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Evolution of Machine Learning in Tourism: A Comprehensive Review of Seminal Research

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Abstract

Machine learning is enabling transformative changes in the tourism industry. Various machine learning algorithms and models can detect patterns in huge amounts of data for the prediction process, recommendations, and decisions without any coding or programming. The tourism sector generates massive data through sources as such online reviews and ratings, social media activity, traffic information, and customer relationship management records. Machine learning is poised to unlock insights and opportunities from this data. This paper provides an overview of how machine learning is currently influencing and may shape the future of tourism. Techniques for predictive analytics, personalized recommendation systems, computer vision, natural language processing, and more are powering applications to improve customer experiences, optimize and automate operations, gain competitive advantage, and support sustainability. Current applications are discussed, including demand forecasting, personalized travel recommendations, automated photo filtering, sentiment analysis of tourism reviews, chatbots for customer service, and others. Emerging opportunities are explored, as machine learning may enhance smart tourism for destinations through intelligent transportation, customized experiences, optimized resource allocation, and improved accessibility. Challenges exist regarding data quality, privacy, bias, and job disruption. However, machine learning is expected to become an integral tool for data-driven, personalized, and sustainable tourism. Overall, this review paper aims to synthesize the state of machine learning in tourism by highlighting current applications, opportunities, considerations, and likely future trends. The conclusions point to machine learning as a catalyst for innovation in tourism that may significantly transform the visitor experience, business operations, and destination management in the years to come.

Keywords: Artificial Intelligence; Machine Learning; Tourism; Literature Review

1. Introduction

Machine Learning (ML) has indeed become a pervasive technology that influences numerous aspects of our lives. It has transformed various industries and become essential in many applications and services. ML algorithms and models power voice assistants like Siri, Cortana, Bixby, and Alexa, enabling them to understand and respond to user commands and queries. These assistants utilize techniques including speech recognition and natural language processing to provide users with the desired information and assistance. Chatbots are another area where ML plays a crucial role. They employ ML algorithms to understand and interpret user inputs, enabling them to engage in human-like conversations and provide relevant responses. Chatbots are used in customer service, e-commerce, and various other domains to enhance user experiences and streamline interactions. Personalized marketing heavily relies on ML techniques to analyze user data, preferences, and behavior patterns. This enables businesses to target specific customer segments with tailored recommendations, advertisements, and promotions, improving the effectiveness of marketing campaigns. ML is instrumental in predicting customer behavior and trends. By analyzing large volumes of data, ML models can identify patterns, correlations, and insights that help businesses understand and anticipate customer needs, preferences, and purchasing decisions. This information can be leveraged to optimize business strategies and improve customer satisfaction. ML also plays a crucial role in optimizing processes and improving efficiency in various domains. From supply chain management to logistics, ML algorithms can analyze large datasets, identify patterns, and make predictions, enabling businesses to make data-driven decisions and streamline operations [1-6]

In the realm of tourism, ML plays a crucial role in enhancing various aspects of the industry. ML algorithms are utilized to analyze vast amounts of data and extract valuable insights that contribute to improving the overall travel experience for individuals. One significant application of ML in tourism is personalized recommendation systems. By leveraging ML models, travel platforms can analyze user preferences, historical data, and behavior patterns to provide tailored recommendations for destinations, accommodations, activities, and attractions. This enables travelers to receive suggestions that align with their interests, making their trip planning more efficient and enjoyable. ML is also instrumental in optimizing pricing and revenue management in the tourism sector. ML

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algorithms can analyze market trends, historical booking data, and competitor pricing to predict demand patterns and dynamically adjust prices for flights, hotels, and other travel services. This helps businesses maximize their revenue by offering competitive prices while accounting for factors such as seasonality, demand fluctuations, and customer preferences. Furthermore, ML techniques are employed in enhancing travel safety and security. ML models can analyze historical data on travel patterns, weather conditions, and security incidents to identify potential risks and anomalies. This allows authorities and travel agencies to implement proactive measures and develop efficient risk management strategies to ensure the safety of travelers. ML also contributes to improving customer service in the tourism industry. Chatbots powered by ML algorithms can provide instant responses to customer queries, offering personalized assistance and support throughout the travel journey. These chatbots can understand natural language, recognize customer preferences, and provide relevant information, thereby enhancing customer satisfaction and engagement. Additionally, ML is utilized in sentiment analysis of customer reviews and social media data related to travel experiences. By analyzing textual data and user-generated content, ML algorithms can identify positive and negative sentiments, helping tourism businesses understand customer feedback and sentiment trends. This enables companies to make data-driven decisions to enhance their offerings and address any areas of concern, ultimately improving customer experiences. Taking everything into account, machine learning plays a significant role in the tourism industry, enabling personalized recommendations, optimizing pricing, enhancing safety and security measures, improving customer service, and analyzing customer sentiment. As ML continues to advance, it holds the potential to revolutionize the way we explore and enjoy the world, making travel experiences more tailored, efficient, and enjoyable for everyone [1-16].

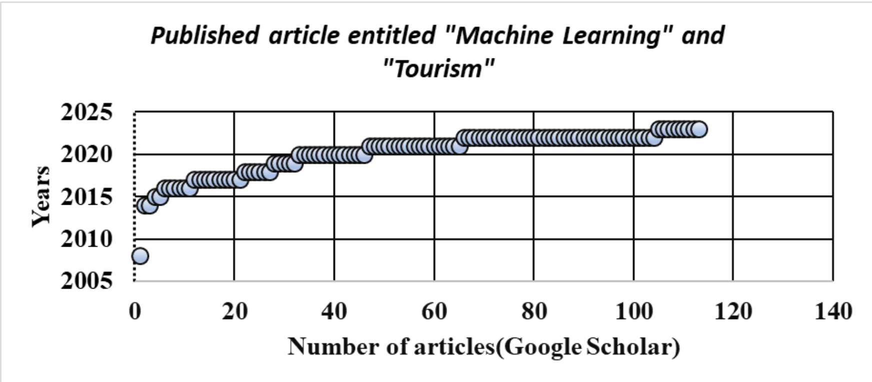
Artificial intelligence (AI), big data, and ML are often mentioned together, particularly in the context of "smart tourism" and "smart destinations." The concept of "smartness" in tourism involves integrating various information and communication technologies (ICTs) into the physical infrastructure, optimizing travel experiences through personalization and real-time analysis, and building a business ecosystem geared towards smartness. Big data plays a crucial role in this context, as it encompasses different types of data, such as transactional data, user-generated content, sensor data, and more. Analyzing and processing this data using ML techniques can provide valuable insights and enable smarter decision-making in the tourism industry. In summary, ML allows computers to learn from data and experience, identifying patterns and making predictions without explicit programming. It involves working with datasets, features, and models, where the trained model can be used to make predictions on new data. In the context of smart tourism, ML and big data play significant roles in optimizing travel experiences and enabling data-driven decision-making [1-21]

In conclusion, the integration of ML into the tourism industry has ushered in a new era of personalized and data-driven travel experiences. This review article explores the diverse applications of ML in tourism, highlighting its role in personalized recommendations, pricing optimization, travel safety, customer service, and sentiment analysis. By harnessing the power of ML algorithms, travel businesses can leverage big data to provide tailored suggestions, optimize pricing strategies, ensure traveler safety, enhance customer service through chatbots, and gain valuable insights from customer sentiment analysis. As ML continues to evolve, it is poised to revolutionize the way we explore the world, making travel more efficient, enjoyable, and customized to individual preferences. This article aims to shed light on the transformative potential of ML in the tourism industry and provide a comprehensive overview of its applications and benefits.

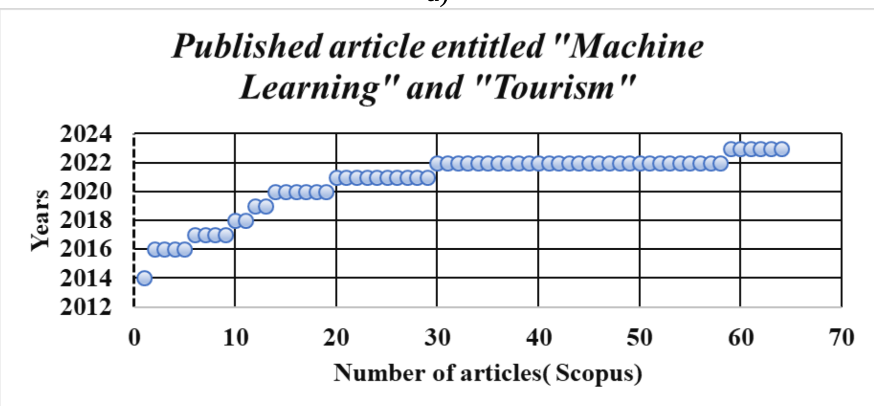
This study presents a detailed overview of the correlation between two fields namely tourism and machine learning to emphasize the demand in the applications of ML approaches within the tourism science. This study also utilizes a systematic search technique by using Web of Science (WoS), Google Scholar, and Scopus databases to determine the publications in the existing literature. Furthermore, this study highlights the pros and cons of using Google Scholar, Web of Science, and Scopus. While Google Scholar's expansive coverage and user-friendly interface are acknowledged, limitations such as potential inaccuracies in citation counts and the lack of advanced tools are also noted. Web of Science and Scopus, on the other hand, are recognized for their selective coverage and more precise citation-matching methodologies. The importance of selecting appropriate journals for publication is also outlined. The analysis of citations from both machine learning and tourism journals underscores the interdisciplinary nature of the research, with potential implications for a broader audience. Additionally, the study also delves into the significance of authors in shaping the credibility and validity of research. Authors with expertise in both machine learning and tourism are identified as crucial contributors to impactful interdisciplinary work. Their ability to bridge the gap between distinct research communities, coupled with established networks, enhances the visibility and influence of their work. In conclusion, this study provides a myriad of the exploration and the landscape where tourism and machine learning intersect. It not only provides insights into the current state of research but also offers valuable guidance for researchers, emphasizing the importance of interdisciplinary collaboration, careful journal selection, and the role of authors in driving impactful research.

2. Published Articles

The analysis of publications related to tourism and machine learning indicates a growing interest in applying ML approaches to various tasks within the tourism domain. A search query combining "Tourism" and "Machine Learning" in keywords resulted in 199 papers in the database of Web of Science for the years 2005 to 2023 [1-200]. Other search queries combining “Tourism” and “Machine Learning” in article titles depicted 42 papers in Web of Science from 2016 to 2023. Then, the Google Scholar database is searched along with title words and keywords separately. 125 paper titled “Machine learning” and “Tourism” is founded in terms of citations of 898, h-index of 14, and g-index of 28. The search query with keywords including machine learning, and tourism is found out as 980 with 25232 citations. The statistical analysis of this search query depicts h-index of 79 and g-index of 145. On the other hand, the published papers titled machine learning and tourism are counted as 64 while the papers with keywords including machine learning and tourism are indicated at 200 via the database of SCOPUS. The most cited paper related to machine learning and tourism searched along with the title is observed by Nilashi et.al titled “A recommender system for tourism industry using cluster ensemble and prediction machine learning techniques” [37]. 144 published article cites this study. Following, another study by Go et.al. titled “Machine learning of robots in tourism and hospitality: interactive technology acceptance model (iTAM) – cutting edge” is among the most cited paper and was published in 2020 [194]. In a short year, the number of citations for this study reached up to 97, The citation results emphasize the importance of the machine learning application in the tourism field. Another most cited paper is proposed by Xie et. al.in 2021 titled “Forecasting Chinese cruise tourism demand with big data: An optimized machine learning approach” along with the number of 83 citations [181]. Another research query utilized by Scopus for titles along with machine learning, and tourism counted on the number of papers as 64. The citations of the overall papers are obtained as 443. The analysis by Scopus depicts the h-index and g-index as 9 and 20, respectively. The most cited paper again is determined as “A recommender system for tourism industry using cluster ensemble and prediction machine learning techniques” titled study by Nilashi et.al. along with the number of 100 citations. Then, the second most cited paper observed “Machine learning of robots in tourism and hospitality: interactive technology acceptance model (iTAM) – cutting edge” titled study by Go et.al. as found in Google Scholar. However, the number of citations observed by Scopus is attained as 59. Figure 1 provides the increment of ML methods in tourism research. The illustrations depict the increasement occurs particularly from 2018 onwards.



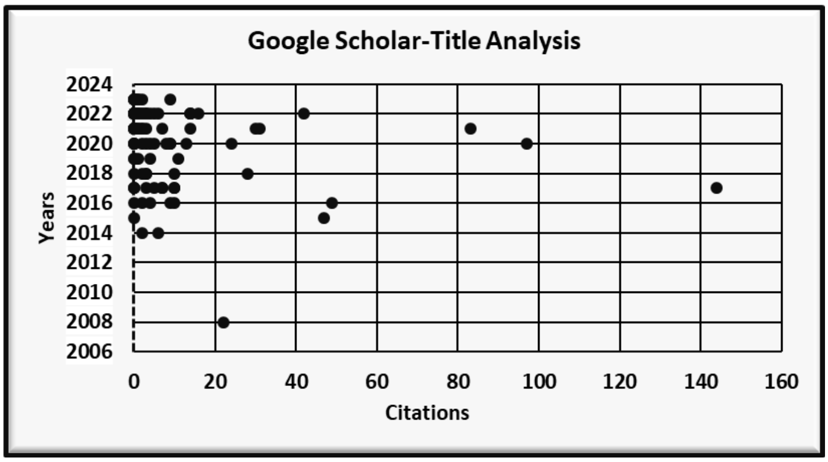
a)



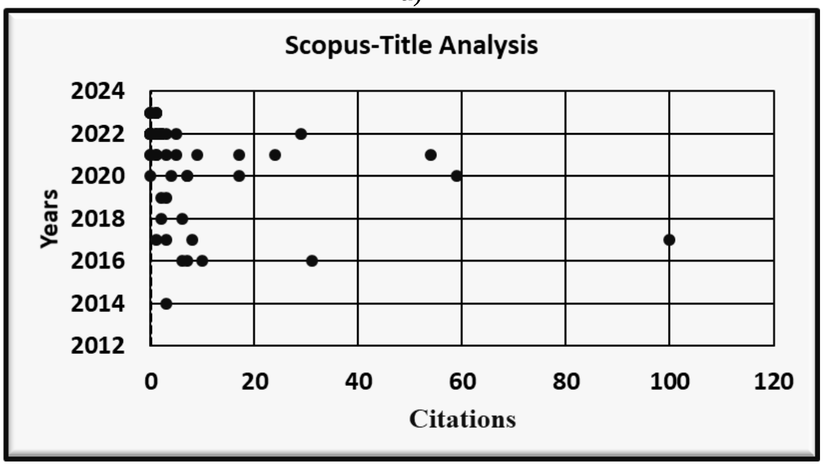
b)

Figure 1. *Published articles with search queries in titles through a) Google Scholar, b) Scopus*

The above results outline that Google Scholar has some advantages and disadvantageous over WoS and Scopus. To sum up these advantages, Google Scholar has a much larger coverage of academic publications compared to WoS and Scopus. It includes most peer-reviewed journals, conference papers, preprints, theses, books, and other scholarly literature. WoS and Scopus have a more selective coverage focused on high-impact journals. Google Scholar has a broader range of languages and includes publications in languages other than English. WoS and Scopus primarily focus on English-language journals and publications. Google Scholar is freely available to anyone. WoS and Scopus are subscription-based databases, so access depends on university or library subscriptions. Google Scholar offers a simple but powerful search interface. Searches in WoS and Scopus may require more advanced skills and knowledge to effectively filter and refine results. Like WoS and Scopus, Google Scholar indexes citation data and shows how many times each publication has been cited. This allows you to track the impact and influence of publications. However, the quality and credibility of sources in Google Scholar can vary. WoS and Scopus have more standardized selection criteria and primarily index reputable, peer-reviewed publications. Google Scholar can contain duplicate records for the same publication. WoS and Scopus have more accurate matching algorithms to avoid duplicates. Citation counts in Google Scholar may include some erroneous citations. WoS and Scopus have more precise citation-matching methodologies. The simple interface of Google Scholar lacks some of the advanced tools and filters available in the WoS and Scopus interfaces. These tools may be useful for more in-depth research and analysis. In summary, Google Scholar is a useful, free discovery tool for researchers thanks to its broad coverage, easy search, and citation tools. For most researchers, using Google Scholar in combination with other databases is a good research strategy. Then, the number of citations about the titled article with machine learning and tourism is outlined in Figure 2. Therefore, in this study, the primary tool selected was Google Scholar to find the most cited papers in the literature. The citation results indicate the importance of this topic.



a)



b)

Figure 2. *Number of citations along with the machine learning and tourism with respect to the years from 2012 to 2023.*

Some journals specifically focus on machine learning, some on tourism and hospitality, and some are interdisciplinary. Choosing a journal, which is most closely related to your topic, exposes any article to the most relevant readers and researchers. Additionally, by selecting a suitable publisher, the potential impact of any work might be increased by this method. On the other hand, the journal you select will determine to a large extent the potential impact and circulation of your research. High-impact journals are more widely read and cited. Journal metrics like the CiteScore or Impact Factor should be considered when assessing the reach of the journal. The prestige and reputation of the journal convey prestige on your own work. Being published in a leading journal in your field is a mark of top-quality research and can open up further networking and collaboration opportunities. Hence, carefully evaluating potential journals and selecting one that will maximize the reach and impact of your work is an important part of the publication process. For interdisciplinary research, finding a journal that balances both fields of study and has expertise in reviewing such work should be a top priority. The rewards of getting published in the right journal can be significant for your career and the influence of your research. That's why, the related journals, conference papers, preprints, theses, books, and other scholarly literature are investigated through SCOPUS and Google Scholar databases. Table 1 and Table 2 depict the journals, conference papers, preprints, and books, where the studies related to machine learning and tourism have been published up to now, along with Scopus and Google Scholar, respectively.

Table 1. *The journals, conference papers, preprints, and books based on SCOPUS*

16th International Middle Eastern Simulation and Modelling Conference 2020, MESM 2020
2016 IEEE/ACIS 15th International Conference on Computer and Information Science, ICIS 2016 - Proceedings
2018 International Conference on Advances in Big Data, Computing and Data Communication Systems, icABCD 2018
2021 IEEE International Conference on Computing, ICOCO 2021
2022 IEEE International Conference on Electrical Engineering, Big Data and Algorithms, EEBDA 2022
2022 International Conference on Computers and Artificial Intelligence Technologies, CAIT 2022
2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing, COM-IT-CON 2022
ACM International Conference Proceeding Series
Acta Astronautica
Acta Geographica
Advances in Intelligent Systems and Computing
African Journal of Hospitality, Tourism and Leisure
Annals of Tourism Research
Applied Economics Letters
Asian Journal of Information Technology
CEUR Workshop Proceedings
Computational and Mathematical Methods in Medicine
Computers and Industrial Engineering
Current Issues in Tourism
Electronics
Environment, Development and Sustainability
Eurasip Journal on Wireless Communications and Networking
European Journal of Innovation Management
Frontiers in Psychology
Handbook of Research on Big Data Clustering and Machine Learning
Heliyon
InCIT 2020 - 5th International Conference on Information Technology
Informatics
Intellectual Economics
International Journal of Advanced Computer Science and Applications
International Journal of Technology Marketing
International Transactions on Electrical Energy Systems
Journal of Theoretical and Applied Information Technology
Journal of Tourism and Development
Journal of Tourism, Heritage and Services Marketing
Journal of Travel Research
Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)
Lecture Notes in Electrical Engineering
Lecture Notes in Networks and Systems
Machine Learning: Advances in Research and Applications
Materials Today: Proceedings
Microprocessors and Microsystems
Mobile Information Systems
Proceedings - 2021 4th International Conference on Computational Intelligence and Communication Technologies, CCICT 2021
Proceedings - 2021 IEEE 23rd Conference on Business Informatics, CBI 2021 - Main Papers
Proceedings - 2022 4th International Workshop on Artificial Intelligence and Education, WAIE 2022
Proceedings of 2021 13th International Conference on Information and Communication Technology and System, ICTS 2021
Research Anthology on Machine Learning Techniques, Methods, and Applications

Revista de Economia Aplicada
Scientific Programming
Soft Computing
Stats
Studies in Computational Intelligence
Tourism Economics
Tourism Management
Tourism Management Perspectives
Tourism Review

Table 2. *The journals, conference papers, preprints, and books based on Google Scholar*

2016 IEEE Eight International Conference on Advanced Computing
2016 IEEE/ACIS 15th International Conference on Computer and Information Science (ICIS)
2018 International Conference on Advances in Big Data, Computing and Data Communication Systems (icABCD)
2020 - 5th International Conference on Information Technology (InCIT)
2020 CEUR Workshop Proceedings
2021 13th International Conference on Information and Communication Technology and System (ICTS)
2021 Fourth International Conference on Computational Intelligence and Communication Technologies (CCICT)
2021 IEEE 23rd Conference on Business Informatics (CBI)
2022 International Conference on Computers and Artificial Intelligence Technologies (CAIT)
7th International Conference, LOD 2021
Acta Astronautica
Acta Geographica Sinica
African Journal of Hospitality, Tourism and Leisure
Annals of the University Dunarea de Jos of Galati: Fascicle: I, Economics and Applied Informatics
Annals of Tourism Research
Applied Data Science in Tourism
Applied Economics Letters
Asian Journal of Information Technology
Asia-Pacific Journal of Management and Technology
Balkan Journal of Electrical and Computer Engineering
Computational and Mathematical Methods in Medicine
Computer and Digital Engineering
Computers and Industrial Engineering
Current Issues in Tourism
Design of Intelligent Applications using Machine Learning and Deep Learning Techniques
ECONVN 2021: Prediction and Causality in Econometrics and Related Topics
Electronics
Environment, Development and Sustainability
EURASIP Journal on Wireless Communications and Networking
Frontiers in Psychology
Handbook of Research on Big Data Clustering and Machine Learning
Health and Technology
Heliyon
Hochschule für nachhaltige Entwicklung Eberswalde
ICGST International Journal on Artificial Intelligence and Machine Learning
IEICE Technical Report
IFC-Bank Indonesia Satellite Seminar on “Big Data” at the ISI Regional Statistics Conference 2017
IJRAR- International Journal of Research and Analytical Reviews
i-Manager's Journal on Computer Science
Informatics
Information Science and Applications 2017 ICISA 2017
INT BUSINESS INFORMATION MANAGEMENT ASSOC-IBIMA
Intelektinė ekonomika
International Conference on Advanced Computing and Intelligent Engineering, ICACIE, 2016
International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)
International Journal of Advanced Trends in Computer Science and Engineering
International Journal of Computer Applications
International Journal of Contemporary Hospitality Management
International Journal of Engineering Applied Sciences and Technology
International Journal of Technology Marketing
International Transactions on Electrical Energy Systems
Information Technology and Tourism

IOSR Journal of Computer Engineering (IOSR-JCE)
ISWC (Posters and Demos)
Journal of Artificial Intelligence, Machine Learning and Neural Network (JAIMLNN)
Journal of Destination Marketing and Management
Journal of Engineering and Sciences
Journal of Theoretical and Applied Information Technology
Journal of Tourism
Journal of Travel Research
Marketing
Materials Today: Proceedings
MIBES Transactions
MLMI '20: Proceedings of the 2020 3rd International Conference on Machine Learning and Machine Intelligence
Mobile Information Systems
Network (Mbps)
PRAJNAN
Proceedings of International Conference on Recent Trends in Computing
Research Square
Scientific Programming
Soft Computing
Sosyoekonomi
SSRN
Stats
Tourism Analytics Before and After COVID-19 Case Studies from Asia and Europe
Tourism Economics
Tourism Management
Tourism Management Perspectives
Tourism review
Women's voices in tourism research
XIII Congreso Internacional Turismo y Tecnologías de la Información y las Comunicaciones

Citations from both machine learning and tourism journals, as well as interdisciplinary publications, show that your work is influencing and advancing an interdisciplinary research area. This is more meaningful than the impact on just one discipline. Citations should be tracked from diverse sources. By being cited in both machine learning venues and tourism venues, your work is exposed to a much larger combined audience from both fields. This amplifies the visibility and potential influence of your research. You have the opportunity to connect both with machine learning experts and tourism experts, which could lead to interesting interdisciplinary collaborations generating innovative new ideas. Effective interdisciplinary work requires researchers from distinct fields to come together. An influential interdisciplinary publication that accumulates many citations can help to define the scope, boundaries, and topics of an emerging combined research domain, like "machine learning in tourism". Your work may be pivotal in shaping how this domain develops. Citations from different fields may point to unique limitations or open questions raised by each group of readers. This points to possible new research directions to explore in order to bridge machine learning and tourism more effectively. Addressing issues from multiple angles will result in more robust, comprehensive work. If cited by researchers focused on applied work, or in industry publications, your theoretical research may be influencing real-world practice. This demonstrates the usefulness and potential for the real-world impact of interdisciplinary work. That's, interdisciplinary research requires reaching, influencing and connecting distinct communities. An article that combines machine learning and tourism through accumulating a diversity of citations across fields will achieve this most effectively. Such influence shapes the growth of this interdisciplinary domain in a way that benefits both theory and practice. Citations point to issues to address across boundaries and possibilities for ground-breaking collaborative work. Table 3 and Table 4 outline the articles with the most citations obtained by SCOPUS and Google Scholar, respectively.

Table 3. *The most cited studies related to machine learning and tourism obtained by SCOPUS*

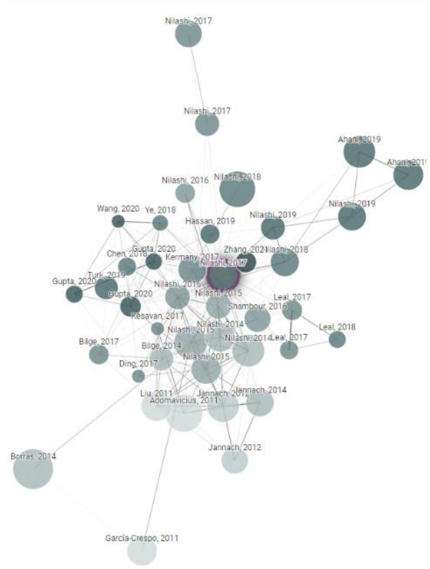
Ref.	Cites	Title	Year
37	144	A recommender system for tourism industry using cluster ensemble and prediction machine learning techniques	2017
194	97	Machine learning of robots in tourism and hospitality: interactive technology acceptance model (iTAM)–cutting edge	2020
181	83	Forecasting Chinese cruise tourism demand with big data: An optimized machine learning approach	2021
19	49	Combination forecasts of tourism demand with machine learning models	2016
201	47	Developing tourism demand forecasting models using machine learning techniques with trend, seasonal, and cyclic components	2015

50	42	Multi-objective hub-spoke network design of perishable tourism products using combination machine learning and meta-heuristic algorithms	2022
136	31	Machine learning in internet search query selection for tourism forecasting	2021
193	30	Exploring China's 5A global geoparks through online tourism reviews: A mining model based on machine learning approach	2021
153	28	Modelling tourism demand to Spain with machine learning techniques. The impact of forecast horizon on model selection	2018
46	24	A human-guided machine learning approach for 5G smart tourism IoT	2020
202	22	Tourism demand forecasting using machine learning methods	2008
203	16	Machine Learning in Tourism: A Brief Overview: Generation of Knowledge from Experience	2022
173	14	International tourism demand forecasting with machine learning models: The power of the number of lagged inputs	2022
204	14	Twitter data sentiment analysis of tourism in Thailand during the COVID-19 pandemic using machine learning	2022
205	14	Structural review of relics tourism by text mining and machine learning	2022
42	14	Proposing a systematic approach for integrating traditional research methods into machine learning in text analytics in tourism and hospitality	2021
206	13	Machine learning in tourism	2020
207	11	Performance of raspberry pi micro clusters for edge machine learning in tourism	2019
208	10	Tourism recommendation using machine learning approach	2018
209	10	Machine learning methods in tourism demand forecasting: Some evidence from Greece	2017
210	10	A machine learning approach to named entity recognition for the travel and tourism domain	2016
211	10	Regional tourism demand forecasting with machine learning models: Gaussian process regression vs. neural network models in a multiple-input multiple-output setting	2017

Table 4. *The most cited studies related to machine learning and tourism obtained by Google Scholar*

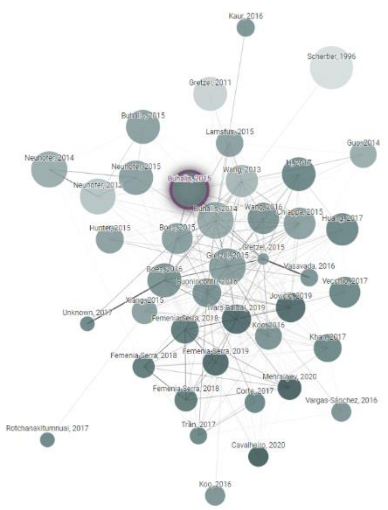
Ref.	Cites	Title	Year
212	881	Smart tourism destinations enhancing tourism experience through personalisation of services	2015
54	855	Sentiment classification of online reviews to travel destinations by supervised machine learning approaches	2009
213	741	Ontology matching: A machine learning approach	2004
175	727	A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism	2017
214	651	Hospitality and tourism online reviews: Recent trends and future directions	2015
215	646	Technology in tourism-from information communication technologies to e-Tourism and smart tourism towards ambient intelligence tourism: a perspective article	2020
216	544	Ontology learning and its application to automated terminology translation	2003
217	545	Technological disruptions in services: lessons from tourism and hospitality	2019
218	524	Real-time co-creation and nowness service: lessons from tourism and hospitality	2019
133	494	Sentiment analysis in tourism: capitalizing on big data	2019
219	477	Support vector regression with genetic algorithms in forecasting tourism demand	2007
220	441	User-generated content as a research mode in tourism and hospitality applications: Topics, methods, and software	2015
221	437	Tourism information technology	2019
222	396	The good, the bad and the ugly on COVID-19 tourism recovery	2021
223	391	Big data analytics for knowledge generation in tourism destinations–A case from Sweden	2014
224	358	A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism	2020
225	343	Forecasting tourism demand with composite search index	2017
226	323	Business intelligence and big data in hospitality and tourism: a systematic literature review	2018
227	293	The digital revolution in the travel and tourism industry	2020
228	275	Tourism demand forecasting: A deep learning approach	2019
6	269	Forecasting tourist arrivals with machine learning and internet search index	2019
229	262	New technologies in tourism: From multi-disciplinary to anti-disciplinary advances and trajectories	2018
230	242	From digitization to the age of acceleration: On information technology and tourism	2018
231	225	SPETA: Social pervasive e-Tourism advisor	2009

Based on Table 3 and Table 4, the most cited papers are observed as [37] and [212] via SCOPUS and Google Scholar, respectively. The prior and derived works of [37] and [212] as given in Figure 3.



Title	Last author	Year	Citations	Graph citations
New Recommendation Techniques for Multicriteria Rating Systems	YoungOk Kwon	2007	500	32
Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions	A. Tuzhilin	2005	10018	24
Improving personalized services in mobile commerce by a novel multicriteria rating approach	Guanggang Geng	2008	65	17
Analysis and Classification of Multi-Criteria Recommender Systems	C. Costopoulou	2007	211	14
Multi-criteria Ratings for Recommender Systems: An Empirical Analysis in the Tourism Domain	M. Zanker	2012	49	13
Research Note - The Halo Effect in Multicomponent Ratings and Its Implications for Recommender Systems: The Case of...	Jamie Callan	2012	86	13
Item-based collaborative filtering recommendation algorithms	J. Riedl	2001	8801	13
Empirical Analysis of Predictive Algorithms for Collaborative Filtering	C. Kadie	1998	5795	13
Experimental Analysis of Design Choices in multiattribute Utility Collaborative Filtering	C. Costopoulou	2007	97	11
Multicriteria User Modeling in Recommender Systems	A. Tsoukiás	2011	169	10

a)



Title	Last author	Year	Citations	Graph citations
Progress in information technology and tourism management: 20 years on and 10 years after the Internet - the state of...	R. Law	2008	2949	17
Marketing the competitive destination of the future.	Dimitrios Buhalis	2000	2799	12
Mediating tourist experiences: access to places via shared videos.	D. Fesenmaier	2009	571	11
The Role of Smartphones in Mediating the Touristic Experience	D. Fesenmaier	2012	623	10
eTourism: Information technology for strategic tourism management	Dimitrios Buhalis	2003	997	10
Smart Cities in Europe	P. Nijkamp	2011	3088	10
A Smart City Initiative: the Case of Barcelona	J. Wareham	2013	816	9
Role of social media in online travel information search	U. Gretzel	2010	2569	8
SMART Destinations: new strategies to manage tourism industry	G. Chiappa	2013	28	8
Agenda for Co-Creation Tourism Experience Research	Teun den Dekker	2009	544	8

b)

Figure 3. *The derived and prior works of a) [37] and b) [212]*

By analyzing the published studies through Google Scholar and Scopus in terms of most citations, the first authors of the studies are determined as given in Table 5. The main reason is to determine these authors that the expertise of the authors defines the extended credibility and validity of the work. Authors with expertise in both machine learning and tourism will produce work grounded in knowledge and experience from both domains. They will have a deeper understanding of how methods and concepts from each field can be connected and integrated effectively. The authors will have access to separate networks in the machine learning and tourism research communities. This exposes the work to more researchers and provides more opportunities to stimulate interest and new collaborations across boundaries. Established authors with large networks will have an easier time bridging between fields. The reputation and recognition of the authors affect the initial and ongoing impact of the work. Well-known authors can draw more attention and citations to the article, helping to speed up its diffusion between research communities. Their reputation also lends more credibility to the work, making researchers from other fields more inclined to cite and build upon it. Authors familiar with both source domains are better equipped to frame and communicate their interdisciplinary work in a way that resonates with multiple audiences. They understand how to convey key machine learning concepts and methods to tourism researchers, and vice versa. This helps to overcome potential barriers when connecting disparate groups. Authors with expertise and connections in both machine learning and tourism are in an ideal position to continue conducting meaningful follow-up research that bridges these domains. They can further develop concepts and methods jointly in innovative ways. This results in a cohesive, progressive research stream rather than isolated publications. Authors linked to industry or applied research may be motivated to combine machine learning and tourism towards achieving a practical real-world goal. Their work will thus be aimed at solving concrete problems, rather than being purely theoretical. Applied authors can better assess where and how machine learning capabilities could transform and improve tourism practices. As a result, authors' interdisciplinarity, expertise, networks and motivations are all significant factors that determine the potential for connecting machine learning and tourism. While single authors may integrate these domains, teams that collectively span multiple communities are better equipped for sustained, high-impact interdisciplinary work. The backgrounds and goals of authors shape how, and how far, the integration between source fields progresses.

Table 5. *The first author of the studies with the most cited*

	Authors	
Order	**Google Scholar**	**Scopus**
1.	M Nilashi	M. Nilashi
2.	H Go	H. Go
3.	G Xie	G. Xie
4.	O Claveria	O. Claveria
5.	S Cankurt	A.P. Chobar
6.	AP Chobar	X. Li
7.	X Li	Y. Luo
8.	Y Luo	O. Claveria
9.	O Claveria	J. Huh
10.	R Peng	A. Imsombut
11.	N Kamel	F. Afsahhosseini
12.	R Egger	Y. Tverdokhlib
13.	JW Bi	A. Dewangan
14.	N Leelawat	J. Vijay
15.	S Das	A. Komninos
16.	TH Le	F.A. Lisi
17.	F Afsahhosseini	D. Yang
18.	A Komninos	J.W. Bi
19.	A Dewangan	C. Srisawatsakul
20.	A Karakitsiou	T. Imam

The increasing number of publications and the presence of ML research in tourism-focused journals suggest a growing recognition of the potential benefits that ML can bring to the tourism industry. ML methods can enable the processing and analysis of large datasets, extraction of meaningful features, and generation of personalized recommendations, among other tasks. The integration of ML in tourism research opens up new possibilities for understanding tourist behaviour, optimizing tourism experiences, and improving decision-making processes in the industry. Feature engineering and feature selection are crucial steps in ML as good features form the backbone of any ML model. The quality of the model relies on the quality of the data it was trained on, and using bad data can lead to significant errors. Therefore, it is important to select only those features that have a meaningful impact on the model's quality. After preparing the data and selecting features, the algorithm is trained using the training data. The data is typically divided into two parts as such training and testing sets, where t training section is applied to educate the algorithm, and the testing data is used to evaluate its performance. Unsupervised learning tasks do not require the separated data, therefore, do not involve cross-validation. As soon as the model is educated, it is evaluated. Depending on supervised technique, the efficacy of the algorithm can be assessed, providing insights for optimizing data processing and hyperparameters. ML systems include hyperparameters that can be adjusted to affect the algorithm's performance, and finding the best settings often involves an iterative process of data preparation, model fitting, hyperparameter tuning, and model evaluation. The validated model is then applied to real-world tasks, such as making predictions, and the results are interpreted and contextualized within the specific domain.

Three main types of ML algorithms which are the kind of learning as such unsupervised, supervised, and reinforcement. Unsupervised learning is covered in detail in chapters on clustering and dimensionality reduction, while supervised learning is discussed in chapters on classification and regression. Reinforcement learning, although less relevant for tourism cases, is another type of ML algorithm. Additionally, natural language processing (NLP) is a specialized ML case, including algorithms for text classification, topic modelling, and sentiment analysis, among others. ML approaches can be classified based on the type of data and the availability of labels for the dependent variable. Supervised algorithms are used when labels are available for either continuous or discrete dependent variables, while unsupervised methods are applied when no labels are given. In addition to the traditional supervised, unsupervised, and reinforcement learning paradigms, several other ML paradigms have evolved in recent years. These include model-based learning, memory-based learning, and deep learning. Deep learning, particularly with neural networks, has played a significant role in the current ML renaissance. It represents a distinct subfield within ML and has the ability to scale with large amounts of data, often yielding superior results compared to traditional approaches. However, it is important to note that neural networks are not always superior to classical ML approaches.

The choice between deep learning and traditional ML methods depends on the specific problem and the available data. For a more comprehensive discussion on neural networks and deep learning, further literature such as Aggarwal [232] or Ekman [233] can provide detailed insights. Machine learning, as a subset of artificial intelligence, can be applied to various types of data in the tourism industry across different stages of a tourist's journey. In fact, there are ML techniques specifically designed for scenarios with limited data, such as transfer learning and few-shot learning. Transfer learning enables the knowledge gained from training on one dataset to be transferred and applied to a related task or domain with smaller amounts of data. Few-shot learning focuses on training models with minimal data instances by leveraging prior knowledge or by utilizing techniques like data augmentation. Even with smaller datasets, ML approaches can still uncover patterns and relationships within complex data. These patterns can then be utilized to make predictions and informed decisions. ML models can generalize from the available data to identify underlying patterns, which enables them to make predictions on new, unseen data points. In scientific research projects, where data collection might be limited or resource-intensive, ML techniques can still be valuable. By employing ML algorithms, researchers can explore their data, identify patterns, and gain insights that may not be immediately apparent through traditional statistical analysis methods. ML can assist in automating the analysis process, saving time and effort, and enabling researchers to focus on interpreting the results and formulating hypotheses. In summary, while the availability of large datasets has undoubtedly expanded the possibilities and potential of ML, it is not a strict requirement for successful application. ML techniques can still yield valuable insights and predictions even with smaller datasets, making it a versatile tool for various domains, including scientific research. Commonly used data types in the literature as given in Table-6. As given in Table 6, a wealth of data types related to tourism exist for fuelling machine learning applications. When integrated and analysed collectively, these diverse data sources provide a multifaceted understanding of destination appeal, tourist behaviour, trends, patterns, experiences, needs, and opportunities for innovation. Machine learning is crucial for harnessing the potential of such data towards more personalized, seamless, and sustainable tourism development.

Table 6. *Key Data Types for Machine Learning and Tourism Applications*

Data Types	Ref.	Examples
Online reviews	[35,54,79,87, 90,92,98,129, 139,158,160, 169,192,214]	Reviews from platforms like TripAdvisor, Yelp, Expedia, etc. provide valuable data for machine learning in tourism. Data includes review text, review sentiment, review ratings, and information about the reviewer and destination. This data is useful for applications like sentiment analysis, recommendation systems, extractive summarization, and predictive analytics.
Images	[39,60,71,80, 89,104,115,1 82,186,187]	Images of tourist destinations, attractions, hotels, etc. from platforms like Instagram or posted with online reviews can be used for machine learning tasks such as image classification, object detection, visual semantic embedding, and automatic hashtag generation. These capabilities can enhance recommendation systems and social media analytics.
Ratings	[36]	The ratings (especially 5-star ratings) that tourists provide on various review and booking platforms represent useful quantitative data for machine learning. Ratings can be analyzed for tasks such as ranking and benchmarking destinations or anticipating peak travel seasons. They provide an indicator of overall tourist satisfaction and experience.
Search data	[88]	Search data from platforms like Google, Bing, Kayak, and Skyscanner contain valuable information about tourist interests, preferences, and intent. Analyzing search query terms, search frequencies, and other metadata through machine learning can uncover patterns to improve recommendation and personalization capabilities. Search data is useful for gaining broad market insights.
Location data	[197]	The location data generated from tourists' mobile devices and wearables as they travel provides significant data for machine learning applications. Analyzing location data can reveal patterns related to how tourists navigate a destination, visit points of interest, choose hotels or dining locations, and more. This data fuels location-aware applications and context-based personalization.
Demograph ic data	[2]	Basic demographic information about tourists such as age, gender, country of origin, income level, family size, etc. represents useful data for machine learning in tourism. Analyzing how different segments of visitors interact with and experience a destination leads to models that provide tailored, targeted recommendations and personalization of services for specific demographic groups.

Transportation data	[149,185,196, 197,198]	Data related to how tourists get around a destination, such as public transport usage, taxi services, walking or biking, vehicle rental or ownership, etc. gives insight into visitor flows and how infrastructure supports tourism. Machine learning analysis of transportation data aims to gain efficiencies, reduce environmental impact, and ensure high quality of experience regardless of transportation mode choice.

ML can be described as a field of study that enables computers to learn from experience and data without being explicitly programmed. It involves the use of computational methods and algorithms that learn patterns and relationships from examples, with the goal of improving performance and making accurate predictions. In ML, datasets consist of examples that contain features, where each row represents an instance and each column represents a feature. Features are measurable pieces of data that are fed into an ML algorithm to help solve a problem or make predictions. By training an ML algorithm with the dataset, a model is created, which represents the learned patterns and knowledge derived from the data. For example, a random forest algorithm can be trained with training data to generate a random forest model. Once the model is trained, it can be used to make predictions on new, unseen data. This predictive model takes in new data and produces predictions or classifications based on the patterns and knowledge it has learned during the training process.

Machine learning contributes a diverse range of techniques to gain insight from data, predict and optimize outcomes, personalize the customer experience and innovate services within tourism. The capabilities offered by machine learning can transform both strategic and operational aspects, with the potential for significant efficiency, sustainability and economic gains. Some key machine learning terms and techniques relevant to tourism as given in Table 7.

Table 7. *Machine Learning Techniques Used in Tourism Settings*

ML Techniques	Reference	The Purpose of Usage
Sentiment analysis	[1,9,10,22,35,54,69,93,107, 113,133,134,161,187,204]	Analyses the emotional tone of text data like onlin reviews to determine whether the sentiment is positive negative or neutral. Useful for analyzing touris satisfaction.
Topic modelling	[195]	Identifies latent topics within unstructured text data Can uncover trends and themes in tourism domains lik reviews, news articles, blogs, etc.
Classification	[1,22,54,69,71,85,152]	Assigns items to categories based on patterns in the data Useful for tasks like segmenting visitors into marke segments, classifying images, or filtering onlin reviews.
Regression	[24,55,157,211,219]	Predicts a continuous numeric value based on input data Can be used for tourism forecasting and prediction, e.g predicting hotel revenue or numbers of visitors
Clustering	[73]	Groups similar items together without pre-define categories. Used for visitor segmentation and als identifying groups of interesting points-of-interes dining venues, events, etc.
Recommender systems	[2,7,12,34,37,65]	Provide personalized recommendations based o analysis of user profiles, interests and behaviors. Play a important role in personalization and destinatio promotion.
Neural networks	[11,47,117]	Identify complex patterns in very large data sets. Use for tourism tasks such as advanced personalization image recognition, forecasting and predictiv modelling. Require huge amounts of data to b effective.
Naïve Bayes	[98, 235, 236]	A probabilistic classifier based on Bayes' theorem tha calculates the probability of an item belonging to particular category. Despite its simplicity, effective fo tasks like sentiment analysis, topic modelling an classification.
Support Vector Machines (SVM)	[1,77,117,219]	Identify patterns that separate categories in the data Effective at handling high-dimensional spaces an widely used for tasks such as text classification forecasting, regression and anomaly detection withi tourism.
Contextual modelling	[154, 234]	Incorporates information about the surrounding contex situation or environment. Important for implementin

		machine learning in complex, real-world application: Could include incorporating knowledge about season: events, companion, location, time, etc. for tourisr personalization.
Decision trees	[38,61,81,86]	Create a flowchart-like model of decisions and thei possible consequences. Useful for tourism application such as optimizing marketing campaigns, transportatio networks and staff scheduling.
Computer Vision	[68,105]	Enables machine learning models to identify an analyse visual content like images or video: Techniques include image classification, objec detection, visual search and automated image taggin; Useful for applications such as analysing tourism photo to determine point of interest density or popularity.

This covers some of the major machine learning techniques and terms that apply to tourism and hospitality. When integrated together, these diverse methods provide a powerful basis for building machine learning applications within the tourism industry

3. Discussion

Considering the article most cited and published along with the different databases namely SCOPUS, Web of Science, and Google Scholar, three of them are detailed to understand the trend of the machine learning application in tourism. Initially, [37] proposes a recommender system for the tourism industry using a combination of clustering and predictive modelling with machine learning. The system provides personalized recommendations for locations and activities to visitors based on their profiles and preferences. The recommender system has two main components:

- Clustering: The cluster ensemble technique is used to group visitors into segments based on demographic attributes like age, gender, occupation and behavioural attributes like interests, preferred locations, and activities. The K-means, hierarchical, and DBSCAN clustering algorithms were used in the ensemble. Ensemble clustering aims to improve robustness and accuracy.
- Predictive Modelling: Machine learning models including kNN, naive Bayes, decision trees, and random forests are trained on visitor profiles and location/activity preference data to make predictions for new visitors based on their cluster segment. The models provide a list of recommendations tailored to visitors in that cluster group.

The paper evaluates the performance of the proposed recommender system using metrics like precision, recall, F-measure, and accuracy. Experimental results show the ensemble cluster model achieved superior performance over individual clustering algorithms and the predictive models enhanced recommendation accuracy compared to basic recommender techniques. The recommender system can provide more personalized and tailored suggestions to visitors in the tourism domain compared to generic or "one-size-fits-all" recommendations. Clustering visitors into meaningful segments allows for targeted recommendations based on shared attributes and preferences within each group. And machine learning predictive models can continue learning and improving over time as new data is collected. Limitations include the need for large amounts of data on visitor profiles, preferences, and behaviours to properly train the machine learning models. Data may be difficult and expensive to obtain from some tourism organizations. Scalability and computational complexity are also challenging as the volume of visitors and locations/activities increase. Future work could explore how to gain additional data to further enhance the models, alternative or hybrid machine learning techniques to improve accuracy and user satisfaction, and how to deploy the recommender system in a way that is customized and valuable for individual tourism destinations and businesses.

[194] proposes an interactive technology acceptance model (iTAM) to explain how factors related to human-robot interaction and machine learning influence the adoption of service robots in the tourism and hospitality industry. The iTAM builds upon the original technology acceptance model (TAM) that focuses on perceived usefulness and ease of use. The interactive technology acceptance model (iTAM) includes 3 additional components:

- Interactivity: The ability of robots to engage in meaningful, responsive, and active social interactions with people. Interactivity contributes to perceived social presence, parasocial relationships, and enjoyment.
- Adaptability: How robots can learn, improve, and modify their knowledge and skills through machine learning based on new data and interactions. Adaptability enhances perceived intelligence, customization, and usefulness.

• Anthropomorphism: Giving human-like qualities and attributes to robots through their design and interactivity. Anthropomorphism positively impacts perceived enjoyment, social presence, and parasocial relationships with robots.

These 3 components, along with perceived usefulness and ease of use from the original TAM, influence people's attitudes toward service robots and their willingness to adopt and engage with them. Positive attitudes and experiences then also further contribute to machine learning as new data is collected to improve the robots. The paper proposes and evaluates a survey instrument to measure the iTAM components and model. Data was collected from over 500 survey respondents on their perspectives related to robot service in tourism and hospitality contexts like hotels, airports, and restaurants. Structural equation modelling validated the proposed interactive technology acceptance model and the relationships between its key factors. The iTAM provides a novel framework for understanding how machine learning-enabled social robots can be designed and improved to maximize acceptance, adoption, and continued use in service environments. A robot's ability to meaningfully interact, adapt to users, and exhibit human-like qualities are key to its success. Applying the iTAM could help researchers and practitioners develop robots that not only have practical, task-oriented benefits but also social and experiential value. Limitations include the need for empirical research with actual long-term human-robot interactions to supplement survey findings. The complexity of real-world service contexts may also challenge the implementation of social robots and machine learning in some situations. Privacy and ethical concerns related to data collection and use are additional considerations. Continued progress in natural language processing, computer vision, and other areas of artificial intelligence would further enhance interactive, learning-based robot services.

[181] aims to forecast demand for cruise tourism in China using an optimized machine learning approach with big data. Cruise tourism is a fast-growing sector, but there is limited research on methods for forecasting emerging cruise markets like China. The study obtains online search query data related to cruise tourism as a proxy for public interest and potential demand. The data consists of weekly search volumes for 120 keywords on the Baidu search engine from 2005 to 2017. The large dataset qualifies as "big data" due to its high volume, velocity, and variety. An optimized machine learning model is proposed that combines feature selection, hyperparameter tuning, and ensemble learning techniques to maximize forecast accuracy:

• Feature selection using Random Forest importance scores reduced the 120 keywords to the 30 most relevant for predicting cruise demand. This simplifies the model and reduces noise.

• Hyperparameter tuning using Random Search optimized settings for the XGBoost (eXtreme Gradient Boosting) algorithm. XGBoost is a highly effective tree ensemble method suitable for large datasets. Optimization helps maximize the power of the model.

• Ensemble learning combines forecasts from XGBoost, Random Forest, and Holt-Winters exponential smoothing to balance machine learning and statistical methods. The ensemble approach aims to improve robustness and accuracy.

The model is evaluated using root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and R-squared for different forecast horizons up to 12 weeks ahead. Results show the optimized machine learning model achieved significantly better accuracy than any single approach alone and, especially, compared to the basic trend forecast. The study demonstrates the potential of using big data and sophisticated machine learning techniques for forecasting in complex domains like tourism where traditional statistical methods may be limited. Cruise tourism appears strongly affected by search and digital trends, so online behaviour can tap into public interest before demand is realized. However, online factors alone may not capture all drivers of emerging cruise demand, especially long-term impacts. Integrating additional variables related to the economy, demographics, and tourism infrastructure with web data could further enhance forecasting performance. Practically, forecasts of cruise tourism demand could help strategic decision-making related to marketing, investment, operations, and management in the cruise industry. More accurate predictions enable stronger preauction and preparation to optimize opportunities related to changes in demand. But policymakers and businesses should also consider that machine learning models may reflect and even amplify biases or inequities in the data. So professional judgment still plays an important role in utilizing AI-enabled forecasts.

All 3 papers [37,181,194] apply machine learning to address key opportunities and challenges related to personalization, acceptance of emerging technologies, and forecasting in the tourism domain. Clustering, predictive modelling, robotics, and big data analytics are promising for industry progress but require consideration of limitations involving data quality, customization, complexity, and human judgment. A mix of methods may maximize benefits. Survey and performance metrics provide initial evaluation but longitudinal, real-world studies most insightful. Progress in neural networks, computer vision, NLP and other AI could greatly enhance techniques while raising additional concerns related to bias or job disruption that researchers are beginning to explore.

The paper of [212] focuses on an important trend: smart tourism and personalization and proposes a conceptual framework for smart destinations that can enhance the tourism experience. This paper covers a very broad, comprehensive scope at a destination level. However, it has some pros, which lack technical depth or empirical evaluation as it takes a more conceptual approach. In [54], machine learning methods (naive Bayes, SVM, neural network) are applied to a tourism-related problem (analysing online reviews), and the performance of different ML techniques is empirically evaluated and compared for the task. This paper could have useful industry applications for review analysis and customer insight. On the other hand, this paper only analyses reviews for tourist destinations in China, limiting wider insight. In [213], a machine learning-based method is proposed for ontology matching that could apply to the tourism domain. The method and approach in significant technical depth are explained. The performance against other existing methods is evaluated for demonstrating good results. However, this study is not tourism-specific and lacks a tourism example application, very theoretically and technically complex. Therefore, it may lack accessibility for some readers and the scope is narrow focusing on just one ML task and method. In summary, the articles take quite different approaches. The first takes a broad conceptual scope but lacks technical depth. The second applies ML to a specific tourism task but has a narrow empirical focus. The third proposes an ML method at a high technical level but lacks a tourism grounding. So, there are trade-offs in terms of scope, application, accessibility and technical proficiency. The articles could be combined by, for example, applying and evaluating the method from the third article on the review analysis task from the second article, set within the smart destination context of the first. This could result in an article with significant scope, technical merit, empirical evidence, and tourism relevance. The diverse citations of these articles, then, point to the potential and need for this type of integrated, in-depth work.

4. Near Future Aspects

Depending on the seminal research in this review paper, A myriad of key gaps and limitations in current machine learning applications for tourism is included as follows:

- **Lack of large datasets:** Many machine learning techniques require huge amounts of data to be effective, especially deep learning methods. Limited availability of large, multidimensional tourism datasets constraints model performance. More open data sharing between industry stakeholders and further integration of diverse data sources could help address this.
- **Narrow focus:** Most studies apply machine learning to a single data type (e.g. online reviews) or for one specific task (e.g. sentiment analysis). A more holistic approach that combines multiple data sources and machine learning techniques is needed. This could provide a broader, multifaceted understanding of tourists and tourism systems.
- **Theoretical rather than practical:** The majority of studies propose a methodological framework or evaluate machine learning techniques on a tourism dataset. There is a lack of real-world implementations and analysis of business metrics to demonstrate practical value. More collaboration with industry is required.
- **Static rather than dynamic:** Machine learning models are often built on static snapshots of data. There is little work on developing models able to adapt in real time based on continuous data streams. This limits the ability to detect and respond to sudden changes or events. Online learning and continuous model evaluation techniques could be explored.
- **Limited personalization:** While significant research exists on recommendation systems, machine learning is limitedly applied to gain a deep, multifaceted understanding of tourists that could enable truly personalized experiences across platforms and vendors. Integrating diverse data types and testing in real usage contexts may progress this capability.
- **Reactively rather than proactively:** Machine learning in tourism largely aims to analyse what has already occurred to gain insights and make predictions. Techniques have not been widely explored to anticipate tourists' future needs and desires before they are explicitly expressed. Proactive personalization will rely on gaining a deeper understanding of individuals.
- **Lack of transparency:** Many of the most advanced machine learning techniques (especially deep learning) act as "black boxes" - their inner workings are opaque. This lack of explainability is problematic when inaccurate or potentially biased predictions have a real impact on people. Approaches are needed to increase transparency and enable the auditing of machine learning systems.
- **Ethical issues:** The collection and use of tourist data by private companies raise ethical concerns related to privacy, consent and data ownership. There is a lack of consistent guidelines for the ethical use of

machine learning and resulting applications within the tourism industry. Frameworks for addressing ethical risks are required to gain trust and encourage adoption.

To conclude, gaps exist in data, scope, real-world integration, dynamic modelling, personalization, proactivity, transparency and ethics for machine learning in tourism. A more holistic, multifaceted approach that addresses both opportunities and risks will be needed to fulfil the potential benefits of moving to AI and data-driven tourism. Overall, greater collaboration between researchers and industry will be key.

References

[1] Zheng, Wenying, and Ye, Qiang (2009). Sentiment Classification of Chinese Traveler Reviews by Support Vector Machine Algorithm. *2009 Third International Symposium On Intelligent Information Technology Application, Vol 3, Proceedings*, 335-338, ISSN 978-0-7695-3859-4, https://dx.doi.org/10.1109/IITA.2009.457.

[2] Wang, Yuanyuan, Chan, Stephen Chi-Fai, and Ngai, Grace (2012). Applicability of Demographic Recommender System to Tourist Attractions: A Case Study on TripAdvisor. *2012 Ieee/Wic/Acm International Conference On Web Intelligence And Intelligent Agent Technology Workshops (Wi-Iat Workshops 2012), Vol 3*, 97-101, https://dx.doi.org/10.1109/WI-IAT.2012.133.

[3] Salman, Man Galih, Kanigoro, Bayu, Heryadi, Yaya, and IEEE (2015). Weather Forecasting using Deep Learning Techniques. *2015 International Conference On Advanced Computer Science And Information Systems (Icacsis)*, 281-285, ISSN 2330-4588

[4] Chang, Yu-Wei, and Tsai, Chih-Yung (2017). Apply deep learning neural network to forecast number of tourists. *2017 31st Ieee International Conference On Advanced Information Networking And Applications Workshops (Ieee Waina 2017)*, 259-264, https://dx.doi.org/10.1109/WAINA.2017.125

[5] Luong, Thai-Le, Cao, Minh-Son, Le, Duc-Thang, and Phan, Xuan-Hieu (2017). Intent Extraction from Social Media Texts Using Sequential Segmentation and Deep Learning Models. *2017 9th International Conference On Knowledge And Systems Engineering (Kse 2017)*, 215-220, ISSN 2164-2508

[6] Sun, Shaolong, Wang, Shouyang, Wei, Yunjie, Yang, Xianduan, and Tsui, Kwok-Leung (2017). Forecasting Tourist Arrivals with Machine Learning and Internet Search Index. *2017 Ieee International Conference On Big Data (Big Data)*, 4165-4169, ISSN 2639-1589

[7] Kbaier, Mohamed Elyes Ben Haj, Masri, Hela, Krichen, Saoussen, and IEEE (2017). A personalized hybrid tourism recommender system. *2017 Ieee/Acs 14th International Conference On Computer Systems And Applications (Aiccsa)*, 244-250, ISSN 2161-5322, https://dx.doi.org/10.1109/AICCSA.2017.12

[8] Son, Kyoungho, Byun, Yungcheol, Lee, Sangjoon, and IEEE (2018). Prediction of Visitors using Machine Learning. *2018 International Conference On Intelligent Informatics And Biomedical Sciences (Iciibms)*, 138-139, ISSN 2189-8723

[9] Ramanathan, Vallikannu, Meyyappan, T., and IEEE (2019). Twitter Text Mining for Sentiment Analysis on People's Feedback about Oman Tourism. *2019 4th Mec International Conference On Big Data And Smart City (Icbdsc)*, 30-34

[10] Yadav, Mukesh, and Bhojane, Varunakshi (2019). Semi-Supervised Mix-Hindi Sentiment Analysis using Neural Network. *2019 9th International Conference On Cloud Computing, Data Science and Engineering (Confluence 2019)*, 309-314

[11] Folgieri, Raffaella, Baldigara, Tea, and Mamula, Maja (2017). Artificial Neural Networks-Based Econometric Models For Tourism Demand Forecasting. *4th International Scientific Conference: Tosee - Tourism In Southern And Eastern Europe 2017, 4*, 169-182, ISSN 1848-4050, https://dx.doi.org/10.20867/tosee.04.10

[12] Deldjoo, Yashar, Schedl, Markus, Cremonesi, Paolo, and Pasi, Gabriella (2020). Recommender Systems Leveraging Multimedia Content. *Acm Computing Surveys*, *53*(5), ISSN 0360-0300, https://dx.doi.org/10.1145/3407190

[13] Siricharoen, Waralak V. (2008). Learning semantic web from e-tourism. *Agent And Multi-Agent Systems: Technologies And Applications, Proceedings*, *4953*, 516-525, ISSN 0302-9743

[14] Birim, Sule, Kazancoglu, Ipek, Mangla, Sachin Kumar, Kahraman, Aysun, and Kazancoglu, Yigit (2022). The derived demand for advertising expenses and implications on sustainability: a comparative study using deep learning and traditional machine learning methods. *Annals Of Operations Research*, ISSN 0254-5330, https://dx.doi.org/10.1007/s10479-021-04429-x

[15] Rice, William L., Park, So Young, Pan, Bing, and Newman, Peter (2019). Forecasting campground demand in US national parks. *Annals Of Tourism Research*, *75*, 424-438, ISSN 0160-7383, https://dx.doi.org/10.1016/j.annals.2019.01.013

[16] Yu, Joanne, and Egger, Roman (2021). Color and engagement in touristic Instagram pictures: A machine learning approach. *Annals Of Tourism Research*, *89*, ISSN 0160-7383, https://dx.doi.org/10.1016/j.annals.2021.103204

[17] Zhang, Chen, and Huang, Zhenfang (2015). Mining Tourist Motive for Marketing Development via Twice-Learning. *Applied Artificial Intelligence*, *29*(2), 119-133, ISSN 0883-9514, https://dx.doi.org/10.1080/08839514.2015.993554

[18] Starosta, Kejo, Budz, Sonia, and Krutwig, Michael (2019). The impact of German-speaking online media on tourist arrivals in popular tourist destinations for Europeans. *Applied Economics*, *51*(14), 1558-1573, ISSN 0003-6846, https://dx.doi.org/10.1080/00036846.2018.1527463

[19] Claveria, Oscar, Monte, Enric, and Torra, Salvador (2016). Combination forecasts of tourism demand with machine learning models. *Applied Economics Letters*, *23*(6), 428-431, ISSN 1350-4851, https://dx.doi.org/10.1080/13504851.2015.1078441

[20] Tsai, Yu Hsin, Stow, Douglas, An, Li, Chen, Hsiang Ling, Lewison, Rebecca, and Shi, Lei (2019). Monitoring land-cover and land-use dynamics in Fanjingshan National Nature Reserve. *Applied Geography*, *111*, ISSN 0143-6228, https://dx.doi.org/10.1016/j.apgeog.2019.102077

[21] Li, Qin, Li, Shaobo, Zhang, Sen, Hu, Jie, and Hu, Jianjun (2019). A Review of Text Corpus-Based Tourism Big Data Mining.

Applied Sciences-Basel, *9*(16), https://dx.doi.org/10.3390/app9163300

[22] Chen, Wen, Xu, Zhiyun, Zheng, Xiaoyao, Yu, Qingying, and Luo, Yonglong (2020). Research on Sentiment Classification of Online Travel Review Text. *Applied Sciences-Basel*, *10*(15), https://dx.doi.org/10.3390/app10155275

[23] Crivellari, Alessandro, and Beinat, Euro (2019). Identifying Foreign Tourists' Nationality from Mobility Traces via LSTM Neural Network and Location Embeddings. *Applied Sciences-Basel*, *9*(14), https://dx.doi.org/10.3390/app9142861

[24] Lv, Sheng-Xiang, Peng, Lu, and Wang, Lin (2018). Stacked autoencoder with echo-state regression for tourism demand forecasting using search query data. *Applied Soft Computing*, *73*, 119-133, ISSN 1568-4946, https://dx.doi.org/10.1016/j.asoc.2018.08.024

[25] Yilmaz, Mustafa K., Kusakci, Ali Osman, Aksoy, Mine, and Hacioglu, Umit (2022). The evaluation of operational efficiencies of Turkish airports: An integrated spherical fuzzy AHP/DEA approach. *Applied Soft Computing*, *119*, ISSN 1568-4946, https://dx.doi.org/10.1016/j.asoc.2022.108620

[26] Guerra-Montenegro, Juan, Sanchez-Medina, Javier, Lana, Ibai, Sanchez-Rodriguez, David, Alonso-Gonzalez, Itziar, and Ser, Javier Del (2021). Computational Intelligence in the hospitality industry: A systematic literature review and a prospect of challenges. *Applied Soft Computing*, *102*, ISSN 1568-4946, https://dx.doi.org/10.1016/j.asoc.2021.107082

[27] Spiliotis, Evangelos, Abolghasemi, Mahdi, Hyndman, Rob J., Petropoulos, Fotios, and Assimakopoulos, Vassilios (2021). Hierarchical forecast reconciliation with machine learning. *Applied Soft Computing*, *112*, ISSN 1568-4946, https://dx.doi.org/10.1016/j.asoc.2021.107756

[28] Bayliss, Christopher (2021). Machine learning based simulation optimisation for urban routing problems. *Applied Soft Computing*, *105*, ISSN 1568-4946, https://dx.doi.org/10.1016/j.asoc.2021.107269

[29] Gajdosik, Tomas, and Marcis, Matus (2019). Artificial Intelligence Tools for Smart Tourism Development. *Artificial Intelligence Methods In Intelligent Algorithms*, *985*, 392-402, ISSN 2194-5357, https://dx.doi.org/10.1007/978-3-030-19810-7_39

[30] Refanidis, Ioannis, Emmanouilidis, Christos, Sakellariou, Ilias, Alexiadis, Anastasios, Koutsiamanis, Remous-Aris, Agnantis, Konstantinos, Tasidou, Aimilia, Kokkoras, Fotios, and Efraimidis, Pavlos S. (2014). MYVISITPLANNER(GR): Personalized Itinerary Planning System for Tourism. *Artificial Intelligence: Methods And Applications*, *8445*, 615-629, ISSN 0302-9743

[31] Deo, Ravinesh C., and Sahin, Mehmet (2015). Application of the Artificial Neural Network model for prediction of monthly Standardized Precipitation and Evapotranspiration Index using hydrometeorological parameters and climate indices in eastern Australia. *Atmospheric Research*, *161*, 65-81, ISSN 0169-8095, https://dx.doi.org/10.1016/j.atmosres.2015.03.018

[32] Monkman, Graham G., Kaiser, Michel J., and Hyder, Kieran (2018). Text and data mining of social media to map wildlife recreation activity. *Biological Conservation*, *228*, 89-99, ISSN 0006-3207, https://dx.doi.org/10.1016/j.biocon.2018.10.010

[33] Peng, Lu, Wang, Lin, Ai, Xue-Yi, and Zeng, Yu-Rong (2021). Forecasting Tourist Arrivals via Random Forest and Long Short-term Memory. *Cognitive Computation*, *13*(1), 125-138, ISSN 1866-9956, https://dx.doi.org/10.1007/s12559-020-09747-z

[34] Altulyan, May, Yao, Lina, Wang, Xianzhi, Huang, Chaoran, Kanhere, Salil S., and Sheng, Quan Z. (2022). A Survey on Recommender Systems for Internet of Things: Techniques, Applications and Future Directions. *Computer Journal*, *65*(8), 2098-2132, ISSN 0010-4620, https://dx.doi.org/10.1093/comjnl/bxab049

[35] Jain, Praphula Kumar, Pamula, Rajendra, and Srivastava, Gautam (2021). A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews. *Computer Science Review*, *41*, ISSN 1574-0137, https://dx.doi.org/10.1016/j.cosrev.2021.100413

[36] Gaur, Loveleen, Afaq, Anam, Solanki, Arun, Singh, Gurmeet, Sharma, Shavneet, Jhanjhi, N. Z., My, Hoang Thi, and Le, Dac-Nhuong (2021). Capitalizing on big data and revolutionary 5G technology: Extracting and visualizing ratings and reviews of global chain hotels. *Computers and Electrical Engineering*, *95*, ISSN 0045-7906, https://dx.doi.org/10.1016/j.compeleceng.2021.107374

[37] Nilashi, Mehrbakhsh, Bagherifard, Karamollah, Rahmani, Mohsen, and Rafe, Vahid (2017). A recommender system for tourism industry using cluster ensemble and prediction machine learning techniques. *Computers and Industrial Engineering*, *109*, 357-368, ISSN 0360-8352, https://dx.doi.org/10.1016/j.cie.2017.05.016

[38] Nilashi, Mehrbakhsh, Samad, Sarminah, Ahani, Ali, Ahmadi, Hossein, Alsolami, Eesa, Mahmoud, Marwan, Majeed, Hamsa D., and Alarood, Ala Abdulsalam (2021). Travellers decision making through preferences learning: A case on Malaysian spa hotels in TripAdvisor. *Computers and Industrial Engineering*, *158*, ISSN 0360-8352, https://dx.doi.org/10.1016/j.cie.2021.107348

[39] Sun, Yeran, Fan, Hongchao, Bakillah, Mohamed, and Zipf, Alexander (2015). Road-based travel recommendation using geo-tagged images. *Computers Environment And Urban Systems*, *53*, 110-122, ISSN 0198-9715, https://dx.doi.org/10.1016/j.compenvurbsys.2013.07.006

[40] Weerdenburg, Demi van, Scheider, Simon, Adams, Benjamin, Spierings, Bas, and Zee, Egbert van der (2019). Where to go and what to do: Extracting leisure activity potentials from Web data on urban space. *Computers Environment And Urban Systems*, *73*, 143-156, ISSN 0198-9715, https://dx.doi.org/10.1016/j.compenvurbsys.2018.09.005

[41] Antonio, Nuno, Almeida, Ana de, and Nunes, Luis (2019). Big Data in Hotel Revenue Management: Exploring Cancellation Drivers to Gain Insights Into Booking Cancellation Behavior. *Cornell Hospitality Quarterly*, *60*(4), 298-319, ISSN 1938-9655, https://dx.doi.org/10.1177/1938965519851466

[42] Le, Truc H., Arcodia, Charles, Novais, Margarida Abreu, and Kralj, Anna (2021). Proposing a systematic approach for integrating traditional research methods into machine learning in text analytics in tourism and hospitality. *Current Issues In Tourism*, *24*(12), 1640-1655, ISSN 1368-3500, https://dx.doi.org/10.1080/13683500.2020.1829568

[43] Zhao, Erlong, Du, Pei, Azaglo, Ernest Young, Wang, Shouyang, and Sun, Shaolong (2023). Forecasting daily tourism volume: a hybrid approach with CEMMDAN and multi-kernel adaptive ensemble. *Current Issues In Tourism*, *26*(7), 1112-1131, ISSN 1368-3500, https://dx.doi.org/10.1080/13683500.2022.2048806

[44] Kim, Jina, Jang, Yeonju, Bae, Kunwoo, Oh, Soyoung, Jeong, Nam Jeong, Park, Eunil, Han, Jinyoung, and Pobil, Angel P. del (2021). Between comments and repeat visit: capturing repeat visitors with a hybrid approach. *Data Technologies And Applications*, *55*(4), 542-557, ISSN 2514-9288, https://dx.doi.org/10.1108/DTA-06-2020-0123

[45] Mingotto, Erica, Montaguti, Federica, and Tamma, Michele (2021). Challenges in re-designing operations and jobs to embody AI and robotics in services. Findings from a case in the hospitality industry. *Electronic Markets*, *31*(3), 493-510, ISSN 1019-6781, https://dx.doi.org/10.1007/s12525-020-00439-y

[46] Peng, Rongqun, Lou, Yingxi, Kadoch, Michel, and Cheriet, Mohamed (2020). A Human-Guided Machine Learning Approach for 5G Smart Tourism IoT. *Electronics*, *9*(6), https://dx.doi.org/10.3390/electronics9060947

[47] Livieris, Ioannis E., Pintelas, Emmanuel, Kotsilieris, Theodore, Stavroyiannis, Stavros, and Pintelas, Panagiotis (2019). Weight-Constrained Neural Networks in Forecasting Tourist Volumes: A Case Study. *Electronics*, *8*(9), https://dx.doi.org/10.3390/electronics8091005

[48] Sidorov, Denis, Panasetsky, Daniil, Tomin, Nikita, Karamov, Dmitriy, Zhukov, Aleksei, Muftahov, Ildar, Dreglea, Aliona, Liu, Fang, and Li, Yong (2020). Toward Zero-Emission Hybrid AC/DC Power Systems with Renewable Energy Sources and Storages: A Case Study from Lake Baikal Region. *Energies*, *13*(5), https://dx.doi.org/10.3390/en13051226

[49] Brzustewicz, Pawel, and Singh, Anupam (2021). Sustainable Consumption in Consumer Behavior in the Time of COVID-19: Topic Modeling on Twitter Data Using LDA. *Energies*, *14*(18), https://dx.doi.org/10.3390/en14185787

[50] Chobar, Adel Pourghader, Adibi, Mohammad Amin, and Kazemi, Abolfazl (2022). Multi-objective hub-spoke network design of perishable tourism products using combination machine learning and meta-heuristic algorithms. *Environment Development And Sustainability*, ISSN 1387-585X, https://dx.doi.org/10.1007/s10668-022-02350-2

[51] Gomez, Diego, Salvador, Pablo, Sanz, Julia, and Casanova, Jose Luis (2021). A new approach to monitor water quality in the Menor sea (Spain) using satellite data and machine learning methods*. *Environmental Pollution*, *286*, ISSN 0269-7491, https://dx.doi.org/10.1016/j.envpol.2021.117489

[52] Martin-Gutierrez, Jorge, Mora, Carlos Efren, Anorbe-Diaz, Beatriz, and Gonzalez-Marrero, Antonio (2017). Virtual Technologies Trends in Education. *Eurasia Journal Of Mathematics Science And Technology Education*, *13*(2), 469-486, ISSN 1305-8215, https://dx.doi.org/10.12973/eurasia.2017.00626a

[53] Kirkos, Efstathios (2022). Airbnb listings' performance: determinants and predictive models. *European Journal Of Tourism Research*, *30*, ISSN 1994-7658

[54] Ye, Qiang, Zhang, Ziqiong, and Law, Rob (2009). Sentiment classification of online reviews to travel destinations by supervised machine learning approaches. *Expert Systems With Applications*, *36*(3), 6527-6535, ISSN 0957-4174, https://dx.doi.org/10.1016/j.eswa.2008.07.035

[55] Wu, Qi, Law, Rob, and Xu, Xin (2012). A sparse Gaussian process regression model for tourism demand forecasting in Hong Kong. *Expert Systems With Applications*, *39*(5), 4769-4774, ISSN 0957-4174, https://dx.doi.org/10.1016/j.eswa.2011.09.159

[56] Belmonte-Fernandez, Oscar, Montoliu, Raul, Torres-Sospedra, Joaquin, Sansano-Sansano, Emilio, and Chia-Aguilar, Daniel (2018). A radiosity-based method to avoid calibration for indoor positioning systems. *Expert Systems With Applications*, *105*, 89-101, ISSN 0957-4174, https://dx.doi.org/10.1016/j.eswa.2018.03.054

[57] Li, Xixi, Kang, Yanfei, and Li, Feng (2020). Forecasting with time series imaging. *Expert Systems With Applications*, *160*, ISSN 0957-4174, https://dx.doi.org/10.1016/j.eswa.2020.113680

[58] King, Michael A., Abrahams, Alan S., and Ragsdale, Cliff T. (2014). Ensemble methods for advanced skier days prediction. *Expert Systems With Applications*, *41*(4), 1176-1188, ISSN 0957-4174, https://dx.doi.org/10.1016/j.eswa.2013.08.002

[59] Yao, Yuan, Cao, Yi, Ding, Xuemei, Zhai, Jia, Liu, Junxiu, Luo, Yuling, Ma, Shuai, and Zou, Kailin (2018). A paired neural network model for tourist arrival forecasting. *Expert Systems With Applications*, *114*, 588-614, ISSN 0957-4174, https://dx.doi.org/10.1016/j.eswa.2018.08.025

[60] Lee, Chung-Hong, and Wang, Shih-Hao (2012). An information fusion approach to integrate image annotation and text mining methods for geographic knowledge discovery. *Expert Systems With Applications*, *39*(10), 8954-8967, ISSN 0957-4174, https://dx.doi.org/10.1016/j.eswa.2012.02.028

[61] Nilashi, Mehrbakhsh, Minaei-Bidgoli, Behrouz, Alrizq, Mesfer, Alghamdi, Abdullah, Alsulami, Abdulaziz A., Samad, Sarminah, and Mohd, Saidatulakmal (2021). An analytical approach for big social data analysis for customer decision-making in eco-friendly hotels. *Expert Systems With Applications*, *186*, ISSN 0957-4174, https://dx.doi.org/10.1016/j.eswa.2021.115722

[62] Sun, Shaolong, Li, Mingchen, Wang, Shouyang, and Zhang, Chengyuan (2022). Multi-step ahead tourism demand forecasting: The perspective of the learning using privileged information paradigm. *Expert Systems With Applications*, *210*, ISSN 0957-4174, https://dx.doi.org/10.1016/j.eswa.2022.118502

[63] Lennox, Robert J., Brownscombe, Jacob W., Cooke, Steven J., and Danylchuk, Andy J. (2018). Post-release behaviour and survival of recreationally-angled arapaima (Arapaima cf. arapaima) assessed with accelerometer biologgers. *Fisheries Research*, *207*, 197-203, ISSN 0165-7836, https://dx.doi.org/10.1016/j.fishres.2018.05.007

[64] Lisi, Francesca A., and Straccia, Umberto (2013). A Logic-based Computational Method for the Automated Induction of Fuzzy Ontology Axioms. *Fundamenta Informaticae*, *124*(4), 503-519, ISSN 0169-2968, https://dx.doi.org/10.3233/FI-2013-846

[65] Santamaria-Granados, Luz, Mendoza-Moreno, Juan Francisco, and Ramirez-Gonzalez, Gustavo (2021). Tourist Recommender Systems Based on Emotion Recognition-A Scientometric Review. *Future Internet*, *13*(1), https://dx.doi.org/10.3390/fi13010002

[66] Do, Hai-Ninh, Shih, Wurong, and Ha, Quang-An (2020). Effects of mobile augmented reality apps on impulse buying behavior: An investigation in the tourism field. *Heliyon*, *6*(8), https://dx.doi.org/10.1016/j.heliyon.2020.e04667

[67] Buckley, S., Ettl, M., Jain, P., Luss, R., Petrik, M., Ravi, R. K., and Venkatramani, C. (2014). Social media and customer behavior analytics for personalized customer engagements. *Ibm Journal Of Research And Development*, *58*(5), ISSN 0018-8646,

https://dx.doi.org/10.1147/JRD.2014.2344515

[68] Bonin-Font, Francisco, Burguera, Antoni, and Lisani, Jose-Luis (2017). Visual Discrimination and Large Area Mapping of Posidonia Oceanica Using a Lightweight AUV. *Ieee Access*, *5*, 24479-24494, ISSN 2169-3536, https://dx.doi.org/10.1109/ACCESS.2017.2764998

[69] Afzaal, Muhammad, Usman, Muhammad, and Fong, Alvis (2019). Tourism Mobile App With Aspect-Based Sentiment Classification Framework for Tourist Reviews. *Ieee Transactions On Consumer Electronics*, *65*(2), 233-242, ISSN 0098-3063, https://dx.doi.org/10.1109/TCE.2019.2908944

[70] Navigli, R, and Velardi, P (2005). Structural semantic interconnections: A knowledge-based approach to word sense disambiguation. *Ieee Transactions On Pattern Analysis And Machine Intelligence*, *27*(7), 1075-1086, ISSN 0162-8828

[71] Deglint, Jason L., Jin, Chao, and Wong, Alexander (2019). Investigating the Automatic Classification of Algae Using the Spectral and Morphological Characteristics via Deep Residual Learning. *Image Analysis And Recognition (Iciar 2019), Pt Ii*, *11663*, 269-280, ISSN 0302-9743, https://dx.doi.org/10.1007/978-3-030-27272-2_23

[72] Shin, Seunghun, Du, Qianzhou, and Xiang, Zheng (2019). What's Vs. How's in Online Hotel Reviews: Comparing Information Value of Content and Writing Style with Machine Learning. *Information And Communication Technologies In Tourism 2019*, 321-332, ISSN 978-3-030-05939-2, https://dx.doi.org/10.1007/978-3-030-05940-8_25

[73] Kaya, Kiymet, Yilmaz, Yaren, Yaslan, Yusuf, Oguducu, Sule Gunduz, and Cingi, Furkan (2022). Demand forecasting model using hotel clustering findings for hospitality industry. *Information Processing and Management*, *59*(1), ISSN 0306-4573, https://dx.doi.org/10.1016/j.ipm.2021.102816

[74] Huh, Jun-Ho, Kim, Han-Byul, and Kim, Jinmo (2017). A Method of Modeling of Basic Big Data Analysis for Korean Medical Tourism: A Machine Learning Approach Using Apriori Algorithm. *Information Science And Applications 2017, Icisa 2017*, *424*, 784-790, ISSN 1876-1100, https://dx.doi.org/10.1007/978-981-10-4154-9_91

[75] . Neidhardt, Julia, and Werthner, Hannes (2018). IT and tourism: still a hot topic, but do not forget IT. *Information Technology and Tourism*, *20*(1), 1-7, ISSN 1098-3058, https://dx.doi.org/10.1007/s40558-018-0115-x

[76] H., V Phan, Truong, and Do, Phuc (2020). BERT+vnKG: Using Deep Learning and Knowledge Graph to Improve Vietnamese Question Answering System. *International Journal Of Advanced Computer Science And Applications*, *11*(7), 480-487, ISSN 2158-107X

[77] Xu, Xin, Law, Rob, and Wu, Tao (2009). Support Vector Machines with Manifold Learning and Probabilistic Space Projection for Tourist Expenditure Analysis. *International Journal Of Computational Intelligence Systems*, *2*(1), 17-26, ISSN 1875-6891

[78] Ali, Faizan, Park, Eunhye (Olivia), Kwon, Junehee, and Chae, Bongsug (Kevin) (2019). 30 years of contemporary hospitality management Uncovering the bibliometrics and topical trends. *International Journal Of Contemporary Hospitality Management*, *31*(7), 2641-2665, ISSN 0959-6119, https://dx.doi.org/10.1108/IJCHM-10-2018-0832

[79] Gour, Alekh, Aggarwal, Shikha, and Erdem, Mehmet (2021). Reading between the lines: analyzing online reviews by using a multi-method Web-analytics approach. *International Journal Of Contemporary Hospitality Management*, *33*(2), 490-512, ISSN 0959-6119, https://dx.doi.org/10.1108/IJCHM-07-2020-0760

[80] Lin, Michael S., Liang, Yun, Xue, Joanne X., Pan, Bing, and Schroeder, Ashley (2021). Destination image through social media analytics and survey method. *International Journal Of Contemporary Hospitality Management*, *33*(6), 2219-2238, ISSN 0959-6119, https://dx.doi.org/10.1108/IJCHM-08-2020-0861

[81] Lee, Minwoo, Kwon, Wooseok, and Back, Ki-Joon (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, ISSN 0959-6119, https://dx.doi.org/10.1108/IJCHM-06-2020-0587

[82] Park, Eunhye (Olivia), Chae, Bongsug, and Kwon, Junehee (2018). Toward understanding the topical structure of hospitality literature: Applying machine learning and traditional statistics. *International Journal Of Contemporary Hospitality Management*, *30*(11), 3386-3411, ISSN 0959-6119, https://dx.doi.org/10.1108/IJCHM-11-2017-0714

[83] Filieri, Raffaele, D'Amico, Elettra, Destefanis, Alessandro, Paolucci, Emilio, and Raguseo, Elisabetta (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, ISSN 0959-6119, https://dx.doi.org/10.1108/IJCHM-02-2021-0220

[84] Ampountolas, Apostolos, and Legg, Mark P. (2021). A segmented machine learning modeling approach of social media for predicting occupancy. *International Journal Of Contemporary Hospitality Management*, *33*(6), 2001-2021, ISSN 0959-6119, https://dx.doi.org/10.1108/IJCHM-06-2020-0611

[85] Liu, Yiran, and Beldona, Srikanth (2021). Extracting revisit intentions from social media big data: a rule-based classification model. *International Journal Of Contemporary Hospitality Management*, *33*(6), 2176-2193, ISSN 0959-6119, https://dx.doi.org/10.1108/IJCHM-06-2020-0592

[86] Lee, Yejin, and Kim, Dae-Young (2021). The decision tree for longer-stay hotel guest: the relationship between hotel booking determinants and geographical distance. *International Journal Of Contemporary Hospitality Management*, *33*(6), 2264-2282, ISSN 0959-6119, https://dx.doi.org/10.1108/IJCHM-06-2020-0594

[87] Nilashi, Mehrbakhsh, Yadegaridehkordi, Elaheh, Ibrahim, Othman, Samad, Sarminah, Ahani, Ali, and Sanzogni, Louis (2019). Analysis of Travellers' Online Reviews in Social Networking Sites Using Fuzzy Logic Approach. *International Journal Of Fuzzy Systems*, *21*(5), 1367-1378, ISSN 1562-2479, https://dx.doi.org/10.1007/s40815-019-00630-0

[88] Kang, Junfeng, Guo, Xingyu, Fang, Lei, Wang, Xiangrong, and Fan, Zhengqiu (2022). Integration of Internet search data to predict tourism trends using spatial-temporal XGBoost composite model. *International Journal Of Geographical Information Science*, *36*(2), 236-252, ISSN 1365-8816, https://dx.doi.org/10.1080/13658816.2021.1934476

[89] Ma, Yufeng, Xiang, Zheng, Du, Qianzhou, and Fan, Weiguo (2018). Effects of user-provided photos on hotel review helpfulness:

An analytical approach with deep leaning. *International Journal Of Hospitality Management*, *71*, 120-131, ISSN 0278-4319, https://dx.doi.org/10.1016/j.ijhm.2017.12.008

[90] Kwok, Linchi, Tang, Yingying, and Yu, Bei (2020). Research Paper The 7 Ps marketing mix of home-sharing services: Mining travelers' online reviews on Airbnb. *International Journal Of Hospitality Management*, *90*, ISSN 0278-4319, https://dx.doi.org/10.1016/j.ijhm.2020.102616

[91] Sanchez-Medina, Agustin J., and C-Sanchez, Eleazar (2020). Using machine learning and big data for efficient forecasting of hotel booking cancellations. *International Journal Of Hospitality Management*, *89*, ISSN 0278-4319, https://dx.doi.org/10.1016/j.ijhm.2020.102546

[92] Le, Truc H., Arcodia, Charles, Novais, Margarida Abreu, and Kralj, Anna (2022). How consumers perceive authenticity in restaurants: A study of online reviews. *International Journal Of Hospitality Management*, *100*, ISSN 0278-4319, https://dx.doi.org/10.1016/j.ijhm.2021.103102

[93] Shi, Yong, Zhu, Luyao, Li, Wei, Gao, Kun, and Zheng, Yuanchun (2019). Survey on Classic and Latest Textual Sentiment Analysis Articles and Techniques. *International Journal Of Information Technology and Decision Making*, *18*(4), 1243-1287, ISSN 0219-6220, https://dx.doi.org/10.1142/S0219622019300015

[94] Perles-Ribes, Jose Francisco, Ramon-Rodriguez, Ana Belen, Moreno-Izquierdo, Luis, and Such-Devesa, Maria Jesus (2020). Machine learning techniques as a tool for predictingovertourism: The case of Spain. *International Journal Of Tourism Research*, *22*(6), 825-838, ISSN 1099-2340, https://dx.doi.org/10.1002/jtr.2383

[95] Zhu, Min, Wu, Jinran, and Wang, You-Gan (2021). Multi-horizon accommodation demand forecasting: A New Zealand case study. *International Journal Of Tourism Research*, *23*(3), 442-453, ISSN 1099-2340, https://dx.doi.org/10.1002/jtr.2416

[96] Moreno-Izquierdo, Luis, Egorova, Galina, Pereto-Rovira, Alexandre, and Mas-Ferrando, Adrian (2018). Exploring the use of artificial intelligence in price maximisation in the tourism sector: its application in the case of Airbnb in the Valencian Community. *Investigaciones Regionales-Journal Of Regional Research*(42), 113-128, ISSN 1695-7253

[97] Gu, Qiushi, Zhang, Haiping, Chen, Min, and Chen, Chongcheng (2019). Regionalization Analysis and Mapping for the Source and Sink of Tourist Flows. *Isprs International Journal Of Geo-Information*, *8*(7), https://dx.doi.org/10.3390/ijgi8070314

[98] Sanchez-Franco, Manuel J., Navarro-Garcia, Antonio, and Rondan-Cataluna, Francisco Javier (2019). A naive Bayes strategy for classifying customer satisfaction: A study based on online reviews of hospitality services. *Journal Of Business Research*, *101*, 499-506, ISSN 0148-2963, https://dx.doi.org/10.1016/j.jbusres.2018.12.051

[99] Garner, Benjamin, Thornton, Corliss, Pawluk, Anita Luo, Cortez, Roberto Mora, Johnston, Wesley, and Ayala, Cesar (2022). Utilizing text-mining to explore consumer happiness within tourism destinations. *Journal Of Business Research*, *139*, 1366-1377, ISSN 0148-2963, https://dx.doi.org/10.1016/j.jbusres.2021.08.025

[100] D'Amato, D., Droste, N., Allen, B., Kettunen, M., Laehtinen, K., Korhonen, J., Leskinen, P., Matthies, B. D., and Toppinen, A. (2017). Green, circular, bio economy: A comparative analysis of sustainability avenues. *Journal Of Cleaner Production*, *168*, 716-734, ISSN 0959-6526, https://dx.doi.org/10.1016/j.jclepro.2017.09.053

[101] Nilashi, Mehrbakhsh, Ahani, Ali, Esfahani, Mohammad Dalvi, Yadegaridehkordi, Elaheh, Samad, Sarminah, Ibrahim, Othman, Sharef, Nurfadhlina Mohd, and Akbari, Elnaz (2019). Preference learning for eco-friendly hotels recommendation: A multi-criteria collaborative filtering approach. *Journal Of Cleaner Production*, *215*, 767-783, ISSN 0959-6526, https://dx.doi.org/10.1016/j.jclepro.2019.01.012

[102] Nilashi, Mehrbakhsh, Ibrahim, Othman, Yadegaridehkordi, Elaheh, Samad, Sarminah, Akbari, Elnaz, and Alizadeh, Azar (2018). Travelers decision making using online review in social network sites: A case on TripAdvisor. *Journal Of Computational Science*, *28*, 168-179, ISSN 1877-7503, https://dx.doi.org/10.1016/j.jocs.2018.09.006

[103] Gabriel, I Penagos-Londono,, Rodriguez-Sanchez, Carla, Ruiz-Moreno, Felipe, and Torres, Eduardo (2021). A machine learning approach to segmentation of tourists based on perceived destination sustainability and trustworthiness. *Journal Of Destination Marketing and Management*, *19*, ISSN 2212-571X, https://dx.doi.org/10.1016/j.jdmm.2020.100532

[104] Arabadzhyan, Anastasia, Figini, Paolo, and Vici, Laura (2021). Measuring destination image: a novel approach based on visual data mining. A methodological proposal and an application to European islands. *Journal Of Destination Marketing and Management*, *20*, ISSN 2212-571X, https://dx.doi.org/10.1016/j.jdmm.2021.100611

[105] Tsang, Wai Kit, and Benoit, Dries F. (2020). Gaussian Processes for Daily Demand Prediction. *Journal Of Forecasting*, *39*(3), 551-568, ISSN 0277-6693, https://dx.doi.org/10.1002/for.2644

[106] Huang, Arthur, Chao, Ying, Velasco, Efren de la Mora, Bilgihan, Anil, and Wei, Wei (2022). When artificial intelligence meets the hospitality and tourism industry: an assessment framework to inform theory and management. *Journal Of Hospitality And Tourism Insights*, *5*(5), 1080-1100, ISSN 2514-9792, https://dx.doi.org/10.1108/JHTI-01-2021-0021

[107] Puh, Karlo, and Babac, Marina Bagic (2022). Predicting sentiment and rating of tourist reviews using machine learning. *Journal Of Hospitality And Tourism Insights*, ISSN 2514-9792, https://dx.doi.org/10.1108/JHTI-02-2022-0078

[108] Shehhi, Mohammed Al, and Karathanasopoulos, Andreas (2020). Forecasting hotel room prices in selected GCC cities using deep learning. *Journal Of Hospitality And Tourism Management*, *42*, 40-50, ISSN 1447-6770, https://dx.doi.org/10.1016/j.jhtm.2019.11.003

[109] Aggarwal, Shikha, and Gour, Alekh (2020). Peeking inside the minds of tourists using a novel web analytics approach. *Journal Of Hospitality And Tourism Management*, *45*, 580-591, ISSN 1447-6770, https://dx.doi.org/10.1016/j.jhtm.2020.10.009

[110] Ahani, Ali, Nilashi, Mehrbakhsh, Zogaan, Waleed Abdu, Samad, Sarminah, Aljehane, Nojood O., Alhargan, Ashwaq, Mohd, Saidatulakmal, Ahmadi, Hossein, and Sanzogni, Louis (2021). Evaluating medical travelers' satisfaction through online review analysis. *Journal Of Hospitality And Tourism Management*, *48*, 519-537, ISSN 1447-6770, https://dx.doi.org/10.1016/j.jhtm.2021.08.005

[111] Moro, Sergio, Rita, Paulo, Ramos, Pedro, and Esmerado, Joaquim (2019). Analysing recent augmented and virtual reality developments in tourism. *Journal Of Hospitality And Tourism Technology*, *10*(4), 571-586, ISSN 1757-9880, https://dx.doi.org/10.1108/JHTT-07-2018-0059

[112] Baggio, Rodolfo, Micera, Roberto, and Chiappa, Giacomo Del (2020). Smart tourism destinations: a critical reflection. *Journal Of Hospitality And Tourism Technology*, *11*(3), 559-574, ISSN 1757-9880, https://dx.doi.org/10.1108/JHTT-01-2019-0011

[113] Bagherzadeh, Sayeh, Shokouhyar, Sajjad, Jahani, Hamed, and Sigala, Marianna (2021). A generalizable sentiment analysis method for creating a hotel dictionary: using big data on TripAdvisor hotel reviews. *Journal Of Hospitality And Tourism Technology*, *12*(2), 210-238, ISSN 1757-9880, https://dx.doi.org/10.1108/JHTT-02-2020-0034

[114] Bilotta, Eleonora, Bertacchini, Francesca, Gabriele, Lorella, Giglio, Simona, Pantano, Pietro Salvatore, and Romita, Tullio (2021). Industry 4.0 technologies in tourism education: Nurturing students to think with technology. *Journal Of Hospitality Leisure Sport and Tourism Education*, *29*, ISSN 1473-8376, https://dx.doi.org/10.1016/j.jhlste.2020.100275

[115] Ren, Meng, Vu, Huy Quan, Li, Gang, and Law, Rob (2021). Large-scale comparative analyses of hotel photo content posted by managers and customers to review platforms based on deep learning: implications for hospitality marketers. *Journal Of Hospitality Marketing and Management*, *30*(1), 96-119, ISSN 1936-8623, https://dx.doi.org/10.1080/19368623.2020.1765226

[116] Jaseena, K. U., and Kovoor, Binsu C. (2022). Deterministic weather forecasting models based on intelligent predictors: A survey. *Journal Of King Saud University-Computer And Information Sciences*, *34*(6), 3393-3412, ISSN 1319-1578, https://dx.doi.org/10.1016/j.jksuci.2020.09.009

[117] Akman, Engin, Karaman, Abdullah S., and Kuzey, Cemil (2020). Visa trial of international trade: evidence from support vector machines and neural networks. *Journal Of Management Analytics*, *7*(2), 231-252, ISSN 2327-0012, https://dx.doi.org/10.1080/23270012.2020.1731719

[118] Rios-Morales, Ruth, Gamberger, Dragan, Jenkins, Ian, and Smuc, Tom (2011). Modelling investment in the tourism industry using the World Bank's good governance indicators. *Journal Of Modelling In Management*, *6*(3), 279-296, ISSN 1746-5664, https://dx.doi.org/10.1108/17465661111183694

[119] Sangkaew, Nichapat, and Zhu, Hongrui (2022). Understanding Tourists' Experiences at Local Markets in Phuket: An Analysis of TripAdvisor Reviews. *Journal Of Quality Assurance In Hospitality and Tourism*, *23*(1), 89-114, ISSN 1528-008X, https://dx.doi.org/10.1080/1528008X.2020.1848747

[120] Ahani, Ali, Nilashi, Mehrbakhsh, Yadegaridehkordi, Elaheh, Sanzogni, Louis, Tarik, A. Rashid, Knox, Kathy, Samad, Sarminah, and Ibrahim, Othman (2019). Revealing customers' satisfaction and preferences through online review analysis: The case of Canary Islands hotels. *Journal Of Retailing And Consumer Services*, *51*, 331-343, ISSN 0969-6989, https://dx.doi.org/10.1016/j.jretconser.2019.06.014

[121] Nilashi, Mehrbakhsh, Abumalloh, Rabab Ali, Minaei-Bidgoli, Behrouz, Zogaan, Waleed Abdu, Alhargan, Ashwaq, Mohd, Saidatulakmal, Azhar, Sharifah Nurlaili Farhana Syed, Asadi, Shahla, and Samad, Sarminah (2022). Revealing travellers' satisfaction during COVID-19 outbreak: Moderating role of service quality. *Journal Of Retailing And Consumer Services*, *64*, ISSN 0969-6989, https://dx.doi.org/10.1016/j.jretconser.2021.102783

[122] Pantano, Eleonora, and Dennis, Charles (2019). Store buildings as tourist attractions: Mining retail meaning of store building pictures through a machine learning approach. *Journal Of Retailing And Consumer Services*, *51*, 304-310, ISSN 0969-6989, https://dx.doi.org/10.1016/j.jretconser.2019.06.018

[123] Arora, Anuja, Srivastava, Aman, and Bansal, Shivam (2020). Business competitive analysis using promoted post detection on social media. *Journal Of Retailing And Consumer Services*, *54*, ISSN 0969-6989, https://dx.doi.org/10.1016/j.jretconser.2019.101941

[124] Agarwal, Pragati, Swami, Sanjeev, and Malhotra, Sunita Kumari (2022). Artificial Intelligence Adoption in the Post COVID-19 New-Normal and Role of Smart Technologies in Transforming Business: a Review. *Journal Of Science And Technology Policy Management*, ISSN 2053-4620, https://dx.doi.org/10.1108/JSTPM-08-2021-0122

[125] Filieri, Raffaele, Lin, Zhibin, Li, Yulei, Lu, Xiaoqian, and Yang, Xingwei (2022). Customer Emotions in Service Robot Encounters: A Hybrid Machine-Human Intelligence Approach. *Journal Of Service Research*, *25*(4), 614-629, ISSN 1094-6705, https://dx.doi.org/10.1177/10946705221103937

[126] Jain, Praphula Kumar, Pamula, Rajendra, and Yekun, Ephrem Admasu (2022). A multi-label ensemble predicting model to service recommendation from social media contents. *Journal Of Supercomputing*, *78*(4), 5203-5220, ISSN 0920-8542, https://dx.doi.org/10.1007/s11227-021-04087-7

[127] Rezapouraghdam, Hamed, Akhshik, Arash, and Ramkissoon, Haywantee (2021). Application of machine learning to predict visitors' green behavior in marine protected areas: evidence from Cyprus. *Journal Of Sustainable Tourism*, ISSN 0966-9582, https://dx.doi.org/10.1080/09669582.2021.1887878

[128] Hardy, Anne, and Aryal, Jagannath (2020). Using innovations to understand tourist mobility in national parks. *Journal Of Sustainable Tourism*, *28*(2), 263-283, ISSN 0966-9582, https://dx.doi.org/10.1080/09669582.2019.1670186

[129] Darko, Adjei Peter, and Liang, Decui (2023). A heterogeneous opinion-driven decision-support model for tourists' selection with different travel needs in online reviews. *Journal Of The Operational Research Society*, *74*(1), 272-289, ISSN 0160-5682, https://dx.doi.org/10.1080/01605682.2022.2035274

[130] Samala, Nagaraj, Katkam, Bharath Shashanka, Bellamkonda, Raja Shekhar, and Rodriguez, Raul Villamarin (2022). Impact of AI and robotics in the tourism sector: a critical insight. *Journal Of Tourism Futures*, *8*(1), 73-87, ISSN 2055-5911, https://dx.doi.org/10.1108/JTF-07-2019-0065

[131] Parvez, M. Omar (2021). Use of machine learning technology for tourist and organizational services: high-tech innovation in the hospitality industry. *Journal Of Tourism Futures*, *7*(2), 240-244, ISSN 2055-5911, https://dx.doi.org/10.1108/JTF-09-2019-0083

[132] Li, Gang, Law, Rob, Rong, Jia, and Vu, Huy Quan (2010). INCORPORATING BOTH POSITIVE AND NEGATIVE ASSOCIATION RULES INTO THE ANALYSIS OF OUTBOUND TOURISM IN HONG KONG. *Journal Of Travel and Tourism Marketing*, *27*(8), 812-828, ISSN 1054-8408, https://dx.doi.org/10.1080/10548408.2010.527248

[133] Alaei, Ali Reza, Becken, Susanne, and Stantic, Bela (2019). Sentiment Analysis in Tourism: Capitalizing on Big Data. *Journal Of Travel Research*, *58*(2), 175-191, ISSN 0047-2875, https://dx.doi.org/10.1177/0047287517747753

[134] Kirilenko, Andrei P., Stepchenkova, Svetlana O., Kim, Hany, and Li, Xiang (Robert) (2018). Automated Sentiment Analysis in Tourism: Comparison of Approaches. *Journal Of Travel Research*, *57*(8), 1012-1025, ISSN 0047-2875, https://dx.doi.org/10.1177/0047287517729757

[135] Hoepken, Wolfram, Eberle, Tobias, Fuchs, Matthias, and Lexhagen, Maria (2021). Improving Tourist Arrival Prediction: A Big Data and Artificial Neural Network Approach. *Journal Of Travel Research*, *60*(5), 998-1017, ISSN 0047-2875, https://dx.doi.org/10.1177/0047287520921244

[136] Li, Xin, Li, Hengyun, Pan, Bing, and Law, Rob (2021). Machine Learning in Internet Search Query Selection for Tourism Forecasting. *Journal Of Travel Research*, *60*(6), 1213-1231, ISSN 0047-2875, https://dx.doi.org/10.1177/0047287520934871

[137] Ma, Shihan (David), and Kirilenko, Andrei P. (2020). Climate Change and Tourism in English-Language Newspaper Publications. *Journal Of Travel Research*, *59*(2), 352-366, ISSN 0047-2875, https://dx.doi.org/10.1177/0047287519839157

[138] Zhang, Chengyuan, Li, Mingchen, Sun, Shaolong, Tang, Ling, and Wang, Shouyang (2022). Decomposition Methods for Tourism Demand Forecasting: A Comparative Study. *Journal Of Travel Research*, *61*(7), 1682-1699, ISSN 0047-2875, https://dx.doi.org/10.1177/00472875211036194

[139] Song, Yang, Wang, Runzi, Fernandez, Jessica, and Li, Dongying (2021). Investigating sense of place of the Las Vegas Strip using online reviews and machine learning approaches. *Landscape And Urban Planning*, *205*, ISSN 0169-2046, https://dx.doi.org/10.1016/j.landurbplan.2020.103956

[140] Koranga, Manisha, Pant, Pushpa, Kumar, Tarun, Pant, Durgesh, Bhatt, Ashutosh Kumar, and Pant, R. P. (2022). Efficient water quality prediction models based on machine learning algorithms for Nainital Lake, Uttarakhand. *Materials Today-Proceedings*, *57*, 1706-1712, ISSN 2214-7853, https://dx.doi.org/10.1016/j.matpr.2021.12.334

[141] Anglisano, Anna, Casas, Lluis, Anglisano, Marc, and Queralt, Ignasi (2020). Application of Supervised Machine-Learning Methods for Attesting Provenance in Catalan Traditional Pottery Industry. *Minerals*, *10*(1), https://dx.doi.org/10.3390/min10010008

[142] Thakker, Urvish, Patel, Ruhi, and Shah, Manan (2021). A comprehensive analysis on movie recommendation system employing collaborative filtering. *Multimedia Tools And Applications*, *80*(19), 28647-28672, ISSN 1380-7501, https://dx.doi.org/10.1007/s11042-021-10965-2

[143] Haklidir, Fusun S. Tut, and Haklidir, Mehmet (2020). Prediction of Reservoir Temperatures Using Hydrogeochemical Data, Western Anatolia Geothermal Systems (Turkey): A Machine Learning Approach. *Natural Resources Research*, *29*(4), 2333-2346, ISSN 1520-7439, https://dx.doi.org/10.1007/s11053-019-09596-0

[144] Hussain, Amir, and Cambria, Erik (2018). Semi-supervised learning for big social data analysis. *Neurocomputing*, *275*, 1662-1673, ISSN 0925-2312, https://dx.doi.org/10.1016/j.neucom.2017.10.010

[145] Pan, Yaoru, Flindt, Mogens, Schneider-Kamp, Peter, and Holmer, Marianne (2021). Beach wrack mapping using unmanned aerial vehicles for coastal environmental management. *Ocean and Coastal Management*, *213*, ISSN 0964-5691, https://dx.doi.org/10.1016/j.ocecoaman.2021.105843

[146] Aamer, Ammar Mohamed, Yani, Luh Putu Eka, and Priyatna, I. Made Alan (2021). Data Analytics in the Supply Chain Management: Review of Machine Learning Applications in Demand Forecasting. *Operations And Supply Chain Management-An International Journal*, *14*(1), 1-13, ISSN 1979-3561, https://dx.doi.org/10.31387/oscm0440281

[147] Haas, Andreas F., Guibert, Marine, Foerschner, Anja, Co, Tim, Calhoun, Sandi, George, Emma, Hatay, Mark, Dinsdale, Elizabeth, Sandin, Stuart A., Smith, Jennifer E., Vermeij, Mark J. A., Felts, Ben, Dustan, Phillip, Salamon, Peter, and Rohwer, Forest (2015). Can we measure beauty? Computational evaluation of coral reef aesthetics. *Peerj*, *3*, ISSN 2167-8359, https://dx.doi.org/10.7717/peerj.1390

[148] Wang, Meng (2020). Applying Internet information technology combined with deep learning to tourism collaborative recommendation system. *Plos One*, *15*(12), ISSN 1932-6203, https://dx.doi.org/10.1371/journal.pone.0240656

[149] Xue, Mingqiang, Wu, Huayu, Chen, Wei, Ng, Wee Siong, Goh, Gin Howe, and ACM (2014). Identifying Tourists from Public Transport Commuters. *Proceedings Of The 20th Acm Sigkdd International Conference On Knowledge Discovery And Data Mining (Kdd'14)*, 1779-1788, https://dx.doi.org/10.1145/2623330.2623352

[150] Tsai, Yu Hsin, Stow, Douglas, Chen, Hsiang Ling, Lewison, Rebecca, An, Li, and Shi, Lei (2018). Mapping Vegetation and Land Use Types in Fanjingshan National Nature Reserve Using Google Earth Engine. *Remote Sensing*, *10*(6), https://dx.doi.org/10.3390/rs10060927

[151] Sun, Yanwei, Gao, Chao, Li, Jialin, Wang, Run, and Liu, Jian (2019). Quantifying the Effects of Urban Form on Land Surface Temperature in Subtropical High-Density Urban Areas Using Machine Learning. *Remote Sensing*, *11*(8), https://dx.doi.org/10.3390/rs11080959

[152] Moya, Luis, Perez, Luis R. Marval, Mas, Erick, Adriano, Bruno, Koshimura, Shunichi, and Yamazaki, Fumio (2018). Novel Unsupervised Classification of Collapsed Buildings Using Satellite Imagery, Hazard Scenarios and Fragility Functions. *Remote Sensing*, *10*(2), https://dx.doi.org/10.3390/rs10020296

[153] Claveria, Oscar, Torra, Salvador, and Monte, Enric (2016). Modelling Tourism Demand To Spain With Machine Learning Techniques. The Impact Of Forecast Horizon On Model Selection. *Revista De Economia Aplicada*, *24*(72), 109-132, ISSN 1133-455X

[154] Hakim, Noorkholis Luthfil, Shih, Timothy K., Arachchi, Sandeli Priyanwada Kasthuri, Aditya, Wisnu, Chen, Yi-Cheng, and Lin, Chih-Yang (2019). Dynamic Hand Gesture Recognition Using 3DCNN and LSTM with FSM Context-Aware Model. *Sensors*, *19*(24), https://dx.doi.org/10.3390/s19245429

[155] Sagheer, Alaa, Hamdoun, Hala, and Youness, Hassan (2021). Deep LSTM-Based Transfer Learning Approach for Coherent Forecasts in Hierarchical Time Series. *Sensors*, *21*(13), https://dx.doi.org/10.3390/s21134379

[156] Crivellari, Alessandro, and Beinat, Euro (2020). Trace2trace-A Feasibility Study on Neural Machine Translation Applied to Human Motion Trajectories. *Sensors*, *20*(12), https://dx.doi.org/10.3390/s20123503

[157] Claveria, Oscar, Monte, Enric, and Torra, Salvador (2016). Modelling cross-dependencies between Spain's regional tourism markets with an extension of the Gaussian process regression model. *Series-Journal Of The Spanish Economic Association*, *7*(3), 341-357, ISSN 1869-4187, https://dx.doi.org/10.1007/s13209-016-0144-7

[158] Kesgin, Muhammet, and Murthy, Rajendran S. (2019). Consumer engagement: the role of social currency in online reviews. *Service Industries Journal*, *39*(7), 609-636, ISSN 0264-2069, https://dx.doi.org/10.1080/02642069.2018.1553237

[159] Saura, Jose Ramon, Reyes-Menendez, Ana, and Alvarez-Alonso, Cesar (2018). Do Online Comments Affect Environmental Management? Identifying Factors Related to Environmental Management and Sustainability of Hotels. *Sustainability*, *10*(9), https://dx.doi.org/10.3390/su10093016

[160] Nilashi, Mehrbakhsh, Mardani, Abbas, Liao, Huchang, Ahmadi, Hossein, Manaf, Azizah Abdul, and Almukadi, Wafa (2019). A Hybrid Method with TOPSIS and Machine Learning Techniques for Sustainable Development of Green Hotels Considering Online Reviews. *Sustainability*, *11*(21), https://dx.doi.org/10.3390/su11216013

[161] Tao, Yuguo, Zhang, Feng, Shi, Chunyun, and Chen, Yun (2019). Social Media Data-Based Sentiment Analysis of Tourists' Air Quality Perceptions. *Sustainability*, *11*(18), https://dx.doi.org/10.3390/su11185070

[162] Sun, Yao, Ma, Hang, and Chan, Edwin H. W. (2018). A Model to Measure Tourist Preference toward Scenic Spots Based on Social Media Data: A Case of Dapeng in China. *Sustainability*, *10*(1), https://dx.doi.org/10.3390/su10010043

[163] Lee, Jee Hoon, Wood, Jacob, and Kim, Jungsuk (2021). Tracing the Trends in Sustainability and Social Media Research Using Topic Modeling. *Sustainability*, *13*(3), https://dx.doi.org/10.3390/su13031269

[164] Pasvisheh, Roghayeh Sadeghi, Forio, Marie Anne Eurie, Ho, Long Tuan, and Goethals, Peter L. M. (2021). Evidence-Based Management of the Anzali Wetland System (Northern Iran) Based on Innovative Monitoring and Modeling Methods. *Sustainability*, *13*(10), https://dx.doi.org/10.3390/su13105503

[165] Arreeras, Tosporn, Arimura, Mikiharu, Asada, Takumi, and Arreeras, Saharat (2019). Association Rule Mining Tourist-Attractive Destinations for the Sustainable Development of a Large Tourism Area in Hokkaido Using Wi-Fi Tracking Data. *Sustainability*, *11*(14), https://dx.doi.org/10.3390/su11143967

[166] Cubric, Marija (2020). Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study. *Technology In Society*, *62*, ISSN 0160-791X, https://dx.doi.org/10.1016/j.techsoc.2020.101257

[167] Yadegaridehkordi, Elaheh, Nilashi, Mehrbakhsh, Nasir, Mohd Hairul Nizam Bin Md, Momtazi, Saeedeh, Samad, Sarminah, Supriyanto, Eko, and Ghabban, Fahad (2021). Customers segmentation in eco-friendly hotels using multi-criteria and machine learning techniques. *Technology In Society*, *65*, ISSN 0160-791X, https://dx.doi.org/10.1016/j.techsoc.2021.101528

[168] Zibarzani, Masoumeh, Abumalloh, Rabab Ali, Nilashi, Mehrbakhsh, Samad, Sarminah, Alghamdi, O. A., Nayer, Fatima Khan, Ismail, Muhammed Yousoof, Mohd, Saidatulakmal, and Akib, Noor Adelyna Mohammed (2022). Customer satisfaction with Restaurants Service Quality during COVID-19 outbreak: A two-stage methodology. *Technology In Society*, *70*, ISSN 0160-791X, https://dx.doi.org/10.1016/j.techsoc.2022.101977

[169] Nilashi, Mehrbakhsh, Abumalloh, Rabab Ali, Alghamdi, Abdullah, Minaei-Bidgoli, Behrouz, Alsulami, Abdulaziz A., Thanoon, Mohammed, Asadi, Shahla, and Samad, Sarminah (2021). What is the impact of service quality on customers' satisfaction during COVID-19 outbreak? New findings from online reviews analysis. *Telematics And Informatics*, *64*, ISSN 0736-5853, https://dx.doi.org/10.1016/j.tele.2021.101693

[170] Nilashi, Mehrbakhsh, Asadi, Shahla, Minaei-Bidgoli, Behrouz, Abumalloh, Rabab Ali, Samad, Sarminah, Ghabban, Fahad, and Ahani, Ali (2021). Recommendation agents and information sharing through social media for coronavirus outbreak. *Telematics And Informatics*, *61*, ISSN 0736-5853, https://dx.doi.org/10.1016/j.tele.2021.101597

[171] Tang, Ling, Zhang, Chengyuan, Li, Tingfei, and Li, Ling (2021). A novel BEMD-based method for forecasting tourist volume with search engine data. *Tourism Economics*, *27*(5), 1015-1038, ISSN 1354-8166, https://dx.doi.org/10.1177/1354816620912995

[172] Schwartz, Zvi, Webb, Timothy, Jean-Pierre, I van der Rest,, and Koupriouchina, Larissa (2021). Enhancing the accuracy of revenue management system forecasts: The impact of machine and human learning on the effectiveness of hotel occupancy forecast combinations across multiple forecasting horizons. *Tourism Economics*, *27*(2), 273-291, ISSN 1354-8166, https://dx.doi.org/10.1177/1354816619884800

[173] Bi, Jian-Wu, Han, Tian-Yu, and Li, Hui (2022). International tourism demand forecasting with machine learning models: The power of the number of lagged inputs. *Tourism Economics*, *28*(3), 621-645, ISSN 1354-8166, https://dx.doi.org/10.1177/1354816620976954

[174] Sun, Shaolong, Li, Yanzhao, Guo, Ju-e, and Wang, Shouyang (2022). Tourism demand forecasting: An ensemble deep learning approach. *Tourism Economics*, *28*(8), 2021-2049, ISSN 1354-8166, https://dx.doi.org/10.1177/13548166211025160

[175] Xiang, Zheng, Du, Qianzhou, Ma, Yufeng, and Fan, Weiguo (2017). A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism. *Tourism Management*, *58*, 51-65, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2016.10.001

[176] Sun, Shaolong, Wei, Yunjie, Tsui, Kwok-Leung, and Wang, Shouyang (2019). Forecasting tourist arrivals with machine learning

and internet search index. *Tourism Management*, *70*, 1-10, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2018.07.010

[177] Taecharungroj, Viriya, and Mathayomchan, Boonyanit (2019). Analysing TripAdvisor reviews of tourist attractions in Phuket, Thailand. *Tourism Management*, *75*, 550-568, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2019.06.020

[178] Giglio, Simona, Bertacchini, Francesca, Bilotta, Eleonora, and Pantano, Pietro (2019). Using social media to identify tourism attractiveness in six Italian cities. *Tourism Management*, *72*, 306-312, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2018.12.007

[179] Rong, Jia, Vu, Huy Quan, Law, Rob, and Li, Gang (2012). A behavioral analysis of web sharers and browsers in Hong Kong using targeted association rule mining. *Tourism Management*, *33*(4), 731-740, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2011.08.006

[180] Kaczmarek, Tomasz, Perez, Katarzyna, Demir, Ender, and Zaremba, Adam (2021). How to survive a pandemic: The corporate resiliency of travel and leisure companies to the COVID-19 outbreak. *Tourism Management*, *84*, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2020.104281

[181] Xie, Gang, Qian, Yatong, and Wang, Shouyang (2021). Forecasting Chinese cruise tourism demand with big data: An optimized machine learning approach. *Tourism Management*, *82*, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2020.104208

[182] Arefieva, Veronika, Egger, Roman, and Yu, Joanne (2021). A machine learning approach to cluster destination image on Instagram. *Tourism Management*, *85*, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2021.104318

[183] Law, Rob, Rong, Jia, Vu, Huy Quan, Li, Gang, and Lee, Hee Andy (2011). Identifying changes and trends in Hong Kong outbound tourism. *Tourism Management*, *32*(5), 1106-1114, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2010.09.011

[184] Brida, Juan Gabriel, Lanzilotta, Bibiana, Moreno, Leonardo, and Santinaque, Florencia (2018). A non-linear approximation to the distribution of total expenditure distribution of cruise tourists in Uruguay. *Tourism Management*, *69*, 62-68, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2018.05.006

[185] Zheng, Weimin, Liao, Zhixue, and Lin, Zhibin (2020). Navigating through the complex transport system: A heuristic approach for city tourism recommendation. *Tourism Management*, *81*, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2020.104162

[186] Payntar, Nicole D., Hsiao, Wei-Lin, Covey, R. Alan, and Grauman, Kristen (2021). Learning patterns of tourist movement and photography from geotagged photos at archaeological heritage sites in Cuzco, Peru. *Tourism Management*, *82*, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2020.104165

[187] Li, Hengyun, Ji, Haipeng, Liu, Hongbo, Cai, Danting, and Gao, Huicai (2022). Is a picture worth a thousand words? Understanding the role of review photo sentiment and text-photo sentiment disparity using deep learning algorithms. *Tourism Management*, *92*, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2022.104559

[188] Chen, Shui-xia, Wang, Xiao-kang, Zhang, Hong-yu, Wang, Jian-qiang, and Peng, Juan-juan (2021). Customer purchase forecasting for online tourism: A data-driven method with multiplex behavior data. *Tourism Management*, *87*, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2021.104357

[189] Li, Peizhe, Xiao, Xiao, and Seekamp, Erin (2022). Climate adaptation planning for cultural heritages in coastal tourism destinations: A multi-objective optimization approach. *Tourism Management*, *88*, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2021.104380

[190] Ramos-Henriquez, Jose M., Gutierrez-Tano, Desiderio, and Diaz-Armas, Ricardo J. (2021). Value proposition operationalization in peer-to-peer platforms using machine learning. *Tourism Management*, *84*, ISSN 0261-5177, https://dx.doi.org/10.1016/j.tourman.2021.104288

[191] Zhang, Chengyuan, Wang, Shouyang, Sun, Shaolong, and Wei, Yunjie (2020). Knowledge mapping of tourism demand forecasting research. *Tourism Management Perspectives*, *35*, ISSN 2211-9736, https://dx.doi.org/10.1016/j.tmp.2020.100715

[192] Khorsand, Ramina, Rafiee, Majid, and Kayvanfar, Vahid (2020). Insights into TripAdvisor's online reviews: The case of Tehran's hotels. *Tourism Management Perspectives*, *34*, ISSN 2211-9736, https://dx.doi.org/10.1016/j.tmp.2020.100673

[193] Luo, Yuyan, He, Jinjie, Mou, Yu, Wang, Jun, and Liu, Tao (2021). Exploring China's 5A global geoparks through online tourism reviews: A mining model based on machine learning approach. *Tourism Management Perspectives*, *37*, ISSN 2211-9736, https://dx.doi.org/10.1016/j.tmp.2020.100769

[194] Go, Hanyoung, Kang, Myunghwa, and Suh, SeungBeum Chris (2020). Machine learning of robots in tourism and hospitality: interactive technology acceptance model (iTAM) - cutting edge. Tourism Review, *75*(4), 625-636, ISSN 1660-5373, https://dx.doi.org/10.1108/TR-02-2019-0062

[195] Egger, Roman, and Yu, Joanne (2022). Identifying hidden semantic structures in Instagram data: a topic modelling comparison. *Tourism Review*, *77*(4), 1234-1246, ISSN 1660-5373, https://dx.doi.org/10.1108/TR-05-2021-0244

[196] Wang, Yuan, Zhang, Dongxiang, Liu, Ying, Dai, Bo, and Lee, Loo Hay (2019). Enhancing transportation systems via deep learning: A survey. *Transportation Research Part C-Emerging Technologies*, *99*, 144-163, ISSN 0968-090X, https://dx.doi.org/10.1016/j.trc.2018.12.004

[197] Hasnat, Md Mehedi, and Hasan, Samiul (2018). Identifying tourists and analyzing spatial patterns of their destinations from location-based social media data. *Transportation Research Part C-Emerging Technologies*, *96*, 38-54, ISSN 0968-090X, https://dx.doi.org/10.1016/j.trc.2018.09.006

[198] Gungor, Osman Erman, and Al-Qadi, Imad L. (2018). Developing Machine-Learning Models to Predict Airfield Pavement Responses. *Transportation Research Record*, *2672*(29), 23-34, ISSN 0361-1981, https://dx.doi.org/10.1177/0361198118780681

[199] Taecharungroj, Viriya (2022). An analysis of tripadvisor reviews of 127 urban rail transit networks worldwide. *Travel Behaviour And Society*, *26*, 193-205, ISSN 2214-367X, https://dx.doi.org/10.1016/j.tbs.2021.10.007

[200] Vonk, Erwin, Cirkel, Dirk Gijsbert, and Blokker, Mirjam (2019). Estimating Peak Daily Water Demand under Different Climate

Change and Vacation Scenarios. *Water*, *11*(9), https://dx.doi.org/10.3390/w11091874

[201] Cankurt, S., and Subasi, A. (2015). Developing tourism demand forecasting models using machine learning techniques with trend, seasonal, and cyclic components. Balkan Journal of Electrical and Computer Engineering, 3(1), 42-49.

[202] Kamel, N., Atiya, A. F., El Gayar, N., and El-Shishiny, H. (2008). Tourism demand foreacsting using machine learning methods. ICGST International Journal on Artificial Intelligence and Machine Learning, 8, 1-7.

[203] Egger, R. (2022). Machine Learning in Tourism: A Brief Overview: Generation of Knowledge from Experience. Applied Data Science in Tourism: Interdisciplinary Approaches, Methodologies, and Applications, 85-107.

[204] Leelawat, N., Jariyapongpaiboon, S., Promjun, A., Boonyarak, S., Saengtabtim, K., Laosunthara, A., and Tang, J. (2022). Twitter data sentiment analysis of tourism in Thailand during the COVID-19 pandemic using machine learning. Heliyon, 8(10), e10894.

[205] Das, S., Mondal, S., Puri, V., and Vrana, V. (2022). Structural review of relics tourism by text mining and machine learning. Marketing, 8(2), 25-34.

[206] Afsahhosseini, F., and Al-Mulla, Y. (2020, September). Machine learning in tourism. In 2020 The 3rd International Conference on Machine Learning and Machine Intelligence (pp. 53-57).

[207] Komninos, A., Simou, I., Gkorgkolis, N., and Garofalakis, J. (2019). Performance of raspberry pi microclusters for edge machine learning in tourism. Network (Mbps), 100(100), 100.

[208] Dewangan, A., and Chatterjee, R. (2018). Tourism recommendation using machine learning approach. In Progress in Advanced Computing and Intelligent Engineering: Proceedings of ICACIE 2016, Volume 2 (pp. 447-458). Springer Singapore.

[209] Karakitsiou, A., and Mavrommati, A. (2017). Machine learning methods in tourism demand forecasting: Some evidence from Greece. MIBES Transactions, 11(1), 92-105.

[210] Vijay, J., and Sridhar, R. (2016). A machine learning approach to named entity recognition for the travel and tourism domain. Asian Journal of Information Technology, 15(21), 4309-4317.

[211] Claveria, O., Monte, E., and Torra, S. (2017). Regional tourism demand forecasting with machine learning models: Gaussian process regression vs. neural network models in a multiple-input multiple-output setting. Neural Network Models in a Multiple-Input Multiple-Output Setting.

[212] Buhalis, D., and Amaranggana, A. (2015). Smart tourism destinations enhancing tourism experience through personalisation of services. In Information and Communication Technologies in Tourism 2015: Proceedings of the International Conference in Lugano, Switzerland, February 3-6, 2015 (pp. 377-389). Springer International Publishing.

[213] Doan, A., Madhavan, J., Domingos, P., and Halevy, A. (2004). Ontology matching: A machine learning approach. Handbook on ontologies, 385-403.

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

[215] Buhalis, D. (2020). Technology in tourism-from information communication technologies to eTourism and smart tourism towards ambient intelligence tourism: a perspective article. Tourism Review, 75(1), 267-272.

[216] Navigli, R., Velardi, P., and Gangemi, A. (2003). Ontology learning and its application to automated terminology translation. IEEE Intelligent systems, 18(1), 22-31.

[217] Buhalis, D., Harwood, T., Bogicevic, V., Viglia, G., Beldona, S., and Hofacker, C. (2019). Technological disruptions in services: lessons from tourism and hospitality. Journal of Service Management.

[218] Buhalis, D., and Sinarta, Y. (2019). Real-time co-creation and nowness service: lessons from tourism and hospitality. Journal of Travel and Tourism Marketing, 36(5), 563-582.

[219] Chen, K. Y., and Wang, C. H. (2007). Support vector regression with genetic algorithms in forecasting tourism demand. Tourism management, 28(1), 215-226.

[220] Lu, W., and Stepchenkova, S. (2015). User-generated content as a research mode in tourism and hospitality applications: Topics, methods, and software. Journal of Hospitality Marketing and Management, 24(2), 119-154.

[221] Benckendorff, Pierre J., Zheng Xiang, and Pauline J. Sheldon. Tourism information technology. Cabi, 2019.

[222] Fotiadis, A., Polyzos, S., and Huan, T. C. T. (2021). The good, the bad and the ugly on COVID-19 tourism recovery. Annals of tourism research, 87, 103117.

[223] Fuchs, M., Höpken, W., and Lexhagen, M. (2014). Big data analytics for knowledge generation in tourism destinations–A case from Sweden. Journal of destination marketing and management, 3(4), 198-209.

[224] Tussyadiah, I. (2020). A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism. Annals of Tourism Research, 81, 102883.

[225] Li, X., Pan, B., Law, R., and Huang, X. (2017). Forecasting tourism demand with composite search index. Tourism management, 59, 57-66.

[226] Mariani, M., Baggio, R., Fuchs, M., and Höepken, W. (2018). Business intelligence and big data in hospitality and tourism: a systematic literature review. International Journal of Contemporary Hospitality Management, 30(12), 3514-3554.

[227] Pencarelli, T. (2020). The digital revolution in the travel and tourism industry. Information Technology and Tourism, 22(3), 455-476.

[228] 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.

[229] Sigala, M. (2018). New technologies in tourism: From multi-disciplinary to anti-disciplinary advances and trajectories. Tourism management perspectives, 25, 151-155.

[230] Xiang, Z. (2018). From digitization to the age of acceleration: On information technology and tourism. Tourism management perspectives, 25, 147-150.

[231] García-Crespo, A., Chamizo, J., Rivera, I., Mencke, M., Colomo-Palacios, R., and Gómez-Berbís, J. M. (2009). SPETA: Social pervasive e-Tourism advisor. Telematics and informatics, 26(3), 306-315.

[232] Aggarwal, C. C. (2018). Neural networks and deep learning. Springer, 10(978), 3.

[233] Ekman, M. (2021). Learning deep learning: theory and practice of neural networks, computer vision, NLP, and transformers using TensorFlow.

[234] Khan, M. A., Ali, M., and Khan, M. A. (2021). Systematic Review of Contextual Suggestion and Recommendation Systems for Sustainable e-Tourism. Sustainability, 13(15), 8141. https://doi.org/10.3390/su13158141.

[235] Putra, I. G. N. A. W., Kadyanan, I. G. A. G. A. (2021). Optimization Of Bali Tourism Recommendations Based On Personal Motivation Of Tourists Using the Naive Bayes Algorithm. JLK, 1(10), 83. https://doi.org/10.24843/jlk.2021.v10.i01.p11.

[236] J. Srisuan and A. Hanskunatai, "The ensemble of Naïve Bayes classifiers for hotel searching," 2014 International Computer Science and Engineering Conference (ICSEC), Khon Kaen, Thailand, 2014, pp. 168-173, doi: 10.1109