Deep Learning in Tourism: A research framework agenda for future research

Journal:	*International Journal of Contemporary Hospitality Management*
Manuscript ID	IJCHM-09-2021-1176.R3
Manuscript Type:	Original Article
Keywords:	Deep learning, Systematic literature review (SLR), Tourism management, Tourism research, Machine Learning, Hospitality management

DEEP LEARNING IN HOSPITALITY AND TOURISM: A RESEARCH FRAMEWORK AGENDA FOR FUTURE RESEARCH

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May 28, 2022

ABSTRACT

Purpose - This study aims to provide a systematic review of the existing literature on the applications of deep learning in hospitality, tourism and travel as well as an agenda for future research.

Methodology - Covering a 5-year time span (2017–2021), this study systematically reviews journal articles archived in four academic databases: Emerald Insight, Springer, Wiley Online Library, and ScienceDirect. All 159 articles reviewed were characterised using six attributes: publisher, year of publication, country studied, type of value created, application area, and future suggestions (and/or limitations).

Findings - Five application areas and six challenge areas are identified, which characterise the application of deep learning in hospitality, tourism and travel. In addition, it is observed that deep learning is mainly used to develop novel models that are creating business value by forecasting (or projecting) some parameter(s) and promoting better offerings to tourists.

Implications - Although a few prior papers have provided a literature review of artificial intelligence in tourism and hospitality, none have drilled-down to the specific area of deep learning applications within the context of hospitality, tourism and travel.

Originality - To the best of the authors' knowledge, this paper represents the first theoretical review of academic research on deep learning applications in hospitality, tourism and travel. An integrated framework is proposed to expose future research trajectories wherein scholars can contribute significant value. The exploration of the deep learning literature has significant implications for industry and practice, given that this, as far as we know, is the first systematic review of existing literature in this research area.

Keywords Deep learning · Machine Learning · Artificial Intelligence · Systematic literature review (SLR) · Hospitality management · Tourism management · Tourism research

1 Introduction

1.1 Artificial Intelligence: A historical perspective

Technological advancement has resulted in the proliferation of analytical tools, algorithms, and models for processing structured and unstructured big (and extreme) data, birthing a field of research referred to as *big data analytics* (BDA). In recent times, artificial intelligence (AI) and Big Data Analytics (BDA) are gaining research interest and being applied in nearly all sectors of human endeavour, such as, engineering, education, transportation management, finance and healthcare. The research field has seen tremendous growth so much so that it is now almost impossible to effectively track its progression in terms of scholarly work. AI is considered a vital avenue for processing intelligence; listed in Gartner's Top 10 strategic technology trends for 2020 (Panetta, 2019).

Although there is no recorded evidence about the commencement of the research field of AI, it is believed to have begun in early 1940 with the introduction of McCulloch Pitts (McCulloch and Pitts, 1943) and Hebb rule (Samuel, 1967), where the authors presented a positional explanation about how the neurons in the human brain function (see Table 1). These works saw the proliferation of AI models, such as, *the perceptron*, a system that uses linear optimisation to simulate the human nervous system (Rosenblatt, 1960), and the Adaptive Linear Unit (Widrow and Hoff, 1960), which was applied towards simple applications such as, weather forecasting (Bibel, 2014). The second wave of AI adoption was ushered in by the Hopfield network circuit (Tank and Hopfield, 1987) and the backpropagation (BP) algorithm for non-linear optimisation in neural networks (LeCun et al., 1988). It was accompanied by a significant growth in statistical learning, with algorithms such as the Support Vector Machine (SVM) (Cortes and Vapnik, 1995). The development of neural networks and statistical algorithms accelerated the acceptance and application of artificial intelligence (AI) and machine learning (ML). Nevertheless, these *conventional* algorithms demanded human interference in analysing the input data, which meant that the accuracy of these algorithms largely depended on the proficiency of the data engineer.

It is suggested that the rise of DL was augmented by the proliferation of ML and statistical algorithms that existed (Goodfellow and Bengio, 2015). Neural networks had critical shortcomings especially their tendency to have diminishing or exploding gradients sometimes during optimisation. The next wave of neural networks saw the introduction of the Recurrent Neural Network (RNN), which significantly outperformed its counterparts in feature learning from sequential data El Hihi and Bengio (1996). However, this model also had its own limitations (Hochreiter, 1998), which were resolved in an improved version referred to as the Long Short-Term Memory (LSTM) neural network (Hochreiter and Schmidhuber, 1997). The Convolutional Neural Network (CNN) was proposed in 1998 as a model that considered three-dimensional inputs (e.g., images) by performing *convolutions* on the input data (LeCun et al., 1988). The most recent wave in the upsurge of DL begun in 2010 with the bidirectional deep Boltzmann machine (Salakhutdinov and Hinton, 2009). In 2012, the deep Convolutional Neural Network (DCNN) emerged and significantly outperformed other algorithms in image recognition and segmentation (Krizhevsky et al., 2012a), and in 2014, the Generative Adversarial Network (GAN) was proposed by Ian Goodfellow (Goodfellow et al., 2014). The GAN is a neural network that comprises two distinct models, with each model acting as adversaries. Finally, the attention-based LSTM, introduced in the mid-2010s, is rapidly gaining popularity as a model that integrates an attention mechanism to the conventional LSTM (Wang et al., 2016b). These have formed the basis for recent architectures applied for natural language processing (NLP). Examples of these include the BERT model – BERT (Devlin et al., 2018; Long et al., 2017), and image recognition algorithms (Krizhevsky et al., 2012a; Qassim et al., 2017) that apply the *you-only-look-once* (YOLO) model for real-time object identification and segmentation (Redmon et al., 2016).

1.2 Contextualising Deep Learning within the field of Artificial Intelligence

It is not uncommon to find some misconception about the distinction is between AI, DL and ML. Although all three concepts are closely related, there are clear differences between them (see Figure 1). AI refers to a research field that comprises the development of machines that can be made *intelligent* via programming, be it using $if - then - else$ loops, explicit programming, or machine learning. Russell and Norvig (2016) define AI as *"the study of agents that receive prompts from the environment and perform actions"* (p. 5). In other words, AI can be seen as any computer program that can do something *smart*. This broadly encompasses familiar items that are encountered in everyday life, ranging from a programmed traffic control light, a computer program playing chess to voice recognition systems, such as, Apple's Siri, or Amazon's Alexa. Machine learning (ML) is a subset of AI that describes a situation where a machine takes data and *"learns"* from the data by itself. In more specific terms, ML refers to machines that can learn – using algorithms – from experience provided by data. Therefore, ML is a subset of AI (i.e., all machine learning counts as AI, but not the other way round!). ML is the most popular subset of AI that is applicable in everyday life, comprising a system that can quickly apply knowledge from large datasets to master tasks, including facial recognition, text identification/classification, tourist demand forecasting, to name a few. It is important to mention that the distinction between ML and hand-coded computer programming is the ability of the former to *"learn"* from the data and make its own predictions without being explicitly programmed to do so. Finally, DL is a subset of ML, referring to a class of artificial neural networks (ANNs) that adopt multi-layered architectures for data training and have been proven to achieve new levels of accuracy in many tasks, including image recognition/segmentation, recommender systems, and natural language processing (NLP).

1.3 Motivation for research

As a relatively recent development in AI, deep learning (DL) allows the development of computational models that are composed of hierarchically-structured, multiple-processing layers to learn data representations via multiple levels of abstraction. It permits complex feature abstraction by cascading multiple layers rather than handcrafted feature representations obtainable in *shallow* or conventional machine learning models. Consequently, DL is gaining research interest having demonstrated exceptional performance in various fields, as evidenced in the many DL applications

Table 1: A Historical Summary of the evolution of Artificial Intelligence and Deep Learning.

Evolution Stage	Model/Algorithm	Limitations/problems solved	Source(s)
First Period (1940s)	MP model	Explain the neural function in the human brain	(McCulloch and Pitts, 1943; Samuel, 1967)
	Hebb rule		
	Perceptron	Simulate the human neural functioning	(Rosenblatt, 1960)
	Adaptive Linear Unit	Used in preliminary applications, e.g., weather forecasting Difficulties in handling non-linear problems (e.g., XOR and XNOR)	(Widrow and Hoff, 1960)
Second Period (1980s)	Hopfield Neural Network	Could reconstruct data after being fed a corrupt version of the data	(Tank and Hopfield, 1987)
	Backpropagation	Highly capable of solving non-linear problems in complex networks	(LeCun et al., 1988)
	Support Vector Machine	Better at solving non-linear problems	(Cortes and Vapnik, 1995)
	Boltzmann Machine	Stopped learning when the machine is scaled up even slightly (impractical)	(Ackley et al., 1989)
	Restricted Boltzmann Machines		(Salakhutdinov et al., 2007)
	Auto Encoder	Unsupervised learning algorithm that had challenges being too lossy	(Rumelhart et al., 1988)
DL Period (2000s)	Recurrent Neural Network	Adept learning ability in sequential data	(El Hihi and Bengio, 1996)
	Long Short-term Memory	Addressed the vanishing gradient problem in RNNs	(Hochreiter and Schmidhuber, 1997)
	Convolutional Neural Network	Two-dimensional data and feature extraction – image recognition	(LeCun et al., 1998)
	Deep Belief Networks	Allowed bidirectional connections in the top layer of the model only, reducing computational complexity	(Hinton et al., 2006)
	Deep Autoencoders	More effective learning by stacking layers	(Deng et al., 2010)
	Deep Boltzmann machines	More effective learning by stacking layers	
	Denoising Autoencoders	Efficiently reconstruct stochastically corrupted input data, robust feature extraction	(Vincent et al., 2010)
	Deep Convolutional neural networks	Best-in-class performance in image recognition	(Krizhevsky et al., 2012a)
	Generative Adversarial Network	Generative modelling using DL methods, such as convolutional neural networks	(Goodfellow et al., 2014)
	Attention-based LSTM	Overcame the limitation of the autoencoder (i.e., fixed input sequence to a fixed length representation)	(Wang et al., 2016a)
	You only look once (YOLO)	Object detection in computer vision	(Redmon et al., 2016)

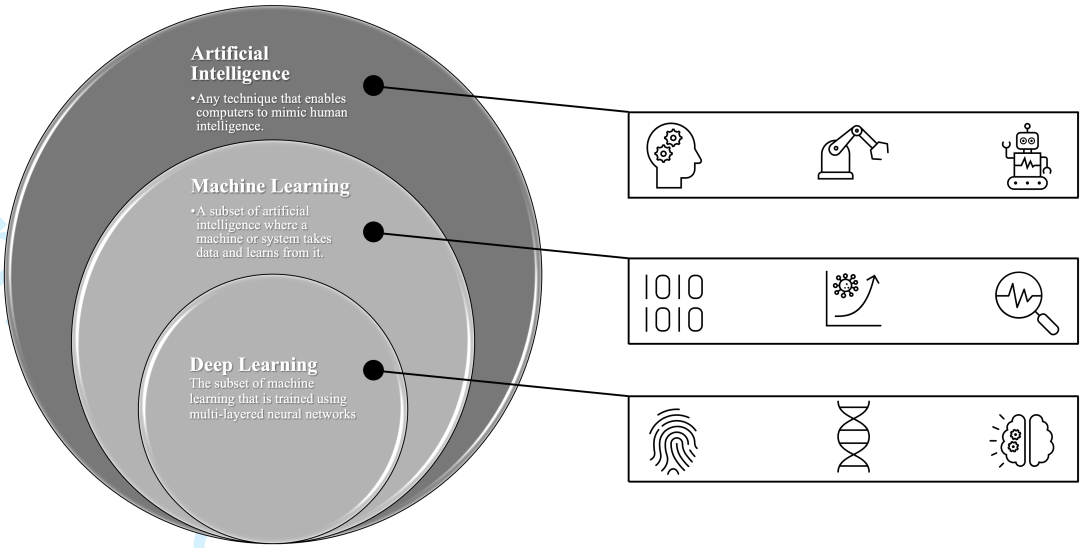

Figure 1: Contextualising deep learning within artificial intelligence.

in use today, including traffic parameter forecasting (Zhang et al., 2019b; Essien et al., 2019a), smart manufacturing (Essien and Giannetti, 2020), speech recognition (Zhang et al., 2018) and image recognition (LeCun et al., 2015).

The application of DL in the hospitality, travel and tourism (HTT) industry is relatively new, and should be considered within the context that not until the past decade was there a conspicuous impact of computing via the evolution and widespread automation of tasks, for example, e-ticketing, destination recommendation, online hotel booking etc. (Law et al., 2014). Buhalis and Law (2008) were pioneer proponents of the concept of *e-tourism*, describing it as *"the digitisation of procedures in the tourism sector"* for fostering the marketing and distribution of products offered in this sector. Consequently, this digitisation has significantly impacted the tourism marketplace, influencing how organisations conduct their businesses (Ashari et al., 2014; Chuang et al., 2017). As a matter of fact, in recent HTT and service literature, there is growing interest in the integration of new and emerging technologies, including robotics (Akdim et al., 2021; Belanche et al., 2020; Romero and Lado, 2021; Byrd et al., 2021), blockchain (Liu and Dong, 2021; Demirel et al., 2022) and AI (Flavián and Casaló, 2021; Mariani and Borghi, 2021; Pelet et al., 2021; Ivanov and Webster, 2021). Although alternative machine learning approaches/algorithms exist, they are limited in their ability to process natural data in raw form (LeCun et al., 2015). To be more detailed, in order to apply conventional ML techniques, there must be expert engineering and domain expertise applied to the design of a feature extractor that transforms the raw data (e.g., the pixel values in an image, frames in a video, etc.) into a suitable internal representation or feature vector from which the ML algorithm could detect or classify patterns in the input. With DL, however, this need is eliminated by learning in a hierarchical manner (known as representation learning), wherein the algorithm *automatically* learns the representations of the data by passing the various representations (starting with the raw input) through various levels of abstraction. The key advantage of DL in comparison to conventional ML algorithms is that the layers of features (in DL algorithms) are not designed by human (data) engineers, but are rather learned from the data using a learning procedure.

Despite the tremendous benefits of DL in practice, there is a scarcity of theoretical studies about the application of DL in HTT, with few studies broadly investigating the impact of AI/BDA (Ardito et al., 2019; Li and Law, 2020; Gaur et al., 2021), reviewing the evolution of AI/BDA in hospitality and tourism literature (Li et al., 2018; Samara et al., 2020; Mariani and Baggio, 2021) and applying data-driven techniques towards tourism management (Martín et al., 2018; Law et al., 2019; Zhang et al., 2019b). Given that DL can be a key enabler of e-tourism, a comprehensive review of the current literature in this field becomes desirable. Although prior research has provided concerted attempts at encapsulating and characterising extant knowledge using systematic literature reviews (SLRs), these studies have mainly focused on big data analytics, sentiment analysis (Ma et al., 2018; Mehraliyev et al., 2021), tourism analytics & demand forecasting (Song and Li, 2008; Goh and Law, 2011; Hsu et al., 2017), and AI (Schuckert et al., 2015; Rashidi et al., 2017). No doubt these studies have contributed to the extant body of knowledge; albeit with focal points around the synthesis and delineation of trends or challenges. Besides, these studies mainly focus on the broad area of AI/BDA, without drilling down into the specific area of DL. Most importantly, to the best of the authors' knowledge, there is no existing framework for advancing research in this field, as well as provide a scaffold for researchers to develop innovative and relevant conceptual frameworks for DL applications. We argue that the proliferation of such studies can also benefit industry practitioners by increasing the likelihood of successfully realising the benefits of

applying DL in HTT. Evidently, the existing literature on DL applications in HTT fails to provide answers to crucial questions that practitioners must answer when implementing DL applications within such organisations. Our work aims to address this need by articulating a structured and systematic perspective within this topical area of research and thereby proposing a theoretical framework for advancing future research on DL applications in HTT. The study commences by systematically reviewing the current research portfolio to identify key concepts, exposing the limitations and barriers to the adoption of DL as obtainable in extant literature.

Our motivation is two-fold in that we not only aim to provide a state-of-the-art snapshot and characterisation of the academic portfolio around DL applications in HTT management, but also pinpoint the important and distinctive characteristics of themes from these applications to enable researchers and practitioners make research-informed decisions relating to their use and application. In addition, we also envisage where the industry should be headed by indicating possible future trajectories. The output of our research is a conceptual framework, which proposes a research agenda to further scholarly efforts in DL applications within the HTT industry, benefiting both industry and research. Therefore, our work contributes to advancing existing research on DL applications by providing a research road-map with future research trajectories. Finally, our work exposes some significant research deficiencies in this research area that need addressing to advance tourism research.

In comparison to existing review papers, the contributions of this current study can be summarised as follows:

1. Providing a state-of-the-art characterisation of existing literature with respect to application areas, limitations, and recommendations, presenting potential themes that point to future directions for the advancement of the research field;
2. To the best of the authors' knowledge, this might be the first attempt at presenting an SLR on DL in hospitality and tourism research;
3. A conceptual research framework, which presents potential themes requiring research attention in order to advance the adoption and application of DL in HTT research.

In summary, our research contributes towards introducing some structure to existing knowledge on the emerging research area of DL applications in the HTT industry by characterising this knowledge using a relevant existing framework. Our proposed framework indicates vital factors that can advance research in the field and enable practitioners to succeed in the implementation of DL applications in their organisations. These contributions are achieved by answering four main research questions:

1. **RQ1** – what are the current application areas of DL in HTT?
2. **RQ2** – can we create a taxonomy of DL studies in existing literature?
3. **RQ3** – what are the current and emergent challenges to the widespread adoption of DL in HTT?
4. **RQ4** – what future opportunities in HTT management can be identified that might benefit from the application of DL?

The remaining part of this paper is structured as follows. Section 2 presents a conceptual framework for characterising the value created by DL applications. Section 3 explicates the methodology adopted for the current study. The findings and discussion of the findings are presented in Section 4, followed by Section 5, where the paper is concluded and a detailed discussion of the implications of the study are presented, alongside the limitations and future directions for research.

2 The 4Ps Framework for Deep Learning (DL) Value Creation

As a conceptual basis for our study, we propose a framework adapted from Bughin et al. (2017), which delineates the value created by big data and AI in business/industry. The rationale behind adopting this framework is due to its applicability and suitability for considering both the customer-related and business-related applications of AI (in our case, DL) in HTT. Alternative theoretical frameworks were considered, for instance, the Value-driven cycle for reusability of information in AI-BDA projects (Wu and Yang, 2018), but the Bughin et al. (2017) framework was the most suitable for this current study in that it adequately allows for the articulation of technical and socio-economic (i.e., customer vs business) perspectives. Based on this framework, the four areas wherein AI/DL can create value in business organisations are: (i) *project*: applications that allow companies to better forecast or predict some parameter, for instance, demand; (ii) *provide*: applications that enable companies to provide rich and personalised services to customers/users; (iii) *promote*: applications that enable the firms to promote their offerings at the right prices, using the right message and/or to the right target customers and (iv) *produce:* referring to applications that enhance the

companies' ability to produce their goods or services at reduced cost and higher quality. Consequently, we apply the above definitions to characterise each paper within our study sample to the most-fitting area of the framework. For instance, if the main focus of an article in our study proposes the use of deep learning models to forecast tourist/hotel demand, it is characterised to the *project* group.

Evidently, given that by nature, DL is application-based (i.e., infrastructural), it may be difficult to draw definitive lines within the four areas (i.e., project, provide, promote, and produce) to group applications, as some articles may fall within more than one area. In this case, we have opted to go for the most-fitting area for the article rather than having overlapping characterisations. Besides, it is important to mention that although our work presents an adaptation of an existing framework/conceptual basis, the characterisation is adopted in our study only for the purpose of grouping/classifying the value generated by DL applications in HTT, rather than on the contributions/content of the individual articles included in the article sample considered in this current study. On this note, our use of the 4Ps framework is as a theoretical basis for discussing the individual papers rather than as a tool for critically analysing the article content. We commence our discussion in the following subsections about these four areas of value creation resulting from the application of DL.

2.1 Project

Data ubiquity creates vast opportunities for organisations to continually forecast, anticipate and act proactively in order to gain competitive advantage. DL can allow for better forecasts in various areas of business, ranging from supply chain design, finance/sales and marketing, allowing the provision of better offerings. DL-based forecast methods are estimated to reduce prediction errors by $30 - 50$ percent in contrast to traditional methods (Bughin et al., 2017). The plethora of DL models and algorithms applied towards forecasting or projecting can be seen in nearly all areas of endeavour, ranging from traffic parameter forecasting (Essien et al., 2019b), predictive maintenance (Essien and Giannetti, 2020), financial timeseries forecasting (Jiao and Chen, 2019), and smart manufacturing (Lindemann et al., 2018). DL models can process both structured and unstructured data and *train* its parameters to perform accurately when presented with new data. DL models significantly outperform their *shallow* learning counterparts by automatically deciphering trends and patterns inherent in the data. Within the HTT industry, businesses can use DL in a number of ways, for instance, to forecast tourist travel demand in order to optimise stock/staff and resources – thereby minimising waste, or forecasting tourism hotspots/trends to engage better with potential clients/customers. In reality, the benefits of forecasting in business cannot be overemphasised, and extends far beyond organisational boundaries. The COVID-19 pandemic significantly disrupted global economies, and DL-enabled demand forecasting in the retail sector proved very useful, resulting in tremendous benefits (Ramos et al., 2021; Chang and Cheng, 2022).

2.2 Provide

DL can also create value for businesses by enabling them to provide rich, convenient and personalised services to customers. This results in better customer experiences, which foster customer loyalty and increase revenue. DL models are used in this way to create customised and personalised services, for instance, in the retail sector where predictive models are applied to recommend buys to the customers based on previous/similar purchase patterns. Most DL applications are tailored to provide better services to customers via recommender systems. For instance, a sentiment analysis recommender system is proposed in Preethi et al. (2017). Some DL applications can also be used to track and analyse customer behaviour to allow for customised experiences to the customers (Generosi et al., 2018). DL is also applied in the healthcare industry to provide personalised user experiences. Of recent, studies have proposed DL for disease diagnosis and prognosis (Oh et al., 2020; Feng et al., 2019). In another study, (Lai et al., 2021), the authors investigate the relationship between customer sentiment and online hotel ratings from the perspective of customers' motives in the context of eWOM. Since big data analytics allows the extraction of hidden patterns, it has been applied within the HTT sector to provide better products and services to consumers, for instance, developing predictive models for review helpfulness (Lee et al., 2021). Given the complexity of the human body, researchers are now using DL to provide personalised and customised treatments to patients, rather than standardised treatments. Adopting these technologies for human disease diagnosis and prognosis has the potential to reduce healthcare expenditure by almost ten percent (Bughin et al., 2017). In the HTT industry, DL models can be used to create rich customer experiences and personalised services at lower costs, for instance, applying augmented reality to deliver virtual tour guides (Chiu et al., 2021).

2.3 Promote

This *P* relates to the application of DL towards enabling businesses *promote* their offerings at the right prices, using the right message and/or to the right target customers. DL can be used to market offerings at the right price, with

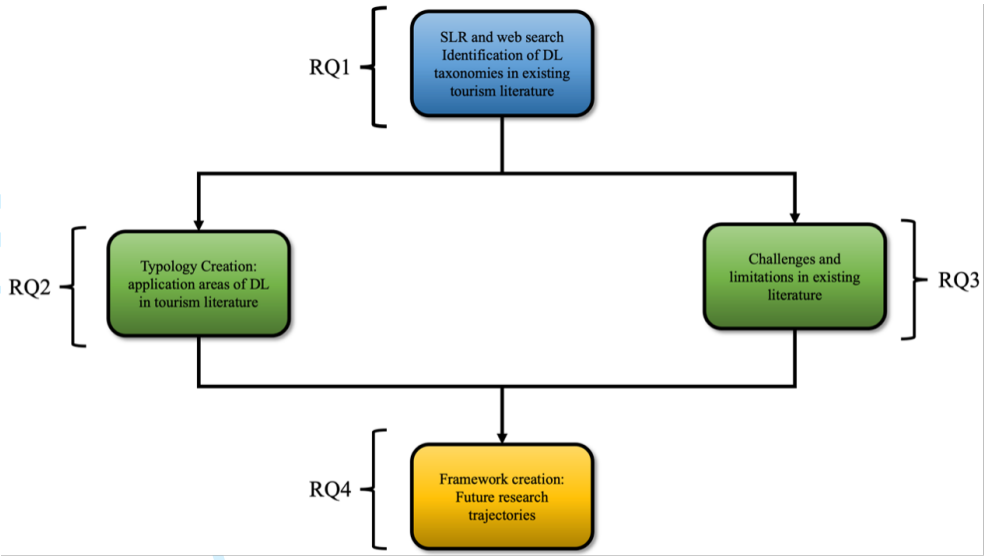

Figure 2: Summary of research process.

the right message, and to the right target. The abundance of data provides a stage that can enable businesses – via DL and AI in general – achieve real-time, dynamic and optimised pricing regimes that respond to demand/supply changes that align with customer willingness and underlying factors or conditions. This is a task that can no longer be manually done due to the changing service landscape – wherein the customers expect low prices and high-quality services. However, it is no longer a straightforward task to know how much the customer is willing to pay for a product or service. Customer willingness is now impacted by many factors, such as, day of the week, time of day, season, location, competitors' prices, brand reputation, amongst others. This means that intelligent price management measures must be integrated to most businesses today to ensure that the optimal price (for both customer and vendor) is always given. For instance, DL has permeated the research area of yield management via dynamic pricing of hotel rooms (Al Shehhi and Karathanasopoulos, 2020; Zhang et al., 2019c), hotel supply chain management (Dash et al., 2019) and airline ticket pricing (Shihab et al., 2019). DL applications in the HTT industry can contribute to achieving the aim of promoting the best offerings at the right prices, using the right message, to the right target customers.

2.4 Produce

DL can be used to create value in business organisations by enhancing production – transforming inputs to outputs, but can also imply the production of higher quality goods and services at lower costs. This value creation can range from the use of DL to recreate/redesign product/service ranges (e.g., through automation and robotics), enhance recruitment, quality assurance, and preventive maintenance to reduce machine down time, amongst other uses. Businesses such as Amazon, Ocado, DHL and FedEx have adopted AI to complement staff operations by using robots to deliver the products from their shelves in warehouses to human packers. In recent times, robots have been adopted to deliver goods and services by unmanned aerial (or road) vehicles. On the other hand, advances in computer vision have resulted in improved image recognition and segmentation Hatami et al. (2017); Redmon et al. (2016), which form the core of image/video recognition applications in use, such as cross-border e-commerce product classification (Rui, 2020; Filieri et al., 2021), medical imaging (Hu et al., 2021), defect detection (Essien and Giannetti, 2020; Wei et al., 2019) and traffic management (Jian et al., 2019).

3 Methodology

A systematic literature review (SLR) provides the reader with an unbiased knowledge of the literature in the specific field under investigation via a holistic and structured process that follows set procedures and standards (Yang et al., 2017). Besides, SLRs expound gaps in literature, allowing the identification of opportunities and limitations, which enable the suggestion of potential avenues for future research. In general, there is a popular consensus on reviewing literature systematically to avoid representing "islands without continents" (Booth et al., 2016; vom Brocke et al., 2020). To conduct the SLR presented in this current study, we adopted the protocols in Khan et al. (2003), namely: (1) framing

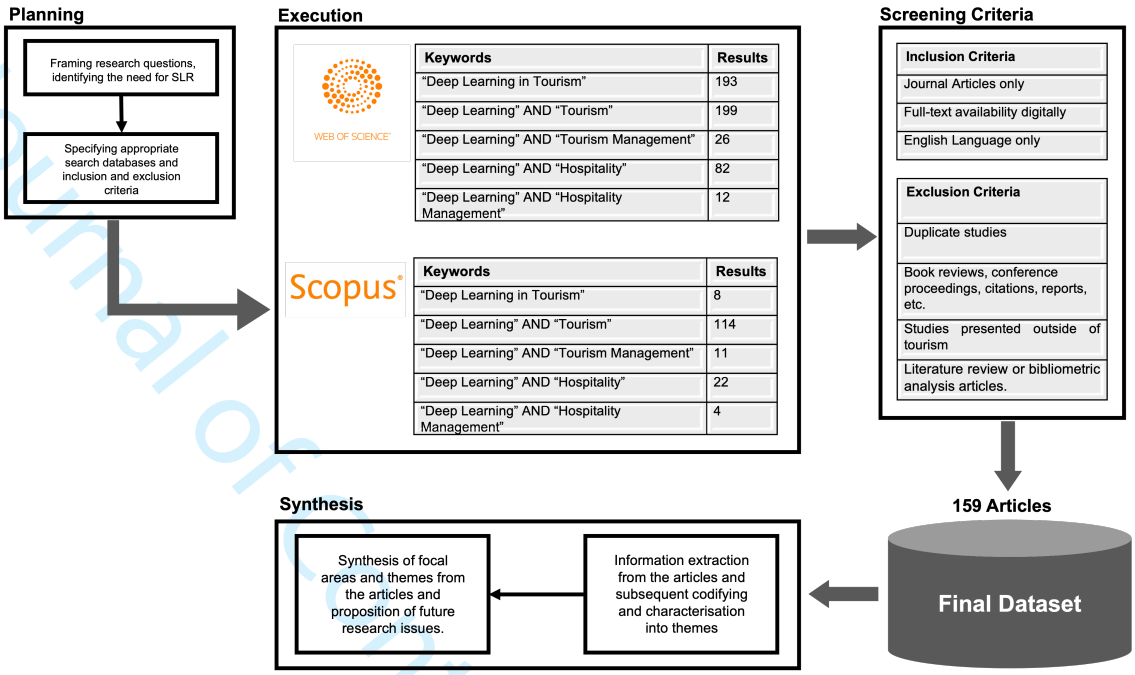

Figure 3: Systematic Literature Review process adopted in this current study

the questions; (2) identifying relevant works; (3) assessing the quality and screening; (4) summarising the evidence; (5) interpreting the findings. Figure 2 summarises the SLR process adopted for this current study.

To address **RQ1**, we identify relevant articles by conducting an electronic search in both the Web of Science and Scopus databases, respectively. These databases were identified by prior studies as popular sources of articles relating to the topic under investigation (Samara et al., 2020). Five keyword combinations were found to be effective for the database searches, performed in December 2021:

1. "Deep Learning in Tourism",
2. "Deep Learning" AND "Tourism",
3. "Deep Learning" AND "Tourism Management"
4. "Deep Learning" AND "Hospitality"
5. "Deep Learning" AND "Hospitality Management"

This study analysed the findings from the search results against three main descriptives (see Table 2): (a) articles published per year; (b) Total citations for each article in this review; (c) contextual analysis of main publications (i.e., the model type, application area, contribution, limitations and future directions). **RQ2** was addressed by identifying previously investigated studies and characterising them according to common themes and application areas based on value created by the application. To address **RQ3**, the findings from the search phase were individually synthesised and summarised in terms of their individual findings and limitations and aggregating these to commonly occurring themes obtainable in these papers. Finally, **RQ4** was addressed by identifying nascent research gaps in existing literature and – by a proposed research synthesis framework – elucidating potential avenues for future research that have the potential to advance the research field. These queries fostered a dedicated synthesis and analysis of the reviewed studies and resulted in pertinent insights that enabled the research questions to be addressed.

Article selection was based on set inclusion and exclusion criteria as summarised in Figure 3. As can be seen, only full-length, peer-reviewed journal articles were considered. Therefore, book reviews, conference proceedings, citations, reports, and other short communications were excluded from the analysis. The rationale for focusing on journal articles alone is to build on insight from reputable and peer-reviewed sources, which have undergone scrutiny and rigour in their development. We believe that this will ensure that our SLR incorporates state-of-the-art research within the existing literature. For each eligible article, important attributes, such as the author's name(s), article title, publication year, country of publication, data type, problem type, model type, number of citations, are recorded. Second, only articles in

Table 2: Database search summary.

Database	Keywords	Count
Web of Science	"Deep Learning in Tourism"	193
	"Deep Learning" AND "Tourism"	199
	"Deep Learning" AND "Tourism Management"	26
	"Deep Learning" AND "Hospitality"	82
	"Deep Learning" AND "Hospitality Management"	12
Scopus	"Deep Learning in Tourism"	8
	"Deep Learning" AND "Tourism"	114
	"Deep Learning" AND "Tourism Management"	11
	"Deep Learning" AND "Hospitality"	22
	"Deep Learning" AND "Hospitality Management"	4

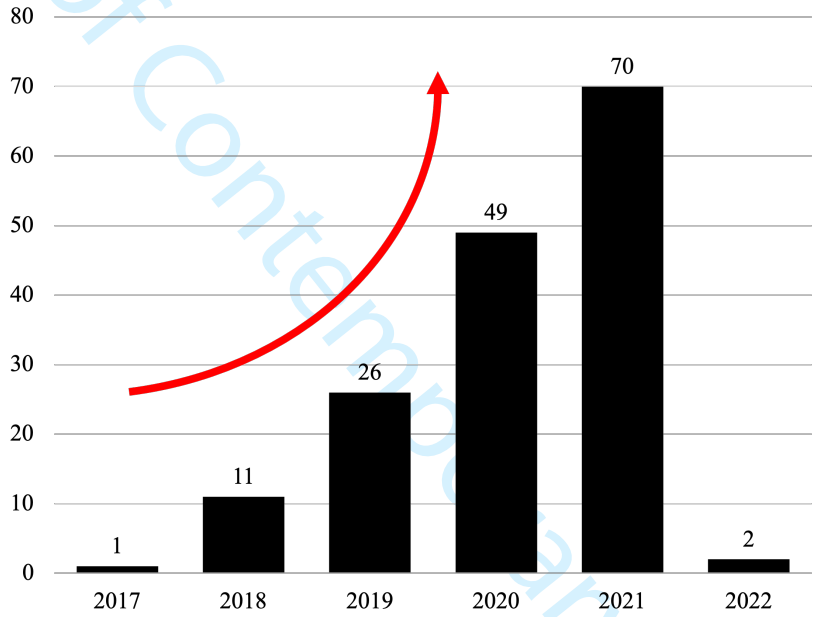

Figure 4: Yearly count of publications.

English language were selected, to provide consistency in the review process. Third, we only included articles that are fully-available online. The exclusion of articles was based on set criteria; first, duplicates were eliminated as well as studies that are outside of the HTT domain.

The articles selected for the final sample were manually screened to ensure that the findings in this current study represent a holistic, transparent and consistent position of the existing literature (Yang et al., 2017; Streimikiene et al., 2021). The authors in this study each performed individual assessments of the articles and resolved the differences in opinions via panel discussions to arrive at a consensus on the final inclusion and exclusion of individual articles. For this purpose, the Fleiss' Kappa value (Landis and Koch, 1977) for inter-coder agreement was used, and the value for this was 0.89, indicating a strong agreement between the independent coders (i.e., authors). The preliminary outcome of this review indicated that DL has a rather recent integration in HTT literature, as the earliest article in the study sample was published in 2017. However, research interest in this area is on the ascendancy, evidenced by a steep increase (year-on-year) in the number of articles (see Figure 4).

4 Results and discussion

This study adopted the Noblit and Hare (1988) meta ethnography-based strategy for the review and synthesis of insights from the articles that were eligible for inclusion – characterising research articles using themes to identify research gaps.

Table 3: Distribution of articles across the four themes.

Theme	Number of Articles	Articles per year						Total Citations
		2017	2018	2019	2020	2021	2022	
Project	81	1	10	13	25	31	1	**801**
Provide	37	0	1	7	10	19	0	**235**
Promote	37	0	0	6	12	18	1	**133**
Produce	4	0	0	0	2	2	0	**12**
Total	**159**	**1**	**11**	**26**	**49**	**70**	**2**	**1181**

We also synthesised the recommendations from the reviewed studies in collaboration with the research gaps to propose a research synthesis framework for expanding scholarly work in this research field. In developing these themes, we considered the delineation of value created by DL by using the *4Ps* research framework (i.e., project, promote, produce and provide), application areas (e.g., parameter forecasting, sentiment analysis or recommendation, etc.), challenge areas (e.g., explainability, data fusion, advanced models, etc.) and contribution (technological advancement, process enhancement/automation and concept development).

4.1 Taxonomy of Hospitality, Travel and Tourism (HTT) Literature – Value creation

Using thematic content analysis (Anderson, 2007; Braun and Clarke, 2006), we categorised each article in the sample into the four distinct themes to correspond with the *4Ps* research framework (see Section 2). To be more specific, we adopted the six-step guideline in Braun and Clarke (2006) to analyse the textual content in the articles (in the data subset) and characterise them into the four broad identified themes. A particular benefit of adopting thematic content analysis relates to its flexibility as there are a plethora of themes which can be identified and expounded upon (Braun and Clarke, 2006). A summary of the distribution of articles analysed in this study across the four themes is presented in Table 3 and it is evident from this table that the focus of scholarly efforts in this field is in the *project* theme (i.e., applying DL to predict/forecast a parameter or some variable), with 81 of the 159 articles (51%) falling in this category.

4.1.1 Deep Learning in Hospitality, Travel and Tourism (HTT) Literature: Project

Most of the studies reviewed in this study applied DL for projecting, forecasting or predicting some parameter – typically tourist demand (see Table 3). Forecasting in tourism can provide support for strategic decision-making to tourist companies, organisations and consumers/tourists alike (Wu et al., 2017; Ampountolas and Legg, 2021). Table 3 also shows a total of 801 citations (excluding self-citations) of the articles falling within this category, which is by far the theme attracting the highest research interest. With regard to the specific algorithm/model applied towards this forecasting/prediction, majority of the articles in our review applied Long Short-Term Memory (LSTM (Hochreiter and Schmidhuber, 1997)) models/algorithms, which can be attributed to the LSTM's adept ability at sequential inference, typically applied to forecasting tasks using historical data (see Table 4).

Another popular application of DL for forecasting in tourism literature is sentiment analysis. Sentiment analysis applies natural language processing (NLP), text mining/analytics, and other computer-based approaches to systematically identify, extract, measure, and study sentimental states and subjective information about a consumer. In our study sample, 28 of 159 articles (18%) applied DL for sentiment analysis (see Table 5). For example, a DL model for detecting deceptive reviews driven by DCWord (Deep Context representation by Word vectors) (Zhang et al., 2019d), a deep-learning-based sentiment analysis model that integrates two-channel CNN–LSTM models, combining CNN and LSTM/BiLSTM branches in a parallel manner (Li and Law, 2020). Besides, the application of text mining for tourist reviews has also been explored (Liu et al., 2022; Pan et al., 2022). In conclusion, the studies classified under this theme have mainly focused on the application of DL towards enhancing the state-of-the-art in two main areas – demand forecasting and sentiment analysis (refer to Table 5).

4.1.2 Deep Learning in Hospitality, Travel and Tourism (HTT) Literature: Provide

AI can be used to create value for businesses by focusing on applications that aid in enhancing the service provided to the customers. This can be via algorithms, models or frameworks that can enhance consumer experience by creating new and/or improved channels for value creation. When DL is applied to provide rich user experiences, it involves applications that enable companies to provide rich and personalised services to customers/users, for instance, being able to provide more accurate recommendations. In this study, we identified 37 (of 159) articles falling within this theme, accounting for 23% of the articles in the data sample (see Table 5). It was observed that most articles within this

Table 4: Distribution of DL models applied in the articles.

Theme	LSTM	CNN	Others	Total
Project	59	18	4	81
Provide	12	23	2	37
Promote	21	13	3	37
Produce	2	2	0	4
Total	**94**	**56**	**9**	**159**

Table 5: Summary of findings.

	Application	Description	Select Article(s)	No. Papers
Project	Forecasting tourism demand/flow	Using DL models for forecasting tourism demand.	(Ampountolas and Legg, 2021; Zhang et al., 2020d,c; Zhu et al., 2021)	39
	Forecasting consumer sentiment	DL is used to predict tourist sentiment, typically using datasets from online reviews.	(Geng et al., 2019; Qi et al., 2019; Han et al., 2018; Zhang et al., 2019b)	27
	Forecasting other parameter	Using DL to forecast other parameters, for instance, hotel room prices, airline ticket prices, etc.	(Zhang et al., 2019d; Nie et al., 2020; Liu and Shen, 2020; Verma et al., 2019; Parimala et al., 2021; Ampountolas and Legg, 2021)	15
Provide	Provide more tailored experience	Using DL to provide a personalised customer experience. For instance, using DL to provide customised advertising or emotion recognition.	(Zhang et al., 2020b; Xiao et al., 2020; Ray et al., 2021; Hossain and Muhammad, 2019)	18
	Provide richer user experience	Applying DL to enable a richer consumer experience. For instance, using DL to understand tourist behaviour to provide better recommendations or itineraries.	(Yu and Egger, 2021; Li et al., 2020; Luo et al., 2021; Tahmasebi et al., 2021)	11
	Convenience or automation	Using DL to automate processes or operations.	(Zhang et al., 2019a; Quan et al., 2020; Chen et al., 2020)	8
Promote	Promoting to the right target	Using DL to better identify the target customers.	(Pramod, 2022), Wang2020d, Zhu2021	15
	Promoting the right price	Using DL to promote the right price to the consumers.	(Zuheros et al., 2021; Nassar et al., 2020)	12
	Promoting the right message	Using DL to promote the right message. For instance, using DL to provide better tourism destination recommendation.	(Bin et al., 2020; Singh and Singh, 2021)	10
Produce	Automation for creating higher quality goods/services at lower cost	Using DL to produce better quality products at lower costs. For instance, by using DL to automatically create customised products/packages for tourists.	(Kang et al., 2021; Zhang, 2021; Tsai et al., 2020)	4

theme applied DL towards providing a richer and more tailored user experience (typically via recommender systems). Recommender systems are proven to be vital marketing tools in e-commerce as they provide personalisation and consumer-oriented offerings (Ricci, 2020). Furthermore, these recommender systems aim to provide recommendations to an individual/consumer based on their interests and behaviour. Ideally, these recommendations should match the user preferences and provide some form of decision support to the user. In this "data era", the constantly growing amount of user-generated data available via the internet, social media, education, and e-commerce systems, makes the implementation of these systems a necessity rather than choice. It is, therefore, no surprise that most scholarly efforts (in the *provide* theme) related to recommender systems. Some interesting architectures have been adopted in our study sample, for instance, using a hybrid deep autoencoder network (Tahmasebi et al., 2021), hybrid DL model for generating itineraries for museum visits, which incorporates an Internet of Things (IoT) architecture of beacons, semantic analysis, and data mining (Torres-Ruiz et al., 2020). The approach adopts multi-source data for generating and these indoor and outdoor itineraries for museums, which are visualized using augmented reality (AR).

It is important to provide richer experiences to consumers of tourist or travel products and services. However, to provide a tailored experience (leading to a richer user experience), it is imperative to understand consumer behaviour. DL can provide an automated approach towards understanding consumer, traveller, or tourist behaviour, by leveraging user-generated content especially in the form of social media data (Essien et al., 2021). This was explored in Zhang et al. (2020a), via the analysis of the visual content of geo-attached photos using DL to understand how tourists differ. The study analysed 29,081 photos shared by tourists from Europe, North America, and Asia in Hong Kong. Besides, DL can perform image analytics for analysing consumer-posted online content relating to dining experiences (Hasan et al., 2021). In this present study, eight (8) studies in the *provide* theme applied DL for enhancing convenience of service via automation (see Table 5). Specifically, DL has been applied to automatically extract accounts from video articles or news items (Zhang et al., 2019a) as well as automatically identify categorical influencers (i.e. people who are active in the targeted categories) in social media channels (Quan et al., 2020). In conclusion, most articles applying DL to provide better or enhance services to consumers developed recommender systems or towards better understanding consumer/tourist behaviour.

4.1.3 Deep Learning in Hospitality, Travel and Tourism (HTT) Literature: Promote

DL can create value in the HTT industry by allowing tourism companies/agencies to promote well-priced, accurately targeted marketing offerings to tourists. In this current study, 37 articles that fell within this research theme and these articles are discussed across three sub-categories – (i) promoting the right prices of goods/services to users, (ii) delivering the right message, and (iii) deciphering the right targets. Within the research portfolio considered in our study, it appears there is an apparent focus towards applying DL for promoting to the right target and at the right price, as Table 5 shows. Specifically, DL has been applied for enhanced personalised attraction recommendation (Bin et al., 2020), group users' dynamic identification and recommendation on the Internet platform using an attention-based DL model (Wang et al., 2020c), and a CNN-based model for reviewing information of users and tourism service items (Pramod, 2022). Other DL applications in the *promote* theme are the use of computational linguistics, visual analytics, and DL techniques to analyse hotel reviews and responses collected on TripAdvisor (Chang et al., 2020).

With technological advancement and data ubiquity, the tourism sector has exploited the prospect of adopting these technologies to send the right messages to tourists. If identifying the right target for a tourism package (or product/service) is important, it goes without saying that sending the right message is even more important. This is key to enhancing sales, profitability, and customer loyalty. Within this context, DL has been used in the literature to ensure this right message is passed to the customer, for instance, by using a DL-enabled intelligent automation framework for identifying tourism photos (Wang et al., 2020a). Furthermore, Ordenes and Zhang (2019) propose an introduction to text and image mining methods for service researchers and practitioners interested in the analysis of unstructured data. It goes without saying that it is beneficial to apply DL for promoting the right prices to the consumer. Existing articles have exploited this research field and contributions, such as, a Multi-Person Multi-Criteria Decision-Making methodology for smarter decision aid (Zuheros et al., 2021) as well applying a multi-criteria collaborative filtering model based on DL, which can be used in suggesting or promoting the best price to the end users (Nassar et al., 2020). In conclusion, the findings from this study show that there is a focus on DL applications that are about promoting to the right target and sending out the right message to tourists.

4.1.4 Deep Learning in Hospitality, Travel and Tourism (HTT) Literature: Produce

Finally, DL can create value in tourism by allowing companies to produce their goods and/or services at lower costs and higher quality. Within this study, the findings indicate the current research portfolio incorporates a reduced interest, evident in the four (4) identified articles that fell within this theme. Table 5 summarises the articles in this category and shows that all four contributions are about automating a process or operation relating to the creation of products

Table 6: Summary of research impact according to application area.

	Parameter forecasting	Sentiment Analysis	Analytical Processing	Recommender Systems	Image Recognition	**Total**
Project	63	15	2	0	1	**81**
Provide	3	6	18	4	6	**37**
Promote	4	7	10	13	3	**37**
Produce	2	0	1	0	1	**4**
Total	**72**	**28**	**31**	**17**	**11**	**159**

Note: Values represent total number of articles in each application area

or services. For instance, a transfer learning based approach to solving the problem of video analysis (Zhao et al., 2020). The work adopted the Faster-RCNN DL model in use in their study for automating video analysis, a task that normally should have been done manually. DL has also been applied for the automatic classification of tourist photos by analysing the photo characteristics using 168,216 Flickr photos, created 75 scenes and 13 categories (Kang et al., 2021). The study adopted a pre-trained DL model (Inception-v3 model) by analysing the characteristics of photos posted by tourists, all crawled using automated computer scripts. In other words, the research efforts have concentrated on automating processes for creating goods and/or services at lower costs and higher quality.

4.2 Trends in current literature – Application Areas

The review within this current study revealed five (5) application areas wherein DL has mainly been applied in the review sample. For the application areas identified, we considered the count of articles as a representative of the research interest within each area. Consequently, the five identified application areas are: (i) parameter forecasting, (ii) sentiment analysis, (iii) analytical processing, (iv) recommendation, and (v) image recognition. Table 6 summarises the articles in our review sample according to the application areas. As can be seen, the application area having the highest research activity is parameter forecasting. In total, the parameter forecasting application area has 72 articles, with the majority of these coming from studies in the *project* category. In the subsequent paragraphs, we explicate the DL application areas and discuss the implications of these areas in practice.

4.2.1 Parameter forecasting

Describes studies that have applied DL to forecast a parameter, for instance, tourism demand, flow, or some other parameter. According to the findings in this study (refer to Table 6), the parameter forecasting application area is the most popular, accounting for 45% (72) of the total research publications for DL studies comprising the HTT research portfolio. Of these, 88% (63) of the publications represent studies that apply DL for forecasting (i.e., within the *project* theme), with four (i.e., 5.5%) in the *promote* research theme. The *provide* and *produce* research themes have each attracted the least research publications (3 and 2, respectively).

4.2.2 Sentiment analysis

This refers to the use of computing techniques to classify sentiments of textual data (typically user reviews) as positive, neutral, or negative, emphasising its significance in HTT management (Thelwall, 2019). Therefore, it may be unsurprising that sentiment analysis is receiving increased research attention. From Table 6, 28 (17.6%) publications in the review sample applied DL models to conduct sentiment analysis. In this application area, most of the studies (53.5%) fell within the *project* theme, with studies applying sentiment analysis to classify user review ratings, hotel score, and areas of improvement. There is a zero article count (see Table 6) for studies applying sentiment analysis to *produce* cheaper products/goods or services, despite the potential for DL to be applied in this regard for product, process or service innovation (Jeong et al., 2019). The rationale for the zero article count on applying sentiment analysis to *produce* is one of the important areas for future research.

4.2.3 Analytical processing

Studies which applied DL to analyse, evaluate, or describe an entity or a phenomenon are classified in this application area. In the study sample analysed, a total of 31 articles that apply DL for the analysis or evaluation of some tourism-related variable (refer to Table 6). For example, DL was used to analyse news articles Zhang et al. (2019a), hotel reviews and responses Chang et al. (2020), as well as tourist behaviour Kim et al. (2017); Hasan et al. (2021). Some of

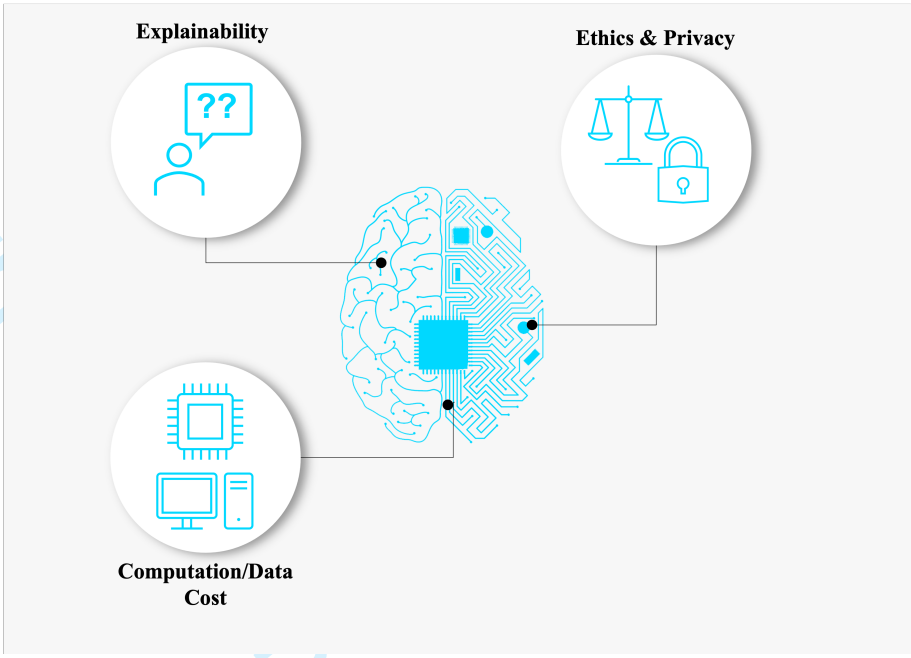

Figure 5: Barriers to the adoption of DL in HTT.

these articles have also enabled the provision of better services (i.e., in the *provide* theme), for example Zhang et al. (2020b), where DL was used to perform spatiotemporal analysis of tourist experiences.

4.2.4 Recommender systems

A recommender system is a system that is used to predict the preference or ranking a user would provide for an item or service. Recommender systems are gaining traction in tourism literature by providing customised information to users based on their preference, situation, restrictions or specific requirements (Borràs et al., 2014). In the HTT literature, DL is rapidly dominating this research subarea and is evident in the growing number of publications this application area is gathering. From Table 6, there are a total of 17 articles – 15 of which have been published in the past two years. This clearly shows increasing research interest in the application of DL for recommending/promoting better services or goods to tourists.

4.2.5 Image recognition

The advancement of computer vision has resulted in the application of DL models for solving tourism-related challenges via video/image segmentation, recognition and/or identification. Image recognition is transforming and disrupting global markets, being applied in almost all areas of endeavour, for instance, healthcare – for the identification and diagnosis of diseases, drug discovery, and cell counting. Besides, image recognition is applied in the education sector for enabling customised services to disabled students. It goes without saying that, due to data ubiquity, the application of image recognition in tourism will significantly disrupt the current business environment. However, within this application area, there are only 11 publications, accounting for 6.9% of the total articles (see Table 6) applying DL to provide rich and personalised services to customers/users.

4.3 Barriers to the adoption of Deep Learning in Hospitality, Travel and Tourism (HTT)

The focus of **RQ3** was to identify the emergent challenges and limitations obtainable from the literature in this research field. The summarisation of the identified research themes allowed the identification of barriers evident in extant literature to provide the answer to this question. From the review conducted in our paper, three main challenge areas are identified (see Figure 5), which limit the widespread adoption of DL in HTT (and in general). These challenge areas are (i) explainability, (ii) ethics and privacy issues, and (iii) computation/data cost. We explicate these three challenge areas in the subsequent paragraphs.

4.3.1 Explainability

The inherent characteristics of deep neural networks, particularly the non-linear computations that occur within the model optimisation, constitute both an advantage and disadvantage. On the one hand, the consequence of these non-linear optimisations results in highly powerful and accurate analytical models, but this makes their interpretability almost impossible, a trait that constitutes a significant barrier to the widespread adoption of DL. The implication is DL being termed a *black-box* in that, despite its very high validation accuracy, it is almost impossible to explain or rationalise the decisions made by DL models. This is evidently a challenge area, as identified by recent studies in the literature (Kong et al., 2021; Samek et al., 2019). In our study, some articles have identified explainability as a limitation or future research direction, with most of these articles relating to the *project* theme. For instance, Luo and Xu (2021) showed that although DL models significantly outperformed conventional/traditional machine learning algorithms in both sentiment analysis and rating prediction, a major limitation/challenge was providing a rationale or explanation for the predictions or forecasts. This represents a challenge area and, in most respects, limits the widespread adoption of DL in the HTT sector.

4.3.2 Ethics and Privacy

Technological advancement via AI and DL has risen several ethical and privacy concerns in recent times, with some events resulting in public scandals for technological giants (e.g., Facebook Cambridge Analytica scandal). Users and organisations are interested in receiving answers to the many questions relating to the adoption and implementation of DL. For instance, what protocols are adopted in the collection, use and storage of personal data (e.g., facial, biometric, personal data, etc.) used in training these models? What data is collected? Where is it stored? Who owns and has access to it? These questions can become a barrier to the adoption of DL in HTT. Specifically, for the DL model training technique, its *black-box* characteristic may be at the risk of revealing user-discriminative features unintentionally (e.g., revealing user details when recommending). These ethical challenges are the more emphasised due to the exponential growth and ubiquitous impact of AI/DL technologies. Given the extremely sensitive role of DL-enabled products in HTT consumers' lives, it becomes a challenge to integrate well-established ethical values in developmental process for the DL models (Etzioni and Etzioni, 2017). As is well articulated in Anderson and Anderson (2011) (p. 1), "ideally, we would like to be able to trust autonomous machines to make correct ethical decisions on their own, and this requires that we create an ethic for machines." By effectively integrating ethical principles into the development of DL models, it not only increases trust on the part of the consumers, but also on the management/organisational perspectives.

4.3.3 Computation/Data Cost

DL models are extremely resource-intensive, due to the inherent complexity of their model architectures. In other words, the training times of these models are significantly higher than their machine learning counterparts. Moreover, DL models strongly rely on massive training data, which typically results in extreme training times. To achieve state-of-the-art accuracies, these datasets (for example, large image recognition datasets) when trained on DL models can take up to weeks (even on supercomputer nodes) to train. As an illustration, the early Deep-CNN model architecture (i.e., AlexNet (Krizhevsky et al., 2012b)) processes 61 million parameters and consumes 249 Megabytes of memory, performing 1.5 billion high-precision operations in order to make a single prediction. When training DL models, it is typical to adopt graphical processing units (GPU), as these accelerate the training time. However, GPUs are very expensive and energy-hungry, such that they are unsuitable for real-time applications (e.g., mobile apps). This cost of computation constitutes a barrier to the widespread adoption of DL in HTT applications. As a solution to this, transfer learning has been introduced in computer science research as the ability to re-use knowledge from pre-trained DL models, thereby significantly reducing the training time and computational demand by upto 99% (Weiss et al., 2016). Therefore, the tourism research field might immensely benefit from exploring a deeper integration of DL technology with other emerging and established technologies, for instance, edge computing (Shi et al., 2016), transfer learning, and distributed DL (Sergeev and Del Balso, 2018) to create robust implementations of DL that can promote, project, produce, and allow companies to provide better offerings to the right consumers/users.

4.4 Emergent research and future directions

We argue that the specific contributions of DL in HTT can be broadly characterised to three levels corresponding to: (i) *Technological Advancement*, (ii) *Process Enhancement (i.e., Automation)* and (iii) *Concept Development*. In the sample reviewed in this current study, majority of the articles contributed towards technological advancement, which refers to the use or application of DL in line with technological advancement. For instance, studies that proposed novel models for performing tasks such as sentiment analysis, image recognition (and classification), location/destination recommendation, etc. all fall within this category. It is, therefore, no surprise to see that most articles with this level of contribution were within the *project* theme (refer to Table 7). With process enhancement/automation, this refers

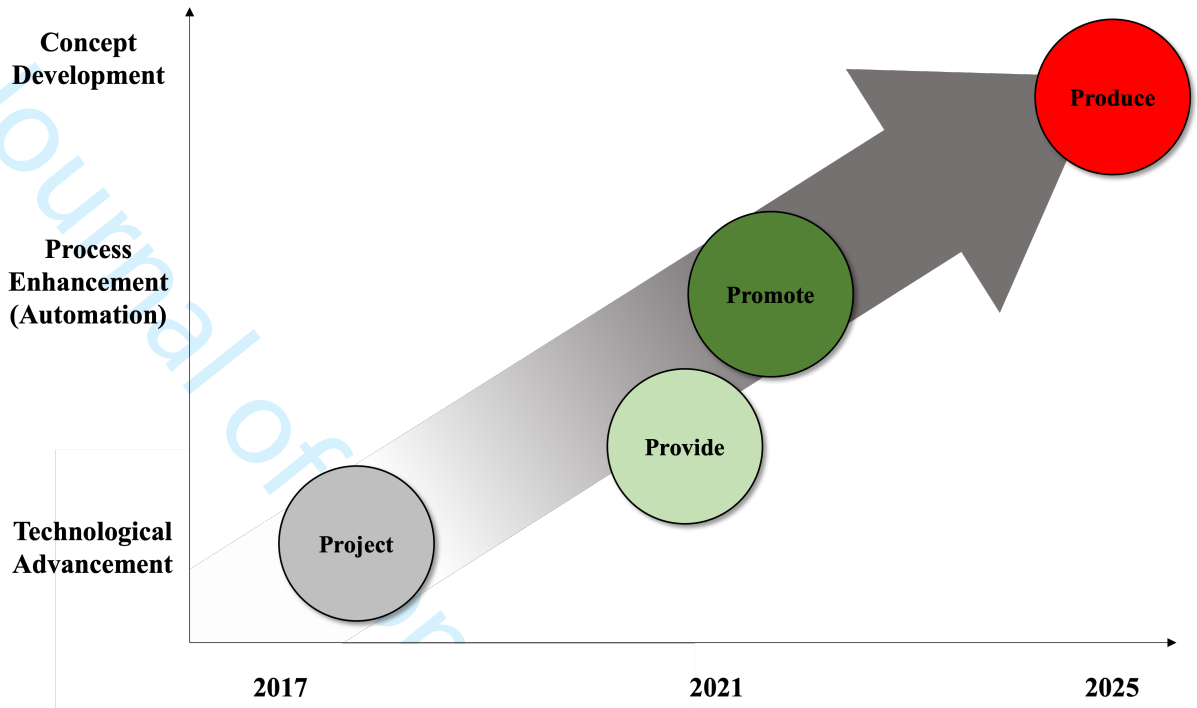

Figure 6: Research synthesis and road-map for future research.

to the application of DL for enhancing processes both for business and consumers, with majority of such articles being in the *promote* theme. Examples of such contributions are holiday/destination automated booking using chatbots (Jiménez-Barreto et al., 2021; Tuomi et al., 2021; Byrd et al., 2021; Loureiro et al., 2021), leisure tourism enterprise management systems (Qian and Ge, 2021) and tourism destination management and automation (Pelet et al., 2021). The third level of contribution, which we argue returns the highest value, is the application of DL for the development and implementation of novel concepts, business models and product offerings to consumers. Within this level of DL applications, we have seen the development of novel and unique experiences to consumers, for example, AR/VR techniques (Doborjeh et al., 2021; Gaur et al., 2021) and computer-generated imaging (Lee and Madera, 2019; Lin et al., 2021).

The findings obtained from the systematic review conducted in this study enabled the development of a research framework that synthesises the research gaps obtained in extant literature as well as the challenge areas explicated in the previous subsection. Figure 6 represents the graphical summary of the research synthesis framework proposed in this study. The framework characterises the research trajectory along a time continuum that considers the research contribution against the four main research themes corresponding to the *4Ps* framework. Our research synthesis framework is informed by the current portfolio of research across the four value areas, considering the growth rate of these value-creation themes over the years (estimated by the sample size analysed within this current study). The framework aims to provide the answer to **RQ4**, which focused on explicating the directions and future opportunities in HTT that might benefit from the application of DL. To answer this question, a synthesis of insights from the identified gaps (and barriers) as well as limitations from extant literature, and recommendations are summarised in a synthesis framework presented in Figure 6.

As can be seen, the framework graphically represents the existing research trajectory along the four (4) main research themes (i.e., project, provide, promote, and produce) with the y-axis representing key areas of contribution from articles in the study (i.e. technological advancement, process enhancement and concept development). These areas of contribution have received varied interest over the years and our findings show a gradual shift from the more saturated contribution area – *technological advancement*, to *process enhancement* and all through to *concept development*, having the highest contribution. The x-axis represents the articles' year of publication, extended to 2025. The centre arrow alongside the *4Ps* illustrate the trajectory of research gradually traversing from applications of DL for technological advancement to the emerging *provide* and *promote* value-creation applications for enhancing processes (e.g., automation of tasks and processes). We argue that to maximise the potential for DL in HTT, research must advance towards

Table 7: Future research trajectories

	2017	2018		2019		2020		2021	
		Papers	% change	Papers	% change	Papers	% change	Papers	% change
Project	1	10	+900	13	+30	25	+92.3	31	+24
Provide	0	1	+100	7	+600	10	+42.9	19	+90
Promote	0	0	N/A	6	+600	12	+100	18	+50
Produce	0	0	N/A	2	+200	2	0	0	−200

Table 8: Future research trajectories

	Papers in contribution areas (count)			Examples of future research studies
	Technological Advancement	Process Enhancement	Concept Development	
Project	75	4	2	Predicting tourist crowd flows using satellite imagery and DL
Provide	26	9	2	Understanding tourist sentiment using DL and computer vision.
Promote	29	8	0	Applying image recognition to promote sustainability of hotels/travel packages to enthusiasts
Produce	1	1	2	Using tourism destination imagery and DL for travel package development
Total	131	22	6	

concept development (e.g., product/service development, business model innovation, etc.), which is closely aligned to the *produce* value-creation applications. In the subsequent paragraphs, we explicate the framework findings across the four (4) value creation dimensions and areas of contribution and propose cogent future research directions. Table 8 summarises the future research trajectories aligned with the contribution areas, proposing some example research projects that can enhance the research field of DL in tourism.

4.4.1 Technological Advancement

The key finding from this current study is that the current research portfolio around DL in HTT is dominated by the application of this approach to predict/forecast some parameter or variable. This is evident in all aspects of the analysis presented in this work. We argue that DL applications for predicting/forecasting is now reaching a saturation state (refer to Figure 6 and Table 7). Although a significant number of articles have proposed DL applications within this category, as Table 7 shows, the growth rate (Y-o-Y) in this value-creation area is in decline compared to previous years (i.e., 2020, 2019 and 2018). DL applications falling within this category have mainly been applied towards technological advancement, for instance, using DL to forecast tourist demand rather than using other forecasting means (e.g., Delphi, statistical, etc.). We argue that although there is a contribution by these applications, some have also focused on applying DL for process enhancement. For instance, Li et al. (2018) proposed a DL model for domain-specific new words detection. Evidently, the literature can benefit from more *project* studies that focus on process enhancement and concept development (refer to Figure 6). Typical applications can range from facial recognition for tourism product recommendation, DL for AR/VR to predict and enhance customer experience and the use of image recognition for emotion response prediction (Hadinejad et al., 2019), tourism destination forecasting, etc. As seen in Table 8, there is a gradual shift in focus from technological advancement (in the *project* theme) towards process enhancement (via the *provide* and *promote* themes).

4.4.2 Process Enhancement and Automation

According to our analysis, the current research landscape growth is seeing the *promote* and *provide* themes emerging in HTT literature (refer to Figure 6). Table 7 shows that in the year of this analysis (i.e., 2021), there was significant growth in the number of articles in the *promote* and *provide* themes – 50% and 90%, respectively. We argue that these value-creation themes are closely aligned to the process enhancement contribution areas. In other words, the

applications proposed in these value-creation areas lead to enhancements in the business/operational processes in the organisations implemented. Within our study sample, the promote and provide themes have each seen almost double the number of articles characterised within this contribution area (Table 8). In Sperlí (2021), a DL model is proposed, which models intangible and tangible cultural objects into a unified data model, for supporting tourists journey. Specifically, the authors have designed a micro-service architecture to provide several services whose tourists can access through a conversational agent based on DL. In another study, Yunus et al. (2018) a framework is proposed that automatically estimates food attributes such as ingredients and nutritional value by classifying the input image of food. The approach uses image recognition techniques to achieve this and falls within the *process enhancement* contribution area. We expect to see further increased research interest in these value-creation (and contribution) areas over the next few years.

4.4.3 Concept Development

The third contribution area that would further the knowledge in the research area of DL in HTT is its application for concept development. This closely aligns to the *produce* (i.e., value-creation) theme obtainable in the 4Ps framework. The current research landscape in DL for HTT management shows that the application of DL for concept development is almost non-existent (refer to Tables 5, 7 and 8). It cannot be further emphasised the fact that AI/BDA and DL is here to stay and will dominate key areas of businesses – including hospitality, travel and tourism. Consequently, a key application area for future research is the application of DL for creating new products and services by adopting these application areas (i.e., image recognition, recommendation, sentiment analysis and analytical processing). Hospitality and tourism have rather complex back-office settings, with various tasks requiring harmonisation and automation. For example, consider a simple tour delivery service, which can be explored as either a route optimisation/planning problem or analytics-based solution to provide the optimal method for implementing and delivering this service. This is a potential avenue for automation involving DL. In other words, a future research direction that will be extremely beneficial to tourism management will be the application of DL for creating better products and/or services. For instance, DL can be applied for creating innovative products and services that can reach a wider audience and promote tourism in real-time or dynamic ways. The proliferation of new and emerging technologies, such as blockchain, IoT and 5G can enable the creation and deployment of highly customised and personalised products/services, shifting the business space towards a customer-centric position (Wang et al., 2020b).

5 Discussion and conclusion

5.1 Conclusions

This study aimed to provide an understanding of the scope of DL applications in the HTT research domain. This necessitated the execution of a systematic review of existing research, incorporating two leading online academic articles databases; adopting systemic protocols to identify and select articles to be reviewed. The findings from the review process were applied towards summarising the extant body of knowledge and encapsulating past and current thematic trends in the existing literature. Future research directions have been proposed by the amalgamation of research limitations in extant literature, recommendations, and the identified gaps in current literature. As discussed in Section 2, our work adapted the Bughin et al. (2017) characterisation of data created by big data and AI to conceptualise the application of DL in tourism research. Figure 7 represents the four areas wherein DL can create value in business organisations (Bughin et al., 2017). As can be seen, the diagram incorporates an x-axis representing a continuum from applications that create value for the customer (i.e., customer-focused) to those applications that create value for the business (or business-focused). The *provide* and *promote P*s are more customer-focused as the value created in these quadrants of the matrix/framework mainly benefit the customer, as opposed to the *produce* and *project P*s that predominantly create value for the business or organisation.

Following our review in this study, we observe that the application of the 4Ps framework spans beyond value creation. Specifically, we argue that in addition to representing the DL applications (via the 4Ps framework) as a continuum representing customer-focused and/to business-focused value creation, DL applications in tourism research can also be characterised as those that either contribute to *create* value, or those that contribute to *deliver* this value. This is what Figure 7 depicts. Findings from our analysis reveal that two *P*s (i.e., *promote* and *project*) were mainly deployed to deliver the value created through (*produce* and *provide*) activities in the upper quadrant of Figure 7 above. To illustrate this, let us consider a practical example within the HTT industry. Consider *Carrier - B*, a budget airline company that seeks to enhance its profitability and competitive edge via enhanced customer experience and lean operations. To achieve this, *Carrier - B* can use a DL model/algorithm (i.e., *produce* quadrant) to compute or determine the optimal (most profitable) routes (Peng et al., 2021) that it can travel to/from and apply DL to *provide* rich, tailored customer experiences to its individual travelers (e.g., customised travel packages, ticket prices, itineraries, recommendations, etc.). For example, recommending the Louvre or Grand Palais (Paris) travel package to an avid art lover. Together,

Figure 7: The 4Ps framework for DL applications in tourism research.

these two applications have *created value* – with the one application creating value for the business (i.e., *produce*) and the other creating value for the customer/tourist (i.e., *provide*).

DL can also contribute towards the *delivery* of the value created by the upper two *P*s. In our example scenario, DL can deliver this value – which has been created by the *produce* and *provide* quadrants – to the customer (i.e., *promote* quadrant), by using DL to promote the *right* message to the *right* customer. A practical example of this is the use of DL chatbots for recommending tourist destinations, packages, etc. to tourists (Alotaibi et al., 2020). Finally, whilst delivering value to the business, DL can be used to project or forecast the tourist demand, for instance, how many potential customers are likely to purchase the promoted packages, what the optimal price should be, etc. *Carrier - B* can therefore use the output of this forecast to better plan or optimise its operations (e.g., staffing requirements, equipment, aircrafts, etc.).

From the simple example scenario above, it can be seen how our *4P*s matrix/framework can be extended towards characterising DL applications in practical HTT business scenarios. From Figure 7, the value creating activities in the upper quadrants (i.e., *promote* and *project*) can be distinguished from those in the lower quadrant (i.e., *produce* and *provide*) in that those in the lower quadrant, rather than solely creating value, can also be deployed towards delivering the created value to both the customers/tourists (i.e., *promote* quadrant) or the businesses/tourist organisations (the *project* quadrant).

5.2 Theoretical implications

The theoretical contributions of this paper are three-fold. First, the work represents a systematic review of existing literature in the field of DL applications in HTT, thereby revealing the main areas wherein DL is creating value in the current literature. By explicating these findings, researchers can benefit by understanding *ab initio* the focal research areas and pursue proposed future research directions recommended herein. Findings showed that scholarly attention is mainly directed towards the application of DL towards the *project* value-creation theme, particularly creating value for enhancing (internal) business operations, in contrary to the other two dimensions, (i.e., *promote* and *provide*) which mainly create value for consumers, indicating an area where more research is required.

Second, the study has explicated (based on gaps in extant literature) implications for future research directions. It is our firm belief that DL will – and probably has already – disrupt(ed) the industry as it is known, reshaping the supply side of the value chain towards the delivery of more efficient and profitable products and services. With rapid technological advancement will come continuous reductions in costs of computation, storage, and transportation. This will create niche markets, better tourism destinations, all of which will expand the industry and drive economic growth at a reduced cost to the environment. We argue that, in order to realise optimal benefits, research in this field should advance towards DL applications for *concept development* and *producing* innovative products/services at lower costs and higher quality.

Third, we propose a research synthesising framework that informs future research directions. By proposing this framework, our paper adds to the tourism literature by summarising and characterising the current/emerging research space, highlighting application (and challenge) areas that are popular within the research society, and delineating pertinent avenues that can inform future research directions. By so doing, we also expand the scope of future research in DL for tourism. Specifically, the findings highlight a substantial dearth of research about the application of DL for creating new and better products/services at lower costs.

5.3 Practical implications

In terms of practical implications, the output of this study can be consumed by many stakeholders, for example, tourism and hospitality organisations, travellers, government agencies, policymakers, etc. First, this study exposes the need to shift the application of DL in hospitality and tourism management towards creating value for the consumers. This involves redirecting the focus of research from *project* and *promote* towards *producing* and *providing* services that create value for the consumers. For example, providing better tourism location suggestion or itinerary by implementing technologies that rely on real-time language translation, virtual and augmented reality (VR/AR) for navigation. Furthermore, our study can inform tourism organisations about what decisions can be made about resource allocation of technologies. Specifically, the results from this study can serve as indicators to potential areas for enhanced value creation, which can enhance the tourism sector.

Second, consistent with the findings in our study, the proliferation of DL applications in hospitality and tourism will be significantly transformed by the continued adoption of new and emerging technologies, such as, IoT, blockchain and AI. We argue that, given the heavy reliance by many tourism and hospitality industry players on big data analytics for decision-making (Mariani and Baggio, 2021), a study of this nature has practical implications around the potential adoption areas for DL applications in the sector, which comprise the key findings in our study (refer to Section 4.4). For example, by recommending emergent research areas and potential applications, we can open up a new wave or upsurge in research interest relating to DL applications, including – but not limited to – facial recognition for tourism product recommendation, DL for AR/VR to enhance customer personalisation and experience as well as the use of image recognition for emotion response prediction (Hadinejad et al., 2019), tourism destination forecasting, to name a few.

Third, by identifying barriers to the adoption of DL in the HTT industry, as well as recommending potential research areas, the findings from our study can serve as a roadmap for travel research companies (e.g., Smith Travel Research, Vision One UK, etc.) to develop and deploy novel solutions that can contribute towards the recovery (from COVID-19) of the HTT sector (Mariani and Wamba, 2020). We argue that the widespread adoption of DL by HTT industry practitioners can increase the likelihood of successfully realising the benefits of applying DL in HTT. Besides, the proliferation of new and emerging technologies, such as blockchain, IoT and 5G can enable the creation and deployment of highly customised and personalised products/services, shifting the business space towards a customer-centric position (Wang et al., 2020b).

5.4 Limitations and future research

It is pertinent to reflect upon the findings of this research in light of some identified limitations. The foremost limitation is that this study was scoped to only articles that are published in peer-reviewed journals available in the selected scholarly online databases only. This implies that other publication forms, including conference articles, book chapters, and blog articles were excluded. Second, despite the rigour involved in this study, it is possible that some articles were screened out due to exclusion criteria and, therefore, were not captured in the study. Besides, the research landscape around DL in HTT is rapidly advancing with contributions emerging on a daily basis. Therefore, it may be interesting to incorporate articles from 2022. Another limitation of our study, which relates to the nature of DL (i.e., being application-based and infrastructural), was the difficulty to characterise the individual articles within the four areas (i.e., project, provide, promote, and produce), as some articles could haven been classified within more than one area, leaving room for ambiguity in the findings and discussion.

Beyond these limitations, the findings from the study have enabled us to recommend future research directions for scholars in the field, as detailed in Section 4.4. First, we can build on this current study to break the barriers or challenges

to the widespread adoption of DL in hospitality and tourism management, which might have significant implications for research and practice. We must acknowledge that this is an initial attempt, which implies the need for a sequel in the near future to analyse the evolution of DL in tourism.

Second, of the articles contained in the sample reviewed within this current study, there was no application of DL towards contributing to sustainability and the circular economy, which is a call for future research in this direction (Zhang et al., 2020b). Generally, only a few references are found in existing hospitality and tourism literature that relate to the circular economy/sustainability, even though it is a sector that is arguably one of the largest consumers of energy and water, food waste, congestion problems and CO2 emissions and pollution (Molina-Collado et al., 2022). This is consistent with findings from recent literature, with scholars suggesting that – given the shortage of attention in this research area – it is an area that deserves significantly more attention from academics, practitioners and public policymakers (del Vecchio et al., 2021; Mody et al., 2021). From the foregoing, using renewable resources instead of conventional energy can result in benefits that are vital aspects in the actualisation of the tourism circular economy. DL can significantly contribute to achieving this by, for instance, predicting the environmental impacts of tourists behaviour (Zhang et al., 2020b), optimising hotel operations, etc. The features of tourism and hospitality programmes shape tourist behaviours, some of which impact the environment. DL can help predict the potential impact certain features of tourism and hospitality programmes have on the environment. For example, planned but flexible guided tours can inform the car rental behaviour of tourists, which in turn affects pollution.

References

Ackley, D. H., Hinton, G. E., and Sejnowski, T. J. (1989). A learning algorithm for Boltzmann machines. *Cognitive science*, 9(1):147–169.

Akdim, K., Belanche, D., and Flavián, M. (2021). Attitudes toward service robots: analyses of explicit and implicit attitudes based on anthropomorphism and construal level theory. *International Journal of Contemporary Hospitality Management*, ahead-of-print(ahead-of-print).

Al Shehhi, M. and Karathanasopoulos, A. (2020). Forecasting hotel room prices in selected gcc cities using deep learning. *Journal of Hospitality and Tourism Management*, 42:40–50.

Alotaibi, R., Ali, A., Alharthi, H., and Almehamadi, R. (2020). Ai chatbot for tourism recommendations: A case study in the city of jeddah, saudi arabia. *International Journal of Interactive Mobile Technologies*, 14(19).

Ampountolas, A. and Legg, M. P. (2021). A segmented machine learning modeling approach of social media for predicting occupancy. *International Journal of Contemporary Hospitality Management*, 33(6):2001–2021.

Anderson, M. and Anderson, S. L. (2011). *Machine ethics*. Cambridge University Press.

Anderson, R. (2007). Thematic content analysis (TCA). *Descriptive presentation of qualitative data*, pages 1–4.

Ardito, L., Cerchione, R., Del Vecchio, P., and Raguseo, E. (2019). Big data in smart tourism: challenges, issues and opportunities. *Current Issues in Tourism*, 22(15):1805–1809.

Ashari, H. A., Heidari, M., Parvaresh, S., et al. (2014). Improving smtes' business performance through strategic use of information communication technology: Ict and tourism challenges and opportunities. *International Journal of Academic Research in Accounting, Finance and Management Sciences*, 4(3):1–20.

Belanche, D., Casaló, L. V., Flavián, C., and Schepers, J. (2020). Service robot implementation: a theoretical framework and research agenda. *The Service Industries Journal*, 40(3-4):203–225.

Bibel, W. (2014). Artificial Intelligence in a historical perspective. *AI Communications*, 27(1):87–102.

Bin, C., Gu, T., Jia, Z., Zhu, G., and Xiao, C. (2020). A neural multi-context modeling framework for personalized attraction recommendation. *Multimedia Tools and Applications*, pages 1–29.

Booth, A., Sutton, A., and Papaioannou, D. (2016). *Systematic approaches to a successful literature review*. SAGE.

Borràs, J., Moreno, A., and Valls, A. (2014). Intelligent tourism recommender systems: A survey. *Expert systems with applications*, 41(16):7370–7389.

Braun, V. and Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology*, 3(2):77–101.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlstrom, P., Henke, N., and Trench, M. (2017). Artificial intelligence the next digital frontier. *McKinsey and Company Global Institute*, 47(3.6).

Buhalis, D. and Law, R. (2008). Progress in information technology and tourism management: 20 years on and 10 years after the internet—the state of etourism research. *Tourism management*, 29(4):609–623.

Byrd, K., Fan, A., Her, E., Liu, Y., Almanza, B., and Leitch, S. (2021). Robot vs human: expectations, performances and gaps in off-premise restaurant service modes. *International Journal of Contemporary Hospitality Management*, 33(11):3996–4016.

Chang, Y.-C., Ku, C.-H., and Chen, C.-H. (2020). Using deep learning and visual analytics to explore hotel reviews and responses. *Tourism Management*, 80:104129.

Chang, Y.-Y. and Cheng, C.-C. (2022). New insights into the measurement model of a new scale for evaluating restaurant service quality during major infectious disease outbreaks. *International Journal of Contemporary Hospitality Management*, 34(5):1629–1648.

Chen, L., Zhang, L., Cao, S., Wu, Z., and Cao, J. (2020). Personalized itinerary recommendation: Deep and collaborative learning with textual information. *Expert Systems with Applications*, 144:113070.

Chiu, C.-C., Wei, W.-J., Lee, L.-C., and Lu, J.-C. (2021). Augmented reality system for tourism using image-based recognition. *Microsystem Technologies*, 27(4):1811–1826.

Chuang, T. C., Liu, J. S., Lu, L. Y., Tseng, F.-M., Lee, Y., and Chang, C.-T. (2017). The main paths of etourism: trends of managing tourism through internet. *Asia Pacific Journal of Tourism Research*, 22(2):213–231.

Cortes, C. and Vapnik, V. (1995). Support vector machine. *Machine learning*, 20(3):273–297.

Dash, R., McMurtrey, M., Rebman, C., and Kar, U. K. (2019). Application of artificial intelligence in automation of supply chain management. *Journal of Strategic Innovation and Sustainability*, 14(3):43–53.

del Vecchio, P., Malandugno, C., Passiante, G., and Sakka, G. (2021). Circular economy business model for smart tourism: the case of Ecobnb. *EuroMed Journal of Business*, 17(1):88–104.

Demirel, E., Zeren, S. K., and Hakan, K. (2022). Smart contracts in tourism industry: a model with blockchain integration for post pandemic economy. *Current Issues in Tourism*, 25(12):1895–1909.

Deng, L., Seltzer, M. L., Yu, D., Acero, A., Mohamed, A.-r., and Hinton, G. (2010). Binary coding of speech spectrograms using a deep auto-encoder. In *Eleventh Annual Conference of the International Speech Communication Association*.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Doborjeh, Z., Hemmington, N., Doborjeh, M., and Kasabov, N. (2021). Artificial intelligence: a systematic review of methods and applications in hospitality and tourism. *International Journal of Contemporary Hospitality Management*, 34(3):1154–1176.

El Hihi, S. and Bengio, Y. (1996). Hierarchical recurrent neural networks for long-term dependencies. In *Advances in neural information processing systems*, pages 493–499.

Essien, Petrounias, I., Sampaio, P., and Sampaio, S. (2019a). Improving Urban Traffic Speed Prediction Using Data Source Fusion and Deep Learning. In *2019 IEEE International Conference on Big Data and Smart Computing (BigComp)*, pages 1–8. IEEE.

Essien, A. and Giannetti, C. (2020). A deep learning model for smart manufacturing using convolutional lstm neural network autoencoders. *IEEE Transactions on Industrial Informatics*, 16(9):6069–6078.

Essien, A., Petrounias, I., Sampaio, P., and Sampaio, S. (2021). A deep-learning model for urban traffic flow prediction with traffic events mined from twitter. *World Wide Web*, 24(4):1345–1368.

Essien, A. E., Chukwkelu, G., and Giannetti, C. (2019b). A Scalable Deep Convolutional LSTM Neural Network for Large-Scale Urban Traffic Flow Prediction using Recurrence Plots. In *2019 IEEE AFRICON*, pages 1–7. IEEE.

Etzioni, A. and Etzioni, O. (2017). Incorporating ethics into artificial intelligence. *The Journal of Ethics*, 21(4):403–418.

Feng, C., Elazab, A., Yang, P., Wang, T., Zhou, F., Hu, H., Xiao, X., and Lei, B. (2019). Deep learning framework for alzheimer's disease diagnosis via 3d-cnn and fsbi-lstm. *IEEE Access*, 7:63605–63618.

Filieri, R., D'Amico, E., Destefanis, A., Paolucci, E., and Raguseo, E. (2021). Artificial intelligence (ai) for tourism: an european-based study on successful ai tourism start-ups. *International Journal of Contemporary Hospitality Management*, 33(11):4099–4125.

Flavián, C. and Casaló, L. V. (2021). Artificial intelligence in services: current trends, benefits and challenges. *The Service Industries Journal*, 41(13-14):853–859.

Gaur, L., Afaq, A., Singh, G., and Dwivedi, Y. K. (2021). Role of artificial intelligence and robotics to foster the touchless travel during a pandemic: a review and research agenda. *International Journal of Contemporary Hospitality Management*, 33(11):4079–4098.

Generosi, A., Ceccacci, S., and Mengoni, M. (2018). A deep learning-based system to track and analyze customer behavior in retail store. In *2018 IEEE 8th International Conference on Consumer Electronics-Berlin (ICCE-Berlin)*, pages 1–6. IEEE.

Geng, Y., Du, J., and Liang, M. (2019). Abnormal event detection in tourism video based on salient spatio-temporal features and sparse combination learning. *World Wide Web*, 22(2):689–715.

Goh, C. and Law, R. (2011). The methodological progress of tourism demand forecasting: a review of related literature. *Journal of Travel Tourism Marketing*, 28(3):296–317.

Goodfellow, I. and Bengio, Y. (2015). *Deep learning*, volume 13. MIT Press.

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. (2014). Generative adversarial networks. *arXiv preprint arXiv:1406.2661*.

Hadinejad, A., Moyle, B. D., Scott, N., and Kralj, A. (2019). Emotional responses to tourism advertisements: The application of FaceReader™. *Tourism Recreation Research*, 44(1):131–135.

Han, S., Ren, F., Wu, C., Chen, Y., Du, Q., and Ye, X. (2018). Using the tensorflow deep neural network to classify mainland china visitor behaviours in hong kong from check-in data. *ISPRS International Journal of Geo-Information*, 7(4):158.

Hasan, M. R., Abdunurova, A., Wang, W., Zheng, J., and Shams, S. M. R. (2021). Using deep learning to investigate digital behavior in culinary tourism. *Journal of Place Management and Development*, 14(1):43–65.

Hatami, N., Gavet, Y., and Debayle, J. (2017). Classification of Time-Series Images Using Deep Convolutional Neural Networks. In *Tenth International Conference on Machine Vision (ICMV)*, page 106960Y.

Hinton, G., Osindero, S., and Teh, Y.-W. (2006). A fast learning algorithm for deep belief nets. *Neural Computation*, 18(7):1527–1554.

Hochreiter, S. (1998). The Vanishing Gradient Problem During Learning Recurrent Neural Nets and Problem Solutions. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 6(2):107–116.

Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, 9(8):1735–1780.

Hossain, M. S. and Muhammad, G. (2019). Emotion recognition using deep learning approach from audio–visual emotional big data. *Information Fusion*, 49:69–78.

Hsu, C. H., Xiao, H., and Chen, N. (2017). Hospitality and tourism education research from 2005 to 2014:"is the past a prologue to the future?". *International Journal of Contemporary Hospitality Management*, 29(1):141–160.

Hu, Q., Huang, B., Qi, H., et al. (2021). Application of target image recognition under mri filtering technology. *Academic Journal of Computing & Information Science*, 4(3).

Ivanov, S. and Webster, C. (2021). Willingness-to-pay for robot-delivered tourism and hospitality services–an exploratory study. *International Journal of Contemporary Hospitality Management*, 33(11):3926–3955.

Jeong, B., Yoon, J., and Lee, J.-M. (2019). Social media mining for product planning: A product opportunity mining approach based on topic modeling and sentiment analysis. *International Journal of Information Management*, 48:280–290.

Jian, L., Li, Z., Yang, X., Wu, W., Ahmad, A., and Jeon, G. (2019). Combining unmanned aerial vehicles with artificial-intelligence technology for traffic-congestion recognition: electronic eyes in the skies to spot clogged roads. *IEEE Consumer Electronics Magazine*, 8(3):81–86.

Jiao, E. X. and Chen, J. L. (2019). Tourism forecasting: A review of methodological developments over the last decade. *Tourism Economics*, 25(3):469–492.

Jiménez-Barreto, J., Rubio, N., and Molinillo, S. (2021). "find a flight for me, oscar!" motivational customer experiences with chatbots. *International Journal of Contemporary Hospitality Management*, 33(11):3860–3882.

Kang, Y., Cho, N., Yoon, J., Park, S., and Kim, J. (2021). Transfer Learning of a Deep Learning Model for Exploring Tourists' Urban Image Using Geotagged Photos. *ISPRS International Journal of Geo-Information*, 10(3):137.

Khan, K. S., Kunz, R., Kleijnen, J., and Antes, G. (2003). Five steps to conducting a systematic review. *Journal of the royal society of medicine*, 96(3):118–121.

Kim, E. S., Hagan, K. A., Grodstein, F., DeMeo, D. L., De Vivo, I., and Kubzansky, L. D. (2017). Optimism and cause-specific mortality: a prospective cohort study. *American journal of epidemiology*, 185(1):21–29.

Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X., and Wang, K. (2021). Influences of artificial intelligence (ai) awareness on career competency and job burnout. *International Journal of Contemporary Hospitality Management*, 33(2):717–734.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012a). ImageNet Classification with Deep Convolutional Neural Networks. In *Advances in Neural information processing systems*, pages 1097–1105.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012b). Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*, 25:1097–1105.

Lai, X., Wang, F., and Wang, X. (2021). Asymmetric relationship between customer sentiment and online hotel ratings: the moderating effects of review characteristics. *International Journal of Contemporary Hospitality Management*, 33(6):2137–2156.

Landis, J. R. and Koch, G. G. (1977). The measurement of observer agreement for categorical data. *biometrics*, pages 159–174.

Law, R., Buhalis, D., and Cobanoglu, C. (2014). Progress on information and communication technologies in hospitality and tourism. *International Journal of Contemporary Hospitality Management*, 25(5):727–750.

Law, R., Li, G., Fong, D. K. C., and Han, X. (2019). Tourism demand forecasting: A deep learning approach. *Annals of Tourism Research*, 75:410–423.

LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *nature*, 521(7553):436–444.

LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324.

LeCun, Y., Touresky, D., Hinton, G., and Sejnowski, T. (1988). A theoretical framework for back-propagation. In *Proceedings of the 1988 connectionist models summer school*, volume 1, pages 21–28.

Lee, L. and Madera, J. M. (2019). Faking it or feeling it: the emotional displays of surface and deep acting on stress and engagement. *International Journal of Contemporary Hospitality Management*, 31(4):1744–1762.

Lee, M., Kwon, W., and Back, K.-J. (2021). Artificial intelligence for hospitality big data analytics: developing a prediction model of restaurant review helpfulness for customer decision-making. *International Journal of Contemporary Hospitality Management*, 33(6):2117–2136.

Li, L., Goh, T.-T., and Jin, D. (2020). How textual quality of online reviews affect classification performance: a case of deep learning sentiment analysis. *Neural Computing and Applications*, 32(9):4387–4415.

Li, W., Guo, K., Shi, Y., Zhu, L., and Zheng, Y. (2018). DWWP: Domain-specific new words detection and word propagation system for sentiment analysis in the tourism domain. *Knowledge-Based Systems*, 146:203–214.

Li, X. and Law, R. (2020). Network analysis of big data research in tourism. *Tourism Management Perspectives*, 33:100608.

Lin, M. S., Liang, Y., Xue, J. X., Pan, B., and Schroeder, A. (2021). Destination image through social media analytics and survey method. *International Journal of Contemporary Hospitality Management*, 33(6):2219–2238.

Lindemann, B., Fesenmayr, F., Jazdi, N., and Weyrich, M. (2018). ScienceDirect Anomaly Detection in Discrete Manufacturing Using Self-Learning Approaches. 00(July):18–20.

Liu, C.-H. S. and Dong, T.-P. (2021). Discovering the relationship among knowledge management, sustainability marketing and service improvement: the moderating role of consumer interest. *International Journal of Contemporary Hospitality Management*, 33(8):2799–2816.

Liu, J., Yu, Y., Mehraliyev, F., Hu, S., and Chen, J. (2022). What affects the online ratings of restaurant consumers: a research perspective on text-mining big data analysis. *International Journal of Contemporary Hospitality Management*, (ahead-of-print).

Liu, N. and Shen, B. (2020). Aspect-based sentiment analysis with gated alternate neural network. *Knowledge-Based Systems*, 188:105010.

Long, M., Zhu, H., Wang, J., and Jordan, M. I. (2017). Deep transfer learning with joint adaptation networks. In *International conference on machine learning*, pages 2208–2217. PMLR.

Loureiro, S. M. C., Japutra, A., Molinillo, S., and Bilro, R. G. (2021). Stand by me: analyzing the tourist–intelligent voice assistant relationship quality. *International Journal of Contemporary Hospitality Management*, 33(11):3840–3859.

Luo, Y., Tang, L. R., and Kim, E. (2021). A picture is worth a thousand words: The role of a cover photograph on a travel agency's online identity. *International Journal of Hospitality Management*, 94:102801.

Luo, Y. and Xu, X. (2021). Comparative study of deep learning models for analyzing online restaurant reviews in the era of the COVID-19 pandemic. *International Journal of Hospitality Management*, 94:102849.

Ma, E., Cheng, M., and Hsiao, A. (2018). Sentiment analysis–a review and agenda for future research in hospitality contexts. *International Journal of Contemporary Hospitality Management*, 34(1):46–77.

Mariani, M. and Baggio, R. (2021). Big data and analytics in hospitality and tourism: a systematic literature review. *International Journal of Contemporary Hospitality Management*, 34(1):231–278.

Mariani, M. and Borghi, M. (2021). Customers' evaluation of mechanical artificial intelligence in hospitality services: a study using online reviews analytics. *International Journal of Contemporary Hospitality Management*, 33(11):3956–3976.

Mariani, M. M. and Wamba, S. F. (2020). Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies. *Journal of Business Research*, 121:338–352.

Martín, C. A., Torres, J. M., Aguilar, R. M., and Diaz, S. (2018). Using deep learning to predict sentiments: case study in tourism. *Complexity*, 2018:1–9.

McCulloch, W. S. and Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*, 5(4):115–133.

Mehraliyev, F., Chan, I. C. C., and Kirilenko, A. P. (2021). Sentiment analysis in hospitality and tourism: a thematic and methodological review. *International Journal of Contemporary Hospitality Management*, 34(1):46–77.

Mody, M. A., Hanks, L., and Cheng, M. (2021). Sharing economy research in hospitality and tourism: a critical review using bibliometric analysis, content analysis and a quantitative systematic literature review. *International Journal of Contemporary Hospitality Management*, 33(5):1711–1745.

Molina-Collado, A., Santos-Vijande, M. L., Gómez-Rico, M., and Madera, J. M. (2022). Sustainability in hospitality and tourism: a review of key research topics from 1994 to 2020. *International Journal of Contemporary Hospitality Management*, ahead-of-print(ahead-of-print).

Nassar, N., Jafar, A., and Rahhal, Y. (2020). A novel deep multi-criteria collaborative filtering model for recommendation system. *Knowledge-Based Systems*, 187:104811.

Nie, R.-x., Tian, Z.-p., Wang, J.-q., and Chin, K. S. (2020). Hotel selection driven by online textual reviews: Applying a semantic partitioned sentiment dictionary and evidence theory. *International Journal of Hospitality Management*, 88:102495.

Noblit, G. W. and Hare, R. D. (1988). *Meta-ethnography: Synthesizing qualitative studies*, volume 11. sage.

Oh, S. L., Hagiwara, Y., Raghavendra, U., Yuvaraj, R., Arunkumar, N., Murugappan, M., and Acharya, U. R. (2020). A deep learning approach for parkinson's disease diagnosis from eeg signals. *Neural Computing and Applications*, 32(15):10927–10933.

Ordenes, F. V. and Zhang, S. (2019). From words to pixels: text and image mining methods for service research. *Journal of Service Management*, 30(5):593–620.

Pan, H., Liu, Z., and Ha, H.-Y. (2022). Perceived price and trustworthiness of online reviews: different levels of promotion and customer type. *International Journal of Contemporary Hospitality Management*, (ahead-of-print).

Panetta, K. (2019). Gartner Top 10 Strategic Technology Trends For 2020.

Parimala, M., Swarna Priya, R. M., Praveen Kumar Reddy, M., Lal Chowdhary, C., Kumar Poluru, R., and Khan, S. (2021). Spatiotemporal-based sentiment analysis on tweets for risk assessment of event using deep learning approach. *Software: Practice and Experience*, 51(3):550–570.

Pelet, J.-É., Lick, E., and Taieb, B. (2021). The internet of things in upscale hotels: its impact on guests' sensory experiences and behavior. *International Journal of Contemporary Hospitality Management*, 33(11):4035–4056.

Peng, L., Wang, L., Ai, X.-Y., and Zeng, Y.-R. (2021). Forecasting tourist arrivals via random forest and long short-term memory. *Cognitive Computation*, 13(1):125–138.

Pramod, D. (2022). Privacy-preserving techniques in recommender systems: state-of-the-art review and future research agenda. *Data Technologies and Applications*, (ahead-of-print).

Preethi, G., Krishna, P. V., Obaidat, M. S., Saritha, V., and Yenduri, S. (2017). Application of deep learning to sentiment analysis for recommender system on cloud. In *2017 International conference on computer, information and telecommunication systems (CITS)*, pages 93–97. IEEE.

Qassim, H., Feinzimer, D., and Verma, A. (2017). Residual squeeze vgg16. *arXiv preprint arXiv:1705.03004*.

Qi, T., Xu, Y., and Ling, H. (2019). Tourism scene classification based on multi-stage transfer learning model. *Neural computing and applications*, 31(8):4341–4352.

Qian, W. and Ge, Y. (2021). The implementation of leisure tourism enterprise management system based on deep learning. *International Journal of System Assurance Engineering and Management*, 12(4):801–812.

Quan, T.-T., Mai, D.-T., and Tran, T.-D. (2020). CID: Categorical Influencer Detection on microtext-based social media. *Online Information Review*, 44(5):1027–1055.

Ramos, V., Yamaka, W., Alorda, B., and Sriboonchitta, S. (2021). High-frequency forecasting from mobile devices' bigdata: An application to tourism destinations' crowdedness. *International Journal of Contemporary Hospitality Management*, 33(6):1977–2000.

Rashidi, T. H., Abbasi, A., Maghrebi, M., Hasan, S., and Waller, T. S. (2017). Exploring the capacity of social media data for modelling travel behaviour: Opportunities and challenges. *Transportation Research Part C: Emerging Technologies*, 75:197–211.

Ray, B., Garain, A., and Sarkar, R. (2021). An ensemble-based hotel recommender system using sentiment analysis and aspect categorization of hotel reviews. *Applied Soft Computing*, 98:106935.

Redmon, J., Divvala, S., Girshick, R., and Farhadi, A. (2016). You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 779–788.

Ricci, F. (2020). Recommender systems in tourism. *Handbook of e-Tourism*, pages 1–18.

Romero, J. and Lado, N. (2021). Service robots and covid-19: exploring perceptions of prevention efficacy at hotels in generation z. *International Journal of Contemporary Hospitality Management*, 33(11):4057–4078.

Rosenblatt, F. (1960). Perceptron simulation experiments. *Proceedings of the IRE*, 48(3):301–309.

Rui, C. (2020). Research on classification of cross-border e-commerce products based on image recognition and deep learning. *IEEE Access*, 9:108083–108090.

Rumelhart, D., Hinton, G., and Williams, R. (1988). *Learning representations by back-propagating errors*. 1 edition.

Russell, S. and Norvig, P. (2016). *Artificial intelligence: a modern approach*.

Salakhutdinov, R. and Hinton, G. E. (2009). Deep Boltzmann Machines. In *International Conference on Artificial Intelligence and Statics*, pages 448–455.

Salakhutdinov, R., Mnih, A., and Hinton, G. (2007). Restricted Boltzmann machines for collaborative filtering. In *Proceedings of the 24th international conference on Machine learning - ICML '07*, pages 791–798.

Samara, D., Magnisalis, I., and Peristeras, V. (2020). Artificial intelligence and big data in tourism: a systematic literature review. *Journal of Hospitality and Tourism Technology*, 11(2):343–367.

Samek, W., Montavon, G., Vedaldi, A., Hansen, L. K., and Müller, K.-R. (2019). *Explainable AI: interpreting, explaining and visualizing deep learning*, volume 11700. Springer Nature.

Samuel, A. L. (1967). Some studies in machine learning using the game of checkers. II—Recent progress. *IBM Journal of research and development*, 11(6):601–617.

Schuckert, M., Liu, X., and Law, R. (2015). Hospitality and tourism online reviews: Recent trends and future directions. *Journal of Travel Tourism Marketing*, 32(5):608–621.

Sergeev, A. and Del Balso, M. (2018). Horovod: fast and easy distributed deep learning in TensorFlow. *arXiv preprint arXiv:1802.05799*.

Shi, W., Cao, J., Zhang, Q., Li, Y., and Xu, L. (2016). Edge computing: Vision and challenges. *IEEE internet of things journal*, 3(5):637–646.

Shihab, S. A. M., Logemann, C., Thomas, D.-G., and Wei, P. (2019). Autonomous airline revenue management: A deep reinforcement learning approach to seat inventory control and overbooking. *arXiv preprint arXiv:1902.06824*.

Singh, S. and Singh, S. (2021). HINDIA: a deep-learning-based model for spell-checking of Hindi language. *Neural Computing and Applications*, 33(8):3825–3840.

Song, H. and Li, G. (2008). Tourism demand modelling and forecasting—A review of recent research. *Tourism management*, 29(2):203–220.

Sperlí, G. (2021). A cultural heritage framework using a deep learning based chatbot for supporting tourist journey. *Expert Systems with Applications*, 183:115277.

Streimikiene, D., Svagzdiene, B., Jasinskas, E., and Simanavicius, A. (2021). Sustainable tourism development and competitiveness: The systematic literature review. *Sustainable Development*, 29(1):259–271.

Tahmasebi, H., Ravanmehr, R., and Mohamadrezaei, R. (2021). Social movie recommender system based on deep autoencoder network using Twitter data. *Neural Computing and Applications*, 33(5):1607–1623.

Tank, D. W. and Hopfield, J. J. (1987). Neural computation by concentrating information in time. *Proceedings of the National Academy of Sciences*, 84(7):1896–1900.

Thelwall, M. (2019). Sentiment analysis for tourism. *Big Data and Innovation in Tourism, Travel, and Hospitality*, pages 87–104.

Torres-Ruiz, M., Mata, F., Zagal, R., Guzmán, G., Quintero, R., and Moreno-Ibarra, M. (2020). A recommender system to generate museum itineraries applying augmented reality and social-sensor mining techniques. *Virtual Reality*, 24(1):175–189.

Tsai, C.-W., Hsia, C.-H., Yang, S.-J., Liu, S.-J., and Fang, Z.-Y. (2020). Optimizing hyperparameters of deep learning in predicting bus passengers based on simulated annealing. *Applied Soft Computing*, 88:106068.

Tuomi, A., Tussyadiah, I. P., and Hanna, P. (2021). Spicing up hospitality service encounters: the case of pepper™. *International Journal of Contemporary Hospitality Management*, 33(11):3906–3925.

Verma, D., Jana, A., and Ramamritham, K. (2019). Transfer learning approach to map urban slums using high and medium resolution satellite imagery. *Habitat International*, 88:101981.

Vincent, P., Larochelle, H., Lajoie, I., Bengio, Y., Manzagol, P.-A., and Bottou, L. (2010). Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion. *Journal of machine learning research*, 11(12).

vom Brocke, J., Schmid, A. M., Simons, A., and Safrudin, N. (2020). It-enabled organizational transformation: a structured literature review. *Business Process Management Journal*, 27(1):204–229.

Wang, J., Yu, L.-C., Lai, K. R., and Zhang, X. (2016a). Dimensional Sentiment Analysis Using a Regional CNN-LSTM Model. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*.

Wang, R., Luo, J., and Huang, S. S. (2020a). Developing an artificial intelligence framework for online destination image photos identification. *Journal of Destination Marketing Management*, 18:100512.

Wang, W., Kumar, N., Chen, J., Gong, Z., Kong, X., Wei, W., and Gao, H. (2020b). Realizing the Potential of Internet of Things for Smart Tourism with 5G and AI. *IEEE Network*, 34(6):295–301.

Wang, X., Tan, Q., and Goh, M. (2020c). Attention-based deep neural network for Internet platform group users' dynamic identification and recommendation. *Expert Systems with Applications*, 160:113728.

Wang, Y., Huang, M., Zhu, X., and Zhao, L. (2016b). Attention-based LSTM for aspect-level sentiment classification. In *Proceedings of the 2016 conference on empirical methods in natural language processing*, pages 606–615.

Wei, X., Yang, Z., Liu, Y., Wei, D., Jia, L., and Li, Y. (2019). Railway track fastener defect detection based on image processing and deep learning techniques: A comparative study. *Engineering Applications of Artificial Intelligence*, 80:66–81.

Weiss, K., Khoshgoftaar, T. M., and Wang, D. (2016). A survey of transfer learning. *Journal of Big data*, 3(1):9.

Widrow, B. and Hoff, M. E. (1960). Adaptive switching circuits. Technical report.

Wu, B. and Yang, W. (2018). What do chinese consumers want? a value framework for luxury hotels in china. *International Journal of Contemporary Hospitality Management*, 30(4):2037–2055.

Wu, D. C., Song, H., and Shen, S. (2017). New developments in tourism and hotel demand modeling and forecasting. *International Journal of Contemporary Hospitality Management*, 29(1):507–529.

Xiao, X., Fang, C., and Lin, H. (2020). Characterizing Tourism Destination Image Using Photos' Visual Content. *ISPRS International Journal of Geo-Information*, 9(12):730.

Yang, E. C. L., Khoo-Lattimore, C., and Arcodia, C. (2017). A systematic literature review of risk and gender research in tourism. *Tourism Management*, 58:89–100.

Yu, J. and Egger, R. (2021). Color and engagement in touristic Instagram pictures: A machine learning approach. *Annals of Tourism Research*, page 103204.

Yunus, R., Arif, O., Afzal, H., Amjad, M. F., Abbas, H., Bokhari, H. N., Haider, S. T., Zafar, N., and Nawaz, R. (2018). A framework to estimate the nutritional value of food in real time using deep learning techniques. *IEEE Access*, 7:2643–2652.

Zhang, H., Boons, F., and Batista-Navarro, R. (2019a). Whose story is it anyway? Automatic extraction of accounts from news articles. *Information Processing Management*, 56(5):1837–1848.

Zhang, K., Chen, D., and Li, C. (2020a). How are tourists different?-Reading geo-tagged photos through a deep learning model. *Journal of Quality Assurance in Hospitality Tourism*, 21(2):234–243.

Zhang, K., Chen, Y., and Li, C. (2019b). Discovering the tourists' behaviors and perceptions in a tourism destination by analyzing photos' visual content with a computer deep learning model: The case of Beijing. *Tourism Management*, 75:595–608.

Zhang, Q., Qiu, L., Wu, H., Wang, J., and Luo, H. (2019c). Deep learning based dynamic pricing model for hotel revenue management. In *2019 International Conference on Data Mining Workshops (ICDMW)*, pages 370–375. IEEE.

Zhang, R. (2021). Exploration of Social Benefits for Tourism Performing Arts Industrialization in Culture-tourism Integration based on Deep Learning and Artificial Intelligence Technology. *Frontiers in Psychology*, 12:37.

Zhang, W., Wang, Q., Li, X., Yoshida, T., and Li, J. (2019d). Dcword: a novel deep learning approach to deceptive review identification by word vectors. *Journal of Systems Science and Systems Engineering*, 28(6):731–746.

Zhang, X., Yang, Y., Zhang, Y., and Zhang, Z. (2020b). Designing tourist experiences amidst air pollution: A spatial analytical approach using social media. *Annals of Tourism Research*, 84:102999.

Zhang, Y., Li, G., Muskat, B., and Law, R. (2020c). Tourism demand forecasting: A decomposed deep learning approach. *Journal of Travel Research*, page 0047287520919522.

Zhang, Y., Li, G., Muskat, B., Law, R., and Yang, Y. (2020d). Group pooling for deep tourism demand forecasting. *Annals of Tourism Research*, 82:102899.

Zhang, Z., Geiger, J., Pohjalainen, J., Mousa, A. E.-D., Jin, W., and Schuller, B. (2018). Deep learning for environmentally robust speech recognition: An overview of recent developments. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 9(5):1–28.

Zhao, H., Zhou, F., and Liu, H. (2020). Deep learning for diplomatic video analysis. *Multimedia Tools and Applications*, 79(7):4811–4830.

Zhu, M., Wu, J., and Wang, Y.-G. (2021). Multi-horizon accommodation demand forecasting: A New Zealand case study. *International Journal of Tourism Research*, 23(3):442–453.

Zuheros, C., Martínez-Cámara, E., Herrera-Viedma, E., and Herrera, F. (2021). Sentiment analysis based multi-person multi-criteria decision making methodology using natural language processing and deep learning for smarter decision aid. Case study of restaurant choice using TripAdvisor reviews. *Information Fusion*, 68:22–36.

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Editor in Chief

Suggestions/comments from the Reviewer	Response from the Author(s)
Dear Dr. Essien: Manuscript ID IJCHM-09-2021-1176.R2 entitled "Deep Learning in Tourism: A research framework agenda for future research" which you submitted to the International Journal of Contemporary Hospitality Management, has been reviewed. The comments of the reviewer(s) are included at the bottom of this letter. I am willing to accept your article contingent upon you making the following changes/improvements: 1. Respond to one of our associate editors' and the reviewers' comments and revise your article accordingly.	We are very pleased at the level of professionalism and rigour that our manuscript has undergone and the significant improvement that is evident in the current quality of the work. We have considered the comments of the associate editors and reviewers and modified our manuscript accordingly. We hope this version meets the requirement and high standard of the journal.
2. Include a structured abstract in page 1 of the main document and make sure that it includes all the required subsections including Purpose, Methodology, Findings, Implications and Originality along with key words. PLEASE change the title to "Deep Learning in Hospitality and Tourism: A research framework agenda for future research".	Thank you. This has now been addressed and title has been changed to "Deep Learning in Hospitality and Tourism: A research framework agenda for future research".
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4. Revisit the Discussion and Conclusions sections one more time to better answer the "So What" question. There should be four sub-sections under this section: (1) Conclusions, (2) Theoretical Implications, (3) Practical Implications and (4) Limitations and Future Research.	Thank you very much for this comment. We have now, on the basis of the recommendation, modified our work and moved some of the sections around to suit the recommendation. To restate, our paper is now structured as follows: 1. Introduction 2. The 4Ps framework for Deep Learning (DL) value creation 3. Methodology 4. Results and discussion 5. Discussion and conclusions In addition, we have thoroughly discussed the theoretical, practical implications, limitations and future research

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REVIEWER 1

Suggestions/comments from the Reviewer	Response from the Author(s)

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1. After reading with attention and interest the revised version of this interesting document, I would like to congratulate the authors for the great effort made and the excellent result achieved. Undoubtedly, this new version includes a relevant contribution to the specialized literature on services and allows to transmit it to the reader in a very fluent and clear way. For this reason, I would like to endorse the publication of this interesting manuscript. Thank you very much for allowing me to participate in this process. In my view, in the two previous revisions, the authors have managed to improve the previous version of this manuscript substantially. In the current version, an average reader can understand much more clearly what the objective of the work is, what the contribution is with respect to previous work, what is done, how it is done, and what we can conclude to learn from the results of this study.	We wish to express our profound gratitude to the respected reviewer for taking our work from the initial stage to what it currently represents. Indeed, there is strong evidence of a significant improvement from the original version, and it is completely attributed to the excellent feedback and comments provided by you. Thank you!

REVIEWER 2

Suggestions/comments from the Reviewer	Response from the Author(s)
1. This version is much better. The paper argues the reasons and processes for its usage of the 4Ps framework. However, I have two concerns.	We are delighted to learn that you find our paper to be of improved quality. We completely attribute this to the highly valued and respected reviewers for their many comments, which all contributed to significantly improving the quality of our manuscript.
2. First, the author should elaborate on how the collected literature is divided into four different subject areas (the 4Ps framework). What kind of process do the authors follow, and in the process of classification, how does the classification inconsistencies been solved. In addition, as an infrastructural technology, it is sometimes difficult to classify the application of AI into a specific category, or its application often belongs to multiple categories. How did the authors resolve this kind of conflict?	Thank you for this very important question, which we had discussed between us as the authors. First, we completely agree that, given the application-based nature of AI (and specifically DL), it may be difficult to draw definitive lines within the four areas (i.e., project, provide, promote, and produce) as some articles may overlap in their categorisation. Although this is a possibility, we focused our article grouping on the most-fitting area (of the 4Ps) when conducting our literature review. Due to your comment, which is extremely important, we have added a short couple of sentences explaining this fact. It can be found in Section 2 (Page 6, first paragraph).
3. Secondly, when discussing future research directions, the three levels proposed by the authors are abrupt. If the paper insists to use the 3 levels framework, I recommend using it in the literature analysis section, not in the "emergent research and future directions section". In the field of IS research, the scholars often divided the IT-enabled business transformation into multiple levels (i.e., vom Brocke et al. (2020); Venkatraman (1994)). The authors could use literature for arguing the appropriation of the three levels they proposed. In addition, as an infrastructural and high permeability technology, it's often hard to classify AI applications into specific levels. For example, a project application can be located at the concept development level if a startup	Following the recommendation from the editor-in-chief and this, we have modified our manuscript accordingly. We agree with the abruptness in introducing these levels as future research in the concluding chapter and have moved it into the review section (Section 4) where we have discussed the findings and proposed the emergent reserch and future direction. We have also obtained guidance from existing, recent and relevant articles to justify our framework

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has a unique project capability in a specific field and sells it as a new service, the project can be a new business model. 4. vom Brocke, J., Schmid, A. M., Simons, A., and Safrudin, N. 2020. "IT-Enabled Organizational Transformation: A Structured Literature Review," *Business Process Management Journal*, pp. 1–28. (https://doi.org/10.1108/BPMJ-10-2019-0423). Venkatraman, N. 1994. "IT-Enabled Business Transformation: From Automation to Business Scope Redefinition," *Sloan Management Review* (35:2), pp. 73–87.	and proposal. The authors particularly found the paper by vom Brocke et al., (2020) extremely useful and interesting. The comment about classifying the applications into the specific levels has also been resolved, and is somewhat similar to the previous comment about the 4Ps. Given the application-based nature of AI and DL (specifically), it is a major challenge to draw these fine lines in application areas. These are some of the limitations that have been identified for further research in our study.