42 selection of AI methods that can potentially improve decision-making and decision-support in
43 the tourism/hospitality industries.

44 **Originality**

45 This paper contributes to the hospitality/tourism literature with an interdisciplinary approach
46 that reflects on theoretical/practical developments regarding data collection, data analysis,
47 and data modelling using AI-driven technology.

48 **Keywords:** Artificial Intelligence, Hospitality/Tourism, AI Methods/Algorithms, AI
49 Applications, Future Studies-in-Tourism

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1. Introduction

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The modern world is rich in data, and big data analysis has grown in prominence in recent years. From a diverse range of industries, many businesses are becoming increasingly reliant on the information derived from massive amounts of data generated in the course of their business. However, in big data analytics, traditional data techniques and platforms are not well equipped to analyse today's large amount of structured and unstructured data, make correlations, and forecast patterns across datasets (Maclaurin *et al.*, 2019). These limitations are more challenging when it comes to real-life scenarios where customer engagement and customer service are at the core of decision-making (So *et al.*, 2021).

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The hospitality and tourism industries are not an exception. Hospitality and tourism businesses increasingly rely on interpreting and analysing large volumes of data, including multimodal datasets (numerical, categorical, time-series, image, and text) (Samara *et al.*, 2020). The enormous amount of data available makes the information extraction phase more complex and requires advanced analytical techniques to perform the analysis. Furthermore, the unprecedented disruption caused by the COVID-19 crisis has necessitated the creation of new theoretical and analytical frameworks capable of transforming potential chaos into a catalyst centred on perceptive, actionable intelligence (Polyzos *et al.*, 2020).

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While data analytics and experimental scientists have long discussed this topic, recent artificial intelligence (AI) technologies have brought new insights into such discussions (Barr and Feigenbaum, 2014). The term "Artificial Intelligence" is utilised to define machines that emulate human mind-related "cognitive functions", such as "learning" and "problem-solving" (Mitchell *et al.*, 2013). AI algorithms have shown an eminent aptitude to learn from the data and obtain profound patterns that can be used to predict and detect events. The influence of AI technology can now be seen across different sectors such as psychology, space exploration, healthcare, marketing, and finance (Pannu, 2015, Doborjeh *et al.*, 2021b, Sanders *et al.*, 2021, Doborjeh *et al.*, 2018b). Statista (2021) reported that the AI market has been rapidly expanding in recent years, with total revenue reaching \$28.1 billion in 2018. A recent report by PricewaterhouseCoopers also predicts that AI will significantly increase the world's GDP— up to 26% for China, 16% for the USA, and 10% for countries like New Zealand. Developments in AI, and its acceptance by service industries, have been translating the hospitality and tourism industries in many ways, impacting on areas including consumer demand, tourist experiences and perceptions, destination management, and prediction of tourists' behaviours (Wu *et al.*, 2017, Filieri *et al.*, 2021). Recent studies confirm this by demonstrating a significant correlation

83 between AI services, the perceptions of quality, consumer happiness, and engagement (Prentice
84 *et al.*, 2020, Mariani and Borghi, 2021, Kong *et al.*, 2021). Several review experiments have
85 been conducted in the hospitality and tourism literature, and many have studied a diverse range
86 of existing AI applications. However, there has been little systematic review of the impacts and
87 trends of AI methods for extensive data analysis and potential AI applications in hospitality
88 and tourism settings has not been provided. In addition, how the applied AI methods and
89 algorithms have been performed efficiently in developing the target applications with respect
90 to the datasets need to be reviewed, and the potential AI application needs to be discussed.
91 Therefore, the current study presents a systematic review of the role of AI methods and
92 algorithms in hospitality and tourism research and industry related to multimodal data
93 processing, data modelling for demand forecasting, tourism destination, and behavior patterns.
94 This comprehensive review of AI methods and algorithms, as well as review on AI applications
95 in tourism, have enabled the discovery of which applied methods perform best concerning the
96 “application types” and the “data domain”. The originality of the paper resides in the new
97 perspective provided by an authorship team that comes from the AI academic disciplines –
98 knowledge engineering, psychology and AI, computer science and AI, and one
99 tourism/hospitality academic. This approach is unique because it brings AI thinking and theory
100 into the tourism literature and through this strengthens the theoretical implications.

101 The novel contributions that emerge from this approach are outlined as follows:

- 102 1. It reviews and compares different well-known AI methods used in hospitality and
103 tourism studies. The most widely used AI algorithms, as stated in the literature,
104 are critically evaluated. These methods range from basic computational methods,
105 such as clustering models for image data in Machine Learning (ML), to more
106 advanced computational techniques, such as classification and prediction using
107 state-of-the-art Artificial Neural Networks (ANN) and Deep Learning algorithms
108 for big time-series and multimodal spatiotemporal data.
- 109 2. The review focuses on adaptation and adoption of AI methods in tourism sectors,
110 including the significant AI applications in tourism such as Virtual Reality,
111 Augmented Reality (AR), Automation and Robotics, chatbots, Natural Language
112 Processing (NLP), and Virtual Assistants (VA)/chatbot. These are discussed in
113 terms of the ways that they are transforming, and in some ways reinventing the
114 hospitality and tourism industries.
- 115 3. The review discovers new knowledge about the efficiency of different AI
116 methods in relation to tourism applications and data domains.

117 4. Finally, it opens new research directions opportunities for hospitality and tourism
118 researchers from the AI perspective.

119 **2. Method**

120 The method was to systematically review the relationship between AI methods and
121 applications in hospitality and tourism through a comprehensive literature search based on
122 ‘title/abstract/keyword’(Moher *et al.*, 2009). The search strategy accounted for a range of
123 search terms, keywords, and phrases that included “AI algorithms in tourism and hospitality
124 settings”, “smart tourism”, and “future AI technologies”. A sample of journals was selected
125 based on A* and A-ranked tourism journals on the Australian Business Deans Council’s
126 (ABDC) journals ranking list (Table I). This ranking was chosen because it is specifically
127 geared towards journals in business, management, and industry. Also, we included journals
128 that focus more specifically on AI and technology, including the Journal of Hospitality and
129 Tourism Technology. As presented in Table I, the review of articles published from 2010 to
130 2021 in the leading hospitality and tourism journals indicates that the “International Journal of
131 Contemporary Hospitality Management” published the highest number of tourism and AI
132 research articles, followed by the “Asia Pacific Journal of Tourism Research”, “Tourism
133 Management”, “Annals of Tourism Research”, the “Current Issues in Tourism” and “Journal
134 of Hospitality and Tourism Technology”. Through this review, 146 articles were identified
135 within the scope of AI in tourism. They were then critically analysed through content analysis
136 into two themes: AI methods/algorithms and AI applications. Table II summarises the
137 contribution of most important articles in the literature in this realm. Based on the referenced
138 articles from the listed journals in Table II, the current review paper also addresses the research
139 questions as the following:

- 140 • What is the contribution of the literature in the form of AI services in hospitality
141 and tourism?
- 142 • What type of AI methods, applications, and data can best contribute to hospitality
143 and tourism industries’ knowledge in the future?

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145 Table I. The number of selected top A* and A ranked journals related to AI in hospitality and tourism, published between 2010
146 to 2021.

Journals	Publishers	Selected	Rating
Annals of Tourism Research	Elsevier	14	A*
Asia Pacific Journal of Tourism Research	Taylor & Francis Online	15	A
Cornell Hospitality Quarterly	Sage Publications	2	A
Current Issues in Tourism	Taylor & Francis Online	13	A
International Journal of Contemporary Hospitality Management	Emerald Group Publishing	50	A
International Journal of Hospitality Management	Elsevier	6	A*
International Journal of Tourism Research	Wiley-Blackwell Publishing	1	A
Journal of Hospitality and Tourism Management	Elsevier	2	A
Journal of Travel & Tourism Marketing	Taylor & Francis Online	8	A
Journal of Vacation Marketing	Taylor & Francis Online	4	A
Tourism Recreation Research	Taylor & Francis Online	3	A
Journal of Hospitality and Tourism Research	Sage Publications	4	A
Tourism Management	Elsevier	14	A*
Journal of Hospitality and Tourism Technology	Emerald Insight	10	B

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148 Table II. Overview of AI Methods-related articles selected from the ABDC journals.

AI Methods-related Content Papers					
Machine learning methods					
Author/Year	Study context	Data	Methodology	Model performance	Industry
Zhang (2014)	Identifying the main elements affecting Chinese citizens' intentions for outbound travel.	Questionnaire consists demographic and personal values variables collected in Nanjing, March-May 2011.	- C4.5 Rule-PANE. - The neural network ensemble - Neural network - logistic regression	The neural network ensemble and C4.5 Rule-PANE outperformed statistical logistic regression and the simple neural network. Error rates: Logistic regression: 0.45 C4.5 Rule: 0.44 Neural network: 0.42 Neural network ensemble: 0.38 C4.5 Rule-PANE: 0.37	Tourism destination
Donaire (2014)	Understanding tourists' behaviours with different perspectives of the same place.	1,786 photos taken by tourists from the valley (Spain) and posted on Flickr website.	Ward's method	The results showed a four-cluster solution as the most proper that were significantly differentiated at p value $\leq .05$	Tourism pattern behavior
Giglio <i>et al</i> (2019)	Identifying clusters surrounding points of interest.	26,392 photos of 6 cities in Italy that was taken from 2014-2016 posted on Flickr website.	- (DBSCAN) - k nearest neighbours - Euclidean distance	DBSCAN method was able to obtain higher accuracy in compared to the k-means technique.	Tourism pattern behavior
Höpken <i>et al</i> (2020)	Investigating tourists' movement and point of interest.	13,545 photos taken by tourists for the year 2015 and posted in media.	- K-mean - (DBSCAN)	DBSCAN method was able to find common and randomly formed clusters when compared to the k-means technique. On a smaller scale, k-means clustering recognised closely associated point of interests more accurately than DBSCAN.	Tourism pattern behavior
Ramos-Henríquez <i>et al</i> (2021)	Identifying the most important characteristics of the value proposition for the Superhosts.	250 features from 5136 listings were collected in the region of Canary Islands.	- Boruta for feature selection - (SVM) for classification	Creating forecasting model of SVM with Boruta feature selection that led to a better accuracy performance.	Hospitality
Xie <i>et al</i> (2021)	Forecasting Chinese cruise tourism demand.	Search query data.	- (LSSVR) model with (LSSVR-GSA)	LSSVR-GSA obtained the highest forecasting performance.	Tourism demand forecasting
Artificial neural network methods					
Authors/Year	Study context	Data	Methodology	Model performance	Industry

Silva <i>et al</i> (2019)	Forecasting tourism demand	Tourism demand of ten European countries.	- NNAR - Denoised neural networks	Results support denoising method for increasing the accuracy of NNAR forecasting capabilities.	Tourism demand forecasting
Liu (2011)	Predicting number of tourists	Time series data on number of tourist visitors between 1998-2009 in Weifang.	- (BPNN) - Gradient descent method	The simulation model of the number of visitors based on BPNN was effective and more accurate.	Tourism demand forecasting
Golmohammadi <i>et al</i> (2011)	Predicting tourists' satisfaction in travel	1,870 questionnaires collected from tourists in the Airport over three months- time.	Hybrid neural network	The hybrid neural network performed well in predicting the tourists' overall satisfaction. Error: (Root-mean-square deviation (RMSE)=0.05246)	Hospitality
Zhu <i>et al</i> (2018)	Forecasting tourist flow	Tourism demand in by six major origins in Singapore, collected between 1995-2013.	The copula-based approach	The proposed copula-based model performed better than the benchmark models.	Tourism demand forecasting
Claveria <i>et al</i> (2016)	Forecasting tourism demand and to compare the performance of three different ANN models	Tourist arrivals, collected between 2001-2012.	- (MLP), - (RBF) - Elman recursive neural network.	MLP and RBF networks' mean absolute percentage error (MAPE) was lower than Elman networks.	Tourism demand forecasting
Sanchez (2020)	Identifying intentions that lead consumers to cancel hotel booking	10,000 bookings records of a four-star hotel in Spain, collected from 2016-2018.	- (SVM) - (ANN) - (GA) -Random forest	When ANN is optimised with GA, it increased the performance of accuracy. Random forest:.80% SVM: .73% ANN (GA optimised): .98%	Hospitality
Kwon (2020)	Identify underlying factors of consumers' preference in restaurants	4,799,240 reviews of restaurants since October 2004, collected from Yelp.com.	- Linear mixed-effect - (NLP)	NLP techniques shown promising results in analysing textual data.	Tourism pattern behavior
Deep learning methods for big data					
Authors/Year	Study context	Data	Methodology	Model performance	Industry
Li (2018)	Tourism flow prediction	Beijing tourist volumes between 2011-2015, collected from the Beijing Tourism Association (BJTA).	- Principal component analysis (PCA)-based index - Generalized dynamic factor model (GDFM)-based index	The forecast accuracy of the GDFM-based index model was higher than the other models. (Increased accuracy over 50%).	Tourism pattern behavior
Zhang B <i>et al</i> (2020)	Forecasting daily tourist flow	Tourist flow in Jiuzhaigou, China, collected between, 2013-2017	- (LSTM) - contextual- Long short-term memory (C-LSTM) - Deep belief network - (BPNN)	LSTM obtained the highest accuracy and low mean relative error .	Tourism pattern behavior
Lado-Sestayo (2019)	Predicting hotel profitability	Hotel and tourist destinations, collected between 2005-2011.	- Multi-layered neural network	The proposed model obtained the high predictive accuracy of hotel profitability.	Hospitality

Chang Y-C (2020)	Predicting hotel reviews and responses	113,685 hotel reviews	- (NLP)	The proposed multi-feature fusion, convolutional neural network model outperforming the other statistical methods.	Tourism/Hospitality
Zhang K (2019)	Understanding tourists' behaviours and perceptions	35,356 tourists' photos from Flickr.	Deep learning technology	Introducing AI-DL technology into tourism destination research.	Tourism pattern behavior
Al Shehhi (2020)	Forecasting hotel room prices in selected Gulf Cooperation Council (GCC) cities	2800 observations of daily room sales, collected between 2010-2017.	- (SARIMA) - Deep belief network - (ANFIS) - Polynomial smooth support vector machine (PSSVM)	This analysis shows that the ANFIS model has performed better compared to other models MAPE error rate are: SARIMA= 0.0056 Deep belief= 0.0043 ANFIS= 0.0021 PSSVM= 0.0030	Tourism demand forecasting
Wu (2021)	Predicting tourist arrivals to Macau, China.		- (SARIMA) - (LSTM)	Combining SARIMA and LSTM resulted higher accuracy and outperform other methods.	Tourism demand forecasting
He (2021)	To increase the forecasting performance accuracy of tourism demand		- (SARIMA) - Convolutional neural network (CNN) - (LSTM)	Combined SARIMA–CNN–LSTM model generates superior forecast accuracy than each model alone.	tourist demand forecasting

3. Analytical AI Methods for Big Data in Hospitality and Tourism

In this section, we use the terms “classification,” “prediction” and “regression” as the well-known tasks conducted by AI models. Classification refers to the process of detecting the category (class label) of the new observation (data sample) to which it belongs. A Prediction task is a process of detecting the class label of an unavailable data sample that will be recorded in the future. Regression refers to modelling time-series data and detecting the numerical values of data variables that will be collected in the future. We also referred to the term “feature selection” which is related to the detection of the most informative data variables that can increase the accuracy of outcome prediction, classification, and regression (Gholami Doborjeh, 2019, Searchfield *et al.*, 2021). Figure 1 summarises the main analytical AI methods that are being applied to tourism and hospitality studies along with the main AI-driven applications. These AI methods algorithms and applications shown in Figure 1 will be discussed in the following sections.

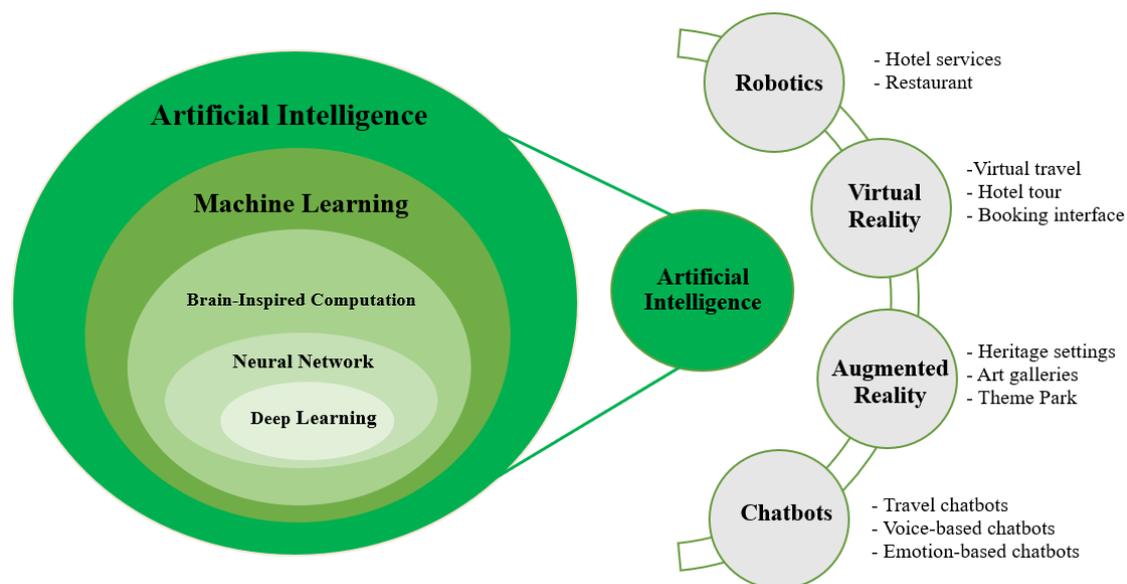


Figure 1. Artificial Intelligence methods and applications in hospitality and tourism.

3.1 Statistical Machine Learning in Hospitality and Tourism

The use of ML methods has increased dramatically in hospitality and tourism research over the past few years. ML applies statistics and computer science concepts to construct mathematical models that are used for future predictions and to recognise data trends (Alpaydin, 2020). In our review, ML algorithms have mostly been used in hospitality and tourism operational aspects such as hotel services, forecasting prices, and customer demand (Zhang *et al.*, 2017).

173 **Clustering Techniques in Hospitality and Tourism:**

174 In hospitality and tourism studies, cluster analysis has been used for a wide range of
175 purposes. That includes determining the purpose or significance of a place (Bi *et al.*, 2020),
176 investigating the actions taken over time by the tourists (Aluri *et al.*, 2019), and assessing what
177 has changed in a place visited (Donaire *et al.*, 2014). Zhang *et al.*, (2014) conducted an
178 experiment to assess the relationship between Chinese people's psychographic and
179 demographic data variables and their travel intentions (Zhang and Zhang, 2014). The authors
180 used twice-learning algorithms in this study and compared four commonly used ML algorithms
181 including logistic regression, neural network, neural network ensemble, C4.5 Rule, and C4.5
182 Rule-PANE. The authors reported that C4.5 Rule-PANE achieved better predictive
183 performance accuracy than the other methods. In Donaire's study, the Ward's method was used
184 to find proof of tourist gaze profiles by reviewing photographs captured by visitors and posted
185 in social medias (Donaire *et al.*, 2014). Giglio *et al.*, (2019) further collected 26,392 photos
186 linked to six Italian cities to assess clusters surrounding points of interest (POI). This research
187 used the Density-based Spatial Clustering of Applications with Noise (DBSCAN) technique to
188 automatically characterise the most frequently visited geographic locations (Giglio *et al.*,
189 2019). Höpken *et al.*, (2018) also analysed the suitability of different clustering methods,
190 including DBSCAN, to investigate tourists' spatial movement and POI visitation behaviour
191 using 13,545 photos for the year 2015 (Höpken *et al.*, 2020).

192 **Classification and Prediction Techniques in Hospitality and Tourism Studies:**

193 In the literature, the most well-known ML methods that have been applied for
194 classification/prediction of tourism data are Support Vector Machine (SVM) and Multiple
195 Linear Regression (MLR) methods (Yao *et al.*, 2004). To forecast tourism demand, Pai and
196 Hong (2005) initially proposed the SVM technique within tourism settings (Pai *et al.*, 2005).
197 Pai demonstrated that the Multifactor Support Vector Machine Model (MSVM) combined with
198 Back-Propagation Neural Networks (BPNN) model can enhance the forecasting tourist
199 arrivals' accuracy for numerical and non-linearly discrete dependent variables. Since then,
200 SVM combined with BP has been used for forecasting tourist arrival problems. An SVM
201 training algorithm builds a model that assigns new examples to one of two categories given a
202 set of training examples. It does so by mapping the original input data space into a higher
203 dimensional space and identifying the data vectors (support vectors) in this space that
204 discriminate the areas of samples from two or more classes (categories) (Alpaydin, 2020).
205 Recently, Ramos-Henríquez *et al.*, (2021) used two different ML methods: the Boruta
206 algorithm for feature selection and the SVM for the prediction of variables that contribute the

207 most to being an Airbnb Super-host (Ramos-Henríquez *et al.*, 2021). Xie *et al.*, (2021), recently
208 proposed a methodology framework for hospitality and tourism big data that can provide
209 valuable predictors for forecasting demand for Chinese cruise. They used Least Squares
210 Support Vector Regression (LSSVR) model for tourism demand' forecasting. The hyper-
211 parameters of the ML method were optimised using Gravitational Search Algorithm (GSA) to
212 achieve the highest forecasting performance accuracy (Xie *et al.*, 2021).

213 3.2. Artificial Neural Networks in Hospitality and Tourism

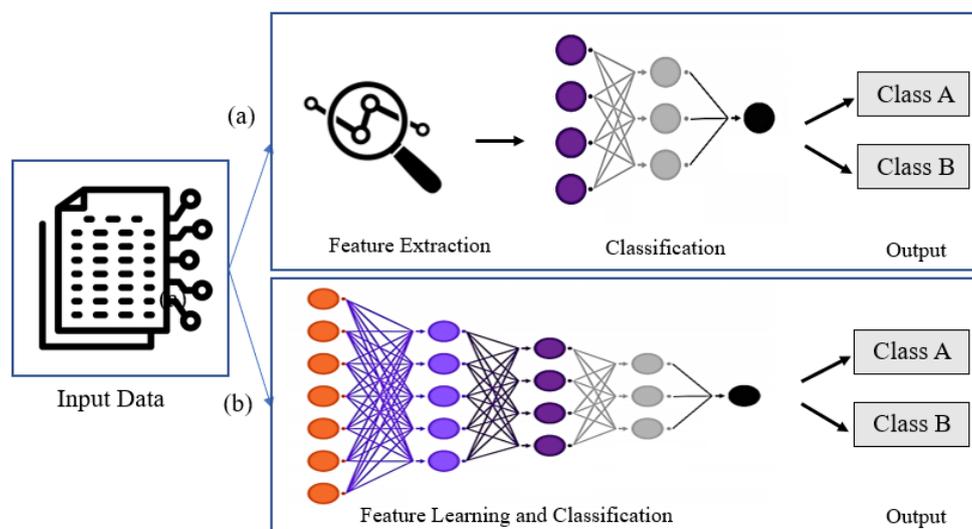
214 ANNs modelling is the AI-based methodology that has emerged mostly in recent tourism
215 literature (van Gerven and Bohte, 2018). An ANN is architecturally modelled using artificial
216 neuron layers of computational units capable of receiving inputs and applying an activation
217 function with a threshold to verify whether messages are being transmitted over the network
218 (Kasabov, 1996). The first layer is the input layer in a basic model of ANN, followed by one
219 or more hidden layers, and finally by the output layer. Models can become more sophisticated
220 and have greater problem-solving abilities through increasing the number of hidden layers, the
221 number of neurons in each layer, and the number of routes between them (Kasabov, 1996). Our
222 review discovered that several ANN models, including MLP, Radial Basis Function (RBF),
223 Back Propagation (BP), Genetic Algorithm (GA), Generalized Regression Neural Network
224 (GRNN), Elman Neural Network (Elman NN), Neural Network Autoregressive NNAR and
225 denoised neural networks have been mostly used in tourism studies (Silva *et al.*, 2019). The
226 ANN algorithms mostly have been applied to longitudinal data in the form of time-series in
227 forecasting tourism and hospitality demands including travel, hotel, transportation, and
228 consumers' values and satisfaction. For example, Liu (2011) applied the BP algorithm to
229 forecasting tourists arrivals to Weifang, China (Liu, 2011). The results obtained not only had
230 higher prediction accuracy in compared with other ML methods but showed a strong model
231 adaptation. Golmohammadi *et al.*, (2011) developed a hybrid neural network model to predict
232 the happiness of travel experience. The suggested hybrid neural network could predict tourists'
233 happiness with a low degree of error (Golmohammadi *et al.*, 2011). ANN further was used to
234 forecast tourism demand from all tourist markets in Catalonia. The accuracy performance of
235 three ANN methods for forecasting tourist demand was compared with MLP, Radial Basis
236 Function (RBF) and an Elman network. The results showed that MLP and RBF models
237 outperform Elman networks (Claveria and Torra, 2014, Claveria *et al.*, 2015). The ANN used
238 in Zhu's research provided a more general context to evaluate tourism demand and forecast for
239 Singapore over a 19-year period. The author conducted a research to resolve the concerns

240 around the structure of dependency between tourist flows as an essential factor in the forecast
241 of tourism demand (Zhu *et al.*, 2018). Sanchez *et al.*, (2020) also used ANN techniques to
242 predict the most contributing variables in hotel booking cancellations using tree decision-based
243 algorithms, C5.0 and random forest, SVM, and GA. When ANN was optimised with GA, this
244 method achieved an accuracy of over 0.95% (Sánchez-Medina and Eleazar, 2020). ANN was
245 also applied to Kwon's research to understand customer value in restaurants by identifying
246 underlying factors of consumers' preferences to improve their experience (Kwon *et al.*, 2020).
247 Kwon analysed the time-series data through ML-based NLP technique and regression method
248 and obtained high accuracy.

249 *3.3 Deep learning Neural Networks in Hospitality and Tourism*

250 Deep learning methods account for the highest revenue slice currently, valued at \$308.4
251 million in 2016 and expected to grow to \$16 billion by 2025, according to Tractica analysts.
252 Figure 2 compares the methods of statistical ML and the methods of DL. As shown in Figure
253 2, DL is an ANN method that consists of many layers of artificial neurons and learning
254 algorithms for identifying complex patterns from a massive amount of data samples. In the DL
255 model, the performance accuracy can be improved by an automated feature extraction function
256 (Goodfellow *et al.*, 2016, Chang *et al.*, 2020). Recent advances in DL techniques have provided
257 more accurate forecasting of tourism demand (Law *et al.*, 2019). Particularly, Recurrent Neural
258 Network (RNN), and Long-Short-Term-Memory (LSTM) are capable of handling complex
259 time-series data and learning long-term dependencies (Wu *et al.*, 2021, He *et al.*, 2021). The
260 DL method offers exceptional benefits in detecting high-dimensional big structural data
261 variables with more accurate prediction and detection when compared with ML and statistical
262 approaches (Zhang *et al.*, 2020). Li and Cao (2018) examined prediction performance of
263 BPNN, Autoregressive Integrated Moving Average (ARIMA), and the LSTM methods on
264 tourism flow. The results showed that the LSTM is simpler, more effective, and accurate than
265 the others. In this research, they also demonstrated the capacity of the DL to model non-linear
266 and stochastic structures that cannot be modelled by previous linear models (Li and Cao, 2018).
267 Chang *et al.*, (2020) analysed hotel reviews using deep learning-based NLP to discover
268 managerial responses through multi-feature fusion. In this model, a feature vector was fed into
269 the convolutional neural network model, and many simple non-linear activation functions were
270 employed to construct a complex and comprehensive model that enhances classification
271 accuracy. Zhang's study used the DL for forecasting the daily tourist flow via user search data.
272 In this research, the LSTM model has contributed to the dynamic observing of tourist flows,

273 which is significant in practical terms for reducing safety risks in tourist destinations, making
274 the achievements of this research very helpful for tourism-related industries (Zhang *et al.*,
275 2020). Al Shehi (2020) used the DL approach in selected Gulf Cooperation Council cities to
276 predict the process of hotel room. The author compared four DL methods: the Seasonal
277 Autoregressive Integrated Moving Average (SARIMA) model, the restricted Boltzmann
278 machine as a deep belief network model, the polynomial smooth SVM model, and finally, the
279 Adaptive Network Fuzzy Interference System (ANFIS) model. The results showed that the
280 ANFIS performance accuracy was higher than other models in predicting prices (Al Shehhi
281 and Karathanasopoulos, 2020). However, recently, researchers are using SARIMA–LSTM
282 model to forecast tourist demand data at daily frequency. The authors reported that when the
283 SARIMA combined with LSTM layers, the model could capture linear and nonlinear data
284 features and resulted in better accuracy in the forecasting problems (He *et al.*, 2021, Wu *et al.*,
285 2021). Zhang *et al.*, (2019) applied the DL method to analyse big data collected from images
286 taken by visitors between 2008-2012 to predict tourism behavior, perceptions, and destinations.
287 They used DL scene recognition to identify the contents of tourist photographs. Zhang’s
288 research was the first study to demonstrate the importance of spatiotemporal data and the DL
289 approach in predicting the tourists’ behaviour trajectory with greater accuracy (Zhang *et al.*,
290 2019). Further, authors designed a multi-layered neural network to predict hotel profitability
291 through DL techniques using spatiotemporal data related to hotel and tourist destinations
292 between 2005-2011. When compared to traditional ML methods, the findings demonstrated
293 that the suggested model has a good prediction capability for hotel profitability (Lado-Sestayo
294 and Vivel-Búa, 2019).



295

296 Figure 2. (a) A statistical machine learning method uses hand crafted features, which is tedious and costly to develop; (b) A
297 deep learning neural network structure learns hierarchical representation from the data, and automatically extract meaningful
298 features, and scales with big data.

299 **4. The Adoption of AI-based Methods in Hospitality and** 300 **Tourism Applications**

301 The AI applications that have been launched more recently including robotics, AR/VR,
302 and chatbot (virtual assistant), seem to be the ones that are changing the tourism and
303 hospitality industries.

304 *4.1 Robotics in Hospitality and Tourism*

305 Robotics is one of the newest AI developments to enter the field of hospitality and
306 tourism (Tussyadiah et al., 2020, Tussyadiah, 2020, Park, 2020). The International Federation
307 of Robotics (IFR, 2016) describes it as “a robot that performs tasks for humans or equipment
308 without the application of industrial automation”. In hospitality and tourism environments, the
309 robotics applications are primarily used for better production management and customers
310 engagement in hotels, restaurants, and airport operations (Noone and Coulter, 2012, Ivanov *et*
311 *al.*, 2019a, Tuomi *et al.*, 2019, Borghi and Mariani, 2020, Choi *et al.*, 2020). The benefits of
312 implementing robotics to the tourism and hospitality industries lie in enhancing service quality,
313 reducing labour costs, and improving the efficiency of hotel operations (Ivanov *et al.*, 2019a,
314 Zemke *et al.*, 2020). Tung and Au (2018) examined that when robot hotel services are provided,
315 hotel guests report better and quality experiences (Tung and Au, 2018). Hotel’s robots mimic
316 human cognition and behaviour, allowing them to recognise and anticipate the guests’ motives
317 and then provide an effective service. This is confirmed by Zhong (2020) research that studied
318 the effect of robotics hotel services on consumers' purchase intention (Zhong *et al.*, 2020).
319 Noone and Coulter (2012) also studied how advances in robotics can enhance quick-service
320 restaurant operations by using the case of Zaxby's (Noone and Coulter, 2012). This system
321 monitors consumer arrivals, starts cooking as consumers arrive, and gives employees precise
322 instructions to speed up cooking and service, thereby reducing waiting times. This data is then
323 combined with historical sales information to forecast the demand for individual food items.
324 Consumers, recently, have been more open and accepting of personalised and individualised
325 experiences from robotic hotel services (Ivanov *et al.*, 2019b, Çakar *et al.*, 2020). The existing
326 pandemic (COVID-19 crisis) may cause in the conversion of hospitality and tourism industries
327 to rely more on robotic service providers (Itani and Hollebeek, 2021, Jiang and Wen, 2020).
328 According to World Health Organisation (WHO) (Organization, 2020), adaption to the robotic
329 service system for both providers and consumers is required as it provides a physically and

330 socially distant service. Robots can be utilised efficiently during pandemics to provide physical
331 separation between hosts and guests (Seyitoğlu and Ivanov, 2021)

332 4.2 *Virtual/Augmented Reality in Hospitality and Tourism*

333 VR technology typically uses a VR headset that simulates a virtual experience in a 3D and
334 digital realms environments (Yung and Khoo-Lattimore, 2019). In the tourism and hospitality
335 businesses, VR technology is becoming popular (Han *et al.*, 2014, Loureiro *et al.*, 2020). These
336 industries demonstrate a 3D video to create “virtual travel”, “hotel tour”, and “booking
337 interface” experiences for customers (Guttentag, 2010, Slevitch *et al.*, 2020, Wei, 2019). For
338 instance, in virtual hotel tours, consumers encounter with the hotel atmosphere, the amenities
339 in the form of 3D visualisations and videos. Customers reported higher levels of enjoyment
340 through virtual hotel tours experiences as VR experiences are believed to elicit greater
341 customers arousal, greater focused attention, and time distortion than sightseeing VR
342 experiences (Huang *et al.*, 2020, Subawa *et al.*, 2021). Furthermore, the research revealed that
343 women are more influenced by VR in a virtual world than males (Lyu *et al.*, 2021). Virtual
344 booking interface is another example that enables customers to walk through an airplane and
345 choose a seat in the aircraft in real-time and simulated experience (Samala *et al.*, 2020). Unlike
346 VR, which is a reality replication that allows users to be engaged in an imaginary environment,
347 Augmented Reality (AR) covers virtual 3D graphics to allow connection with virtual graphics
348 (Lau *et al.*, 2019). By overlaying knowledge on learning, AR connects high-level abstract ideas
349 with physical and real environments, which helps learners in constructivist learning (Tsai,
350 2020). AR has been used in several tourism settings of historic tourist places including art
351 exhibitions (tom Dieck *et al.*, 2018), city tours, and parks (Lau *et al.*, 2019). It is believed that
352 VR knowledge and interaction can provide compelling immersive experiences and ensure
353 environmental and socio-cultural sustainability by enhancing and expanding the experience of
354 travel (Shin and Jeong, 2021). In a smartphone AR app, Jiang *et al.*, (2019) explored the
355 experiences of 323 tourists through a tourism destination in National Park in Shangri (Jiang *et*
356 *al.*, 2019). The findings demonstrated a strong correlation between preferences of AR
357 experience and perceived value's functional and social dimensions. These results illustrate how
358 AR could protect national parks while also improving the experience of tourists. Tsai (2019)
359 also found that location-based AR technologies can improve site satisfaction for heritage
360 tourism in Beijing (Tsai, 2020). In Dick's study (2018), visitors to an art gallery experiencing
361 VR tours achieved better results in terms of enhancing knowledge, satisfaction, changing
362 values, improved creativity and activity in contrast to visitors who participated the gallery

363 without access to VR technology (tom Dieck *et al.*, 2018). The introduction of AR can further
364 promote the smooth operation of events and enrich the experience of participants. For instance,
365 Lau *et al.*, (2019) explored the experiences of 161 stakeholders and their intention to take part
366 in two international conferences through an established AR app (Lau *et al.*, 2019). This
367 research can further provide helpful information on the adoption of AR in tourism and what
368 kind of knowledge and functionality customers will be willing to see in the future.

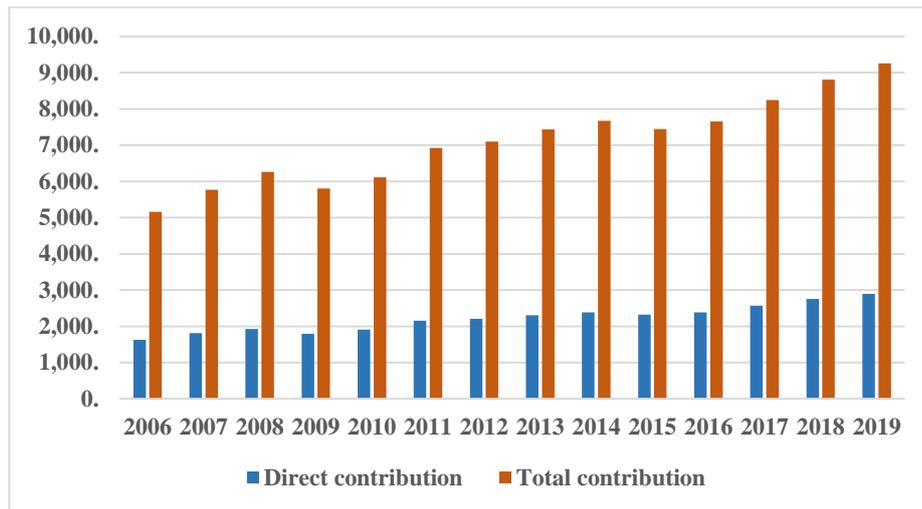
369 4.3 Chatbots/Virtual Assistant in Hospitality and Tourism

370 A chatbot or VA is a software program that interacts with users in a natural language
371 (Ukpabi *et al.*, 2019). It is projected that by 2025, 85 percent of customers will connect to
372 companies without a human, according to a report by Gartner, 2020. The chatbots have also
373 been an active part of the hospitality and tourism industry. Hotels or other tourism companies
374 have their chatbots on social media or instant messaging applications, which is available 24/7
375 for all 365 days in a year (Ukpabi *et al.*, 2019). The tourism sectors in that chatbots are now
376 being used chiefly are “travel chatbots”, “voice-based chatbots”, and “emotion-based chatbots”
377 (Lv *et al.*, 2021, Melián-González *et al.*, 2019). Voice-based chatbots are designed to answer
378 consumers questions, such as ordering food services, taxi services, reading notes, arranging
379 tasks and appointments, setting alarms, room services, housekeeping services, informing hotel
380 facilities, and etc. (Pillai and Sivathanu, 2020). Recently, the programmers are now developing
381 the chatbot platform, which is more customer-centred and not programmer-centred, to
382 genuinely create a chatbot that can perceive and better understand the customers’ behavior,
383 feelings, and intentions (Pillai and Sivathanu, 2020). This is called as the emotion-related
384 chatbots. In recent years, the technology behind emotion-related chatbot has advanced to allow
385 the VA to convey emotions. In the traveling chatbots application, travellers can drive with no
386 guide using the travel chatbots, as the travel chatbot can be installed in the vehicle and describe
387 each location. This technology is also referred to as an audio tour, sometimes preferred by
388 travellers who want privacy and travel alone with their families (Boiano *et al.*, 2019, Samala
389 *et al.*, 2020).

390 5. Artificial Intelligence: The Future of the Hospitality and 391 Tourism Industries

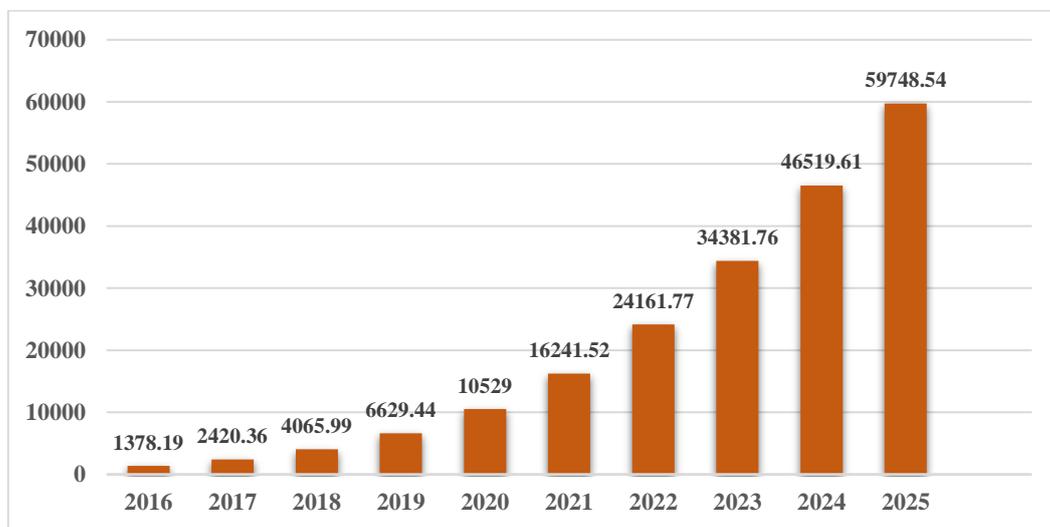
392 The statistics and presence of AI technologies at every step of this industry show the
393 importance of AI in hospitality and tourism and how, by the 2030s (Statista, 2021), AI
394 techniques and applications will become an important asset for many aspects of tourism

395 organisation. Figure 3 presents the global economic contribution of the tourism sector that has
 396 estimated over \$9 billion in 2019, according to Statista (Gross Domestic Product (GDP))
 397 (Statista, 2021). It is projected that the development of the global AI revenue in the world
 398 market will grow rapidly in coming years and will reach from \$1378.1 million in 2016 to
 399 \$59748.5 million in 2025 (Statista, 2021), presented in Figure 4.



400

401 Figure 3. The global economic contribution of travel and tourism to Gross Domestic Product (GDP) from 2006 to 2019. From
 402 2006 to 2019, the direct and total contribution of travel and tourism to GDP was calculated (in billion U.S. dollars).



403

404 Figure 4. The revenues projection for AI market worldwide from 2016-2025 (in million U.S. dollars).

405 In this section, we propose a new research model that still needs to be discussed in
 406 hospitality, tourism, and AI. The proposed model depicted in Figure 5 suggests a new AI model
 407 for big multimodal data collection, proper data analysis and potential future direction in tourism
 408 and hospitality. The following sections discuss the implementations of AI in tourism and
 409 hospitality in two aspects "methodological" and "application".

410 *5.1 Methodological-based Hospitality and Tourism Studies*

411 *5.1.1 Spatio-Temporal Data Analysis*

412 Tourist behaviour is always contextualised in time and space. The locations influence in
413 visitor travel patterns visited as well as the passage of time (Yunxian *et al.*, 2020). In tourism,
414 spatiotemporal data contains geographic and time information that can be used to analyse the
415 tourists' activities, behavior, movement, and distribution (Yao *et al.*, 2021) (Figure 5a).
416 However, accurately integrating spatial and temporal information into a systematic model
417 remains a challenge in tourism research. Most existent techniques in tourism literature create
418 models by separately processing the space and time dimension of data. Scrutinising the
419 interactions between geographic features in time-series data demands incorporating the
420 temporal aspects of all features into one unifying computational model (Doborjeh *et al.*, 2019).
421 Another issue with the current statistical ML analytical tools for spatiotemporal data analysis
422 is the lack of a deep model's interpretability (Kugele *et al.*, 2020). This means understanding
423 the relationships between temporal patterns of input variables and the projected over time
424 outputs (Doborjeh *et al.*, 2021a). Building a computational brain-inspired AI-based model
425 could be an effective method for discovering knowledge in tourists behavior at a high-level
426 scale. The brain-inspired spiking neural networks (SNNs) are known as the third generation of
427 NN and are a promising architecture for creating new knowledge for spatiotemporal data. This
428 novel computational models are considered an appropriate approach for studying the
429 multimodal data, where both time and space components are critical to be integrated and
430 analysed (Kasabov, 2012). In tourism studies, spatiotemporal analysis has an advantage over
431 simply spatial or time-series analysis. It allows researcher to investigate the trajectory of
432 behavioural patterns while also highlighting dynamic changes over time. This approach will
433 result in a better understanding of tourist behaviour and perception, more accurate data
434 interpolation, and greater accuracy in tourism demand forecasting applications.

435 *5.1.2 Neuro-Tourism*

436 As reviewed in the literature, tourism and hospitality data collection relies mainly on
437 surveys, focus groups and observation on gathering data about tourists' thoughts, feeling, and
438 behaviours. However, these traditional methods are suitable for revealing tourists'
439 conscious decision-making processes. Tourists' choices involve a complex interplay of
440 cultural, social, personal, and psychological factors. Moreover, human behaviour, preferences,
441 feelings, and motivations are strongly affected by past experiences and stored in the

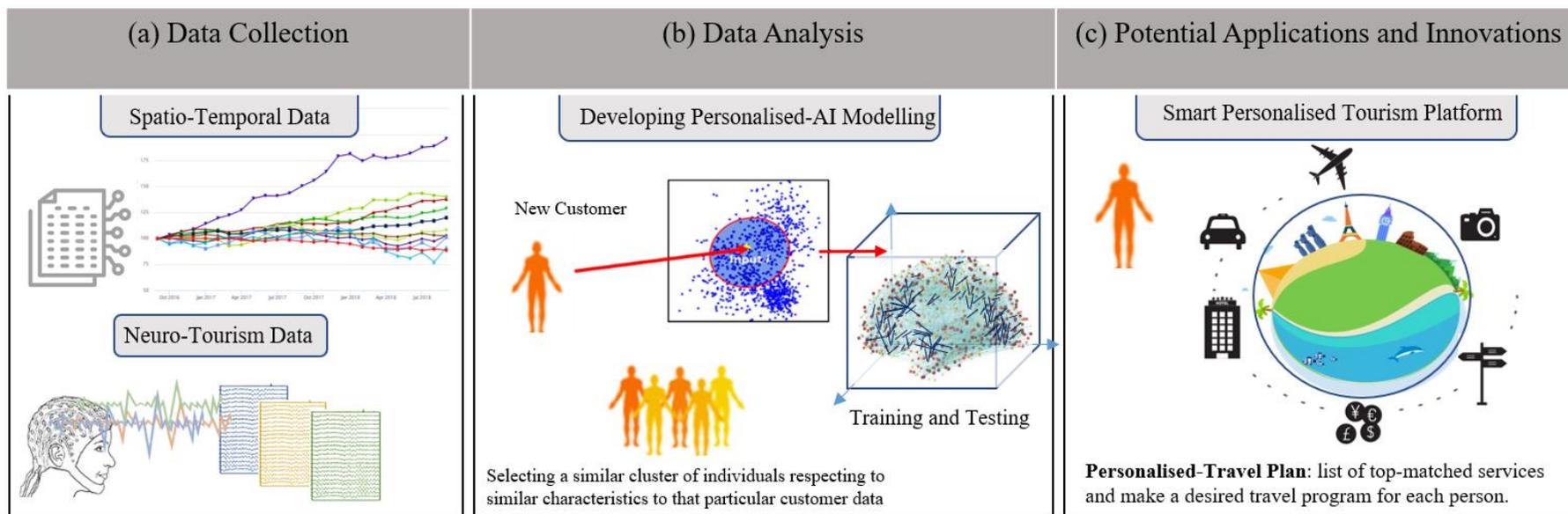
442 unconscious mind (Doborjeh et al., 2018a). Techniques that can provide more detailed and
443 objective information to understand and uncover these behaviours are therefore needed.
444 Working across disciplines enables a better understanding of the characteristics of consumers
445 behavior and how it can affect their decision and emotions (Lv et al., 2021). Novel technologies
446 for exploring the neurobiological foundations of mind and behaviour have enthused the fields
447 of tourism and hospitality studies to be open toward cognitive neuroscience and, more
448 specifically, to brain imaging data. The neural processes underpinning behaviours that control
449 the consumers' responses in tourism settings can be studied through brain recording techniques
450 (Tosun et al., 2016). This includes Spatiotemporal Brain Data (STBD), such as
451 Electroencephalogram (EEG), Event-Related Potential (ERP), Functional Magnetic Resonance
452 Imaging (fMRI), and Magnetic **Resonance Imaging**. Brain data can be modelled and studied
453 using advanced brain-inspired AI technologies for analysing tourists' cognitive responses to
454 tourism-related stimuli. This leads to a comprehensive understanding of the emotional and
455 cognitive processes of the tourists' behaviour. In the future, this interdisciplinary knowledge
456 could initiate a new area of tourism research, called Neuro-Tourism (Tosun et al., 2016). This
457 combines disciplines from traditional tourism, psychology, neuroscience, and information
458 technology. Neuro-Tourism suggests investigating the neural mechanisms underpinning
459 tourists' behaviour and data collection techniques to observe time-series data from human
460 neurocognitive and behavioural features and provide big data about tourists' emotional
461 impression, satisfaction, and acceptance (Figure 5a). AI and machine learning tools could
462 further be employed to learn from the trend of data and extract meaningful patterns to precisely
463 predict and classify tourism choice and behaviour (Li et al., 2021) (Figure 5b). This can be
464 developed to make a smart Tourism system for forecasting tourism demand at different space
465 and time points (Figure 5c) (Xiang et al., 2021).

466 5.2 *Application-based Hospitality and Tourism Studies*

467 5.2.1 *Personalised AI applications*

468 Our literature showed that consumers have recently been more accepting of personalised
469 services and engagement, increasing the overall satisfaction of their experiences. Personalised
470 approaches allow for the creation of personalised profiles of individuals that can be addressed
471 in tourism marketing and management services (Doborjeh et al., 2021b). Personalised
472 modelling is an emerging approach that creates a model for everyone based using a group of
473 individuals' data with similar characteristics (Doborjeh et al., 2019). In contrast to global
474 modelling (the conventional AI systems), personalised modelling offers an enhanced accuracy

475 of classification/prediction of an individual tourist behaviour as it only learns from the most
476 relevant datasets to the individual. It also increases the model efficiency as a smaller chunk of
477 available big data can be selected and used for AI learning algorithms (Doborjeh *et al.*, 2019).
478 Personalised modelling using AI-driven technologies can develop smart tourism platforms that
479 learn from an individual lifestyle and past experiences to offer a list of top-matched services
480 and make a desired travel program for each person (Figure 5c).



481

482 Figure 5. Proposing a model of AI research opportunities in tourism and hospitality for (a) data collection; (b) data analysis; and (c) potential application for future directions. The diagram of the
 483 data collection protocol (including demographics, self-report, and neurobiological assessments from customers; (c) In this personalised modelling system, for every new customer, a group of
 484 individuals with similar characteristics to that customer will be selected, (d) then EEG data of this group of individuals will be used to train a personalised AI model; (e) then the EEG data of the
 485 selected new customer which was excluded from the training will be used to test the model and to detect and predict a desired plan for this new customer.

6. Discussion

486
487 This paper systematically reviewed a wide range of existing and well-known AI methods
488 in international hospitality and tourism ranging from data processing/data analysis to enhanced
489 customer service/experience. This is the first study that reviewed and discovered new
490 knowledge in identification of proper AI methods and algorithms with respect to the
491 applications and the type of multimodal datasets in both hospitality and tourism. It also
492 provided the vision of the authors (from AI perspectives) for the future use of AI algorithms in
493 multidimensional datasets in hospitality and tourism settings. In the following a comparison of
494 different AI approaches and their suitability for analysis and pattern mining in different
495 application scenarios will be discussed.

496 In our review, ML algorithms have mostly been used in several aspects of hospitality and
497 tourism tourists for clustering, classification, and predictions tasks. In terms of clustering
498 approach, ML showed that the techniques such as K-mean and DBSCAN were mostly applied
499 to image data and to detect POIs and sought to analyse the interests of visitors and their
500 movements around the cities; and providing reasonably forecasts of the behaviours of tourists.
501 DBSCAN is one of the most widely used clustering algorithms, as well as one of the most
502 frequently cited in scientific literature. DBSCAN, unlike the k-means method, can detect
503 clusters of any type of data with no limits and without specifying the clusters' number.
504 Furthermore, because DBSCAN specifically detects noise locations, no outlier detection is
505 required (Höpken *et al.*, 2020). On the other hand, k-means method is sensitive to outliers,
506 therefore, a distance-based outlier detection must be performed as part of the data preparation
507 process. In terms of classification/prediction approaches, a large growth in the use of SVM
508 method can be seen in the tourism literature, particularly for numerical data (questionnaires) in
509 demand and consumer's behaviour forecasting applications. Unlike most traditional ML
510 models, which use the empirical risk minimisation principle to reduce the training error, SVM
511 use the structural risk minimisation principle to reduce an upper bound on the generalisation
512 error (Rätsch *et al.*, 2006). To enhance the forecasting performance and accuracy to support
513 investment decision-making and planning for big data analysis, researchers attempted to find
514 the best suitable methods by combining ML with other methods from ANN and DL.

515 According to our review, DL algorithms have recently gained traction in the tourist and
516 hospitality industries, particularly after demonstrating superior performance in analysing large
517 spatiotemporal data and forecasting accuracy when compared to other ML methods (Lado-
518 Sestayo and Vivel-Búa, 2019). The benefit of DL models is that they reduce errors by using

519 gradient descent. As an example, as previously indicated, BP is one of the DLNN approaches
520 that uses gradient descent as a core component. Liu's research confirmed the significant
521 progress made in the field of DLNN (BP) in tourism and also explains the poor performance
522 of ML and NNs alone in forecasting tourism demand in the early years of adaptation, as well
523 as the limitations in the learning processes in traditional models for forecasting and analysis of
524 big tourism data (Liu, 2011). However, it is important to point out some of the BP-DLNN
525 model's drawbacks as reported by Claveria, (2015) study. The Elman Networks-BP did not
526 perform as accurate as the other methods of MLP, RBF. This was determined to be due to the
527 feedback process's inability to assess the time-series' data characteristics (Claveria *et al.*, 2015).

528 According to the overview of forecasting literature, DL models such as DL-
529 ARIMA/SARIMA are extensively used in prediction tasks due to their simplicity of setup and
530 use. ARIMA is used successfully in time-series data in the hospitality industry as it has the
531 potential to carry out linear data through mapping and finding the relationship between the
532 features. However, these models did not obtain high accuracy in forecasting task compared
533 with other ML models.

534 Deep NNs have recently dominated in the various forecasting disciplines in tourism and
535 hospitality research, having surmounted that barrier. Li and Cao (2018) applied the LSTM
536 approach using longitudinal time series data to forecast tourism flows. The authors stressed the
537 necessity of having more accurate models for tourism demand forecasting that will improve
538 industry decision-makers in terms of financial sustainability. LSTM models outperformed
539 other models in forecasting accuracy when using longitudinal tourist arrival data. The authors
540 also demonstrated the DNN's ability to model non-linear and stochastic data that had previously
541 been impossible to model using linear models. Furthermore, by automating feature selection
542 engineering (Figure 2), a DL approach decreases human intervention, and hence error, from an
543 AI standpoint. The model will optimise the features and use only the highly appropriate ones
544 for the purpose of forecasting process. This is also confirmed by recent studies that combining
545 SARIMA with deep learning LSTM layers potentially improved the accuracy of the forecasting
546 problems (He *et al.*, 2021, Wu *et al.*, 2021).

547 *6.1 Conclusions*

548 This study gives insights on using proper AI algorithms through mining and comparing
549 the suitability and applicability of the AI methods in the tourism environments. This review
550 paper has been written by experts from interdisciplinary knowledge of AI and tourism that
551 opens a door for widely applying the interdisciplinary technologies such as “Neuro-Tourism”

552 and “Spatio-Temporal Data” into tourism research. Arising from this study, the merits of the
553 new personalised AI methods provide researchers with “an enhanced accuracy of
554 classification/prediction”, “development of smart tourism platforms” and “quickly operations
555 under unprecedented crisis (e.g., Covid)”.

556 *6.2 Theoretical Implications*

557 Theoretically, this study adds to the body of knowledge in the fields of hospitality,
558 tourism, and technology by shedding light on selecting proper use of AI algorithms in the
559 advancement of hospitality and tourism application to accurately forecast future business
560 conditions, revenues, as well as identifying current and potential trends in guest/tourist demand.
561 This paper also discussed a future theoretical direction in AI that can open new applications in
562 tourism research, which is the development of new methods for data collection, data analysis,
563 and data modelling to have a deep knowledge representation that presents the essence of the
564 data in a precise, concise, and understandable way.

565 *6.3 Practical Implications*

566 The results of this study can be used by researchers, practitioners, and decision-makers,
567 such as private agencies and commercial companies, to select appropriate approaches and
568 algorithms to explore AI in various tourism and hospitality situations. This paper might also
569 serve as a useful guide for spurring future interdisciplinary research into using AI to support
570 the development of hospitality and tourism, particularly in the post COVID-19 environment.

571 *6.4 Limitations and Future Research*

572 Every study output, rationally, is bound by some limitations. Similarly, there are certain
573 limits to this article. Firstly, keywords are chosen at the expertise of the research team (AI and
574 tourism perspectives), and much attention was taken in selecting the keywords, with a strong
575 emphasis on the study’s theme and scope. Therefore, conducting different bibliometric
576 techniques could provide a valuable evaluation of AI. Secondly, the method of study was based
577 on hospitality and tourism journals on the Australian Business Deans Council’s (ABDC)
578 journals ranking list, and future research might look at additional tools for analysis of literature
579 that could result in a larger number of publications to be examined. As the future study, the last
580 section of the paper emphasised on the need for a more interdisciplinary approach to tourism
581 and hospitality that includes a wide range of academic study fields to properly comprehend the
582 unique area of neuro-tourism and use of proper AI algorithms to make sense of data. Future
583 research could also investigate the significant concerns associated with using AI algorithms to
584 manage operations in various tourism sectors and industries.

585

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