A critical reflection on analytics and artificial intelligence based analytics in hospitality and tourism management research

Article

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A Critical Reflection on Analytics and Artificial Intelligence based Analytics in Hospitality and Tourism Management Research

Abstract

Purpose – This work consists of a critical reflection on the extent to which hospitality and tourism management scholars have accurately used the term 'analytics' and its five types (i.e., descriptive, exploratory, predictive, prescriptive, and cognitive analytics) in their research. Only cognitive analytics, the latest and most advanced type, is based on artificial intelligence (AI) and requires machine learning (ML). As cognitive analysis constitutes the cutting edge in industry application, we examine in depth the extent *cognitive analytics* has been covered in the literature.

Design/methodology/approach – This study is based on a systematic literature review (SLR) of the hospitality and tourism literature on the topic of 'analytics'. Our SLR findings were complemented by the results of an additional search query based on "machine learning" and "deep learning" that was used as a robustness check. Moreover, the SLR findings were triangulated with recent literature reviews on related topics (e.g., big data and AI) to generate additional insights.

Findings – Our finding show that: (1) there is a growing and accelerating body of research on analytics; (2) the literature lacks a consistent use of terminology and definitions related to analytics. Specifically, publications rarely use scientific definitions of analytics and their different types; (3) although AI and ML are key enabling technologies for cognitive analytics, hospitality and tourism management research did not explicitly link these terms to analytics and did not distinguish cognitive analytics from other forms of analytics that do not rely on ML. In fact, the term 'cognitive analytics' is apparently missing in the hospitality and tourism management literature.

Research limitations/implications – We generate a set of eight theoretical and three practical implications and advance theoretical and methodological recommendations for further research.

Originality/value – This is the first study that explicitly and critically examines the use of analytics in general, and cognitive analytics in particular, in the hospitality and tourism management literature.

Keywords: Analytics; cognitive analytics; artificial intelligence; big data; hospitality; tourism.

Paper type: Critical reflection paper.

1. Introduction

Advancement in digital technologies has engendered a digital transformation of business activities and enabled the fourth industrial revolution (Schwab, 2017). Propelled by data and data capabilities, algorithmic models have been developed by computer engineers and scientists in the broad area of data science to generate data analytics that support policy makers, business leaders and managers in their decisions.

Over the last decade, hospitality and tourism firms and their services have been profoundly modified by analytics which has been defined as "the scientific process of transforming data into insight for making better decisions" (Boyd, 2012, p. 1). The growing importance of analytics in the hospitality and tourism sectors is reflected by the increasing number of conceptual and empirical studies that have been published. These mostly relied on two specific forms of analytics: descriptive and predictive analytics (Mariani and Baggio, 2022). Despite recent intellectual efforts aimed at providing an overview of analytics covering studies published until 2020 (e.g., Mariani and Baggio, 2022), we still do not know (1) how hospitality and tourism management scholars define analytics, (2) what types of analytics they refer to in their research, and (3) the extent to which the analytics produced or discussed are related to artificial intelligence (AI) and machine learning (ML).

To bridge those knowledge gaps, this critical reflection paper sets out to achieve two objectives to understand: (1) if and to what extent analytics has been accurately and consistently defined in the hospitality and tourism management literature; and (2) if and to what extent cognitive analytics has been explicitly researched. The latter type is the most advanced type of analytics and is the only one based on AI and ML (Hair et al., 2022). By addressing these issues, hospitality and tourism management scholars can build a more consistent and connected body of knowledge on analytics and gain awareness of the most advanced type of analytics: cognitive analytics. Consequently, this study aims to answer the following two inter-related research questions:

RQ1: Have analytics been accurately and consistently defined in hospitality and tourism management research?

RQ2: Has *cognitive analytics*, the most advanced type of analytics, and the only one based on AI and ML, been analyzed explicitly in hospitality and tourism management research?

To address our research questions, we have conducted a systematic literature review (SLR) of the hospitality and tourism management literature on the topic of 'analytics' published until July 2022. Our SLR findings were complemented by the results of an additional search query based on "machine learning" and "deep learning" that was used as a robustness check. Moreover, the SLR findings were triangulated with recent literature reviews on related topics (e.g., big data and AI) to generate additional insights.

2. Conceptual underpinnings and recent debate on analytics and AI-based analytics

2.1 Analytics

The etymology of the word analytics stems from the ancient Greek word *analȳtikós* which literally means "pertaining to analysis". The underlying concept is rooted in logic and mathematics and was discussed by Aristotle in two treatises that are part of the collection titled *Organon* (Smith, 2018). Analytics differ from analysis as the former represents a body of knowledge and principles. While analytics has a long tradition in mathematics, it has become increasingly relevant in management and data science over the last few decades to the point that the Institute for Operations Research and the Management Sciences (INFORMS), an international society for practitioners in the fields of operations research, management science, and analytics, engaged with its members to provide a precise and today widely accepted definition. The definition was published in 2012 and reads as follows: "analytics is the scientific process of transforming data into insight for making better decisions" (Boyd, 2012, p. 1).

As clarified by several management scholars, data (be them small or big) are not sufficient to help managers extract meaningful insights and solve real world business problems (Davenport, 2006). Accordingly, managers should focus on *data analytics* as a holistic process to access, warehouse, analyze and interpret data (Mariani and Wamba, 2020; Wamba et al., 2020) rather than on the quantity of data itself. Modern analytics has been traditionally classified into four categories by hospitality and tourism management scholars: descriptive, exploratory, predictive, and prescriptive analytics (Mariani and Baggio, 2022). A recent SLR on big data and analytics in the context of hospitality and tourism management (Mariani and Baggio, 2022) found that the majority of scholars examined descriptive and exploratory analytics, while a smaller share used predictive analytics. Interestingly, this literature review also found that hospitality and tourism scholars very rarely labelled the type of analytics they examined in their studies.

Analytics is a fast-paced and competitive field in business (Davenport, 2006) that increasingly relies on advanced technologies such as AI and ML as reviewed in the next subsection.

2.2 Analytics, AI, and ML

While researchers do not agree on who was the first scholar working on AI, there is more consensus of when AI was first described. This was not a scientific article, but the fiction book '*Runaround'* published in 1942 by American author Isaac Asimov. Fifteen years later, scientists Marvin Minsky and John McCarthy hosted the Dartmouth summer research project on AI at Dartmouth College, USA (Haenlein and Kaplan, 2019). In the following years up until 2010, AI received relatively low levels of attention by both computer scientists and management scholars. However, in the last ten years, interest in AI by researchers and the public press has been growing exponentially.

Researchers recognized that AI has important implications for business (Davenport and Ronanki, 2018; Mariani and Nambisan, 2021; Mariani et al., 2022) and takes on three different forms that are especially relevant for services, including hospitality and tourism. They are: mechanical, thinking and feeling AI that are related to routine, rule-based, and emotional tasks, respectively (Huang and Rust, 2020). Mechanical AI (e.g., in the guise of robots) and thinking AI (e.g., in the form of conversational agents) are being progressively introduced into the operations of hospitality and tourism firms (Borghi and Mariani, 2021; Pitardi et al., 2022; Tussyadiah, 2020; Wirtz et al., 2018). Two recent literature reviews and bibliometric studies (Doborjeh et al., 2022; Huang et al., 2021) have provided an overview of hospitality and tourism management research covering AI. However, neither of those studies has critically assessed the relationship between analytics and AI.

The latest and most advanced type of analytics is *cognitive analytics* (Hair et al., 2022). Cognitive analytics is typically associated with a cognitive system. A cognitive system is a computational system that resembles the human brain and has the capability to *learn* from data and through experience, make decisions based on data and experience, and process natural language. Cognitive analytics cannot exist without AI and ML. Indeed, cognitive analytics are designed to mimic human-like intelligence for certain tasks and "uses machine learning to understand new data and patterns that have never been identified" before (Hair et al., 2022, p. 67). ML "addresses the question of how to build computers that improve automatically through experience. It is one of today's most rapidly growing technical fields, lying at the intersection of computer science and statistics, and at the core of artificial intelligence and data science." (Jordan and Mitchell, 2015, p. 255).

Cognitive analytics is used by cognitive systems to make decisions and communicate them (in natural language) to humans. Cognitive analytics is superior to the other forms of analytics (i.e., descriptive, exploratory, predictive, and prescriptive) as it implies a higher level of data management maturity which is conducive to higher levels of competitive advantage (Hair et al., 2022). As has been shown in recent research (Hair et al., 2022), there is a progression in modern analytics from descriptive to cognitive analytics (see Figure 1).

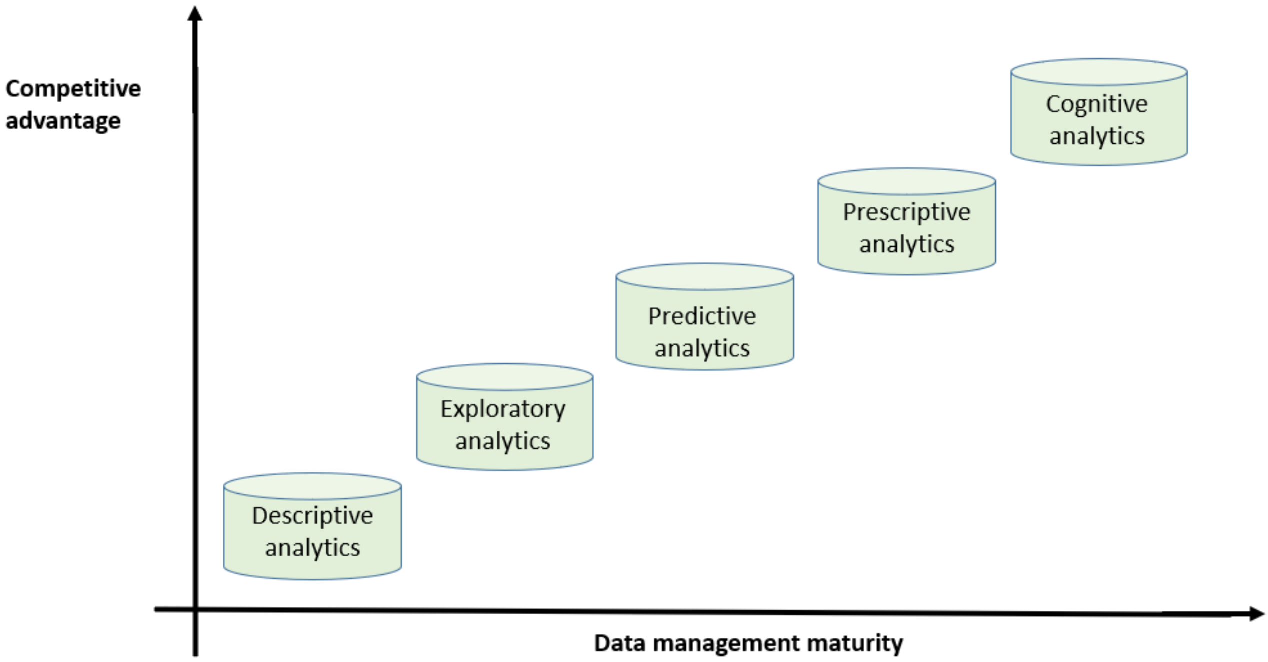

Fig. 1 – Types of analytics. Source: adapted from Hair et al. (2022)

Based on the definitions advanced by Hair et al. (2022), descriptive analytics entails descriptive statistics, data visualization, and data query. Exploratory analytics entails cluster analysis, and factor analysis. Predictive analytics entails forecasting techniques, predictive modelling, and association rules. Prescriptive analytics includes optimization modelling and decision analysis techniques. Finally, cognitive analytics entails data pattern discovery techniques, image, and text and speech recognition techniques (see Table 1 for the definitions). Examples of cognitive analytics applications include: (1) data pattern discovery techniques deployed by IBM Cognos to understand customer purchasing patterns and optimize inventory levels at Pebble Beach Resort in Monterrey, California (Hair et al., 2022); (2) the onCall AI system in retailing employed by the retailer Macy's to answer shoppers' questions and guide them in the store.

Table 1. Definitions of key terms.

Term	Definition
Analytics	"Analytics is the scientific process of transforming data into insight for making better decisions" (Boyd, 2012, p. 1).
Data	"Data is facts and figures collected, organized, and presented for analysis and interpretation. Data is available in two main forms: structured and unstructured" (Hair et al., 2022, p. 13).
Big data	"High volume, velocity and variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision-making" (Beyer and Laney, 2012, p.1).
Artificial intelligence (AI)	AI is "the use of computational machinery to emulate capabilities inherent in humans, such as doing physical or mechanical tasks, thinking, and feeling" (Huang and Rust, 2021, p.31)
Machine learning (ML)	"Machine learning addresses the question of how to build computers that improve automatically through experience." It lies "at the intersection of computer science and statistics, and at the core of artificial intelligence and data science" (Jordan and Mitchell, 2015, p. 255). ML is used by cognitive analytics and none of the lower-level types of analytics.
Descriptive analytics	"Descriptive analytics are a set of techniques used to explain or quantify the past." "Examples of descriptive analytics include data queries, visual reports, and descriptive statistics" (Hair et al., 2022, p. 5).
Exploratory analytics	Exploratory analytics are a set of techniques used to explore and understand the data. Examples of those techniques include cluster and factor analysis (Hair et al., 2022).
Predictive analytics	Predictive analytics are a set of techniques "used to build models based on the past to explain the future. Mathematical models examine historical data to predict new values, needs and opportunities" (Hair et al., 2022, p. 6).
Prescriptive analytics	Prescriptive analytics are a set of techniques used to identify "the best optimal course of action" and entail optimization modelling and decision analysis techniques (Hair et al., 2022, p. 6).
Cognitive analytics	"Cognitive analytics use machine learning to understand new data and patterns that have never been identified" (Hair et al., 2022, p. 6). As such, it is the only type of analytics that relies entirely on AI and ML.

3. Research design and data collection

We conducted a systematic literature review (SLR) to understand to what extent analytics has been accurately and consistently defined in hospitality and tourism management research and if *cognitive analytics* has been analyzed explicitly. In particular, we examined articles indexed in two leading academic databases: Elsevier Scopus and Clarivate Web of Science. The two databases were chosen as they have been widely adopted in prior academic research (Liñán & Fayolle, 2015; Zupic & Čater, 2015) and are considered the most comprehensive sources of studies in the social sciences (Mongeon & Paul-Hus, 2016).

The SLR methodology was adopted as it has important advantages over narrative literature review: it follows a replicable method that makes it objective, and it is holistic as it captures quantitatively the body of research of interest (e.g., Tanfield *et al*., 2003). This approach is particularly suitable to address our research questions as it allows capturing quantitatively the research on analytics in general and cognitive analytics in particular.

We developed a search protocol to gather the data. First, consistent with past research on the topic (e.g., Mariani *et al*., 2022), we built search queries using a combination of the focal keyword "analytics" with the hospitality and tourism words "*hospitality", "hotel", "touris*", "travel*", "leisure"* in the title, abstract, and keywords. Second, we retained only articles written in English and pertaining to the domains of business and management, decision sciences, and social sciences. Third, the data used for this study cover all articles in the analyzed databases until July 31, 2022. Fourth, we dropped articles that did not directly pertain to the topic of the analysis and eliminated duplicate records. This yielded a combined dataset containing 583 articles. Finally, and different from the approach taken by Mariani & Baggio (2022), we only retained articles published in hospitality and tourism journals, resulting in our final sample of 141 articles. The search protocol followed, with details of exclusion criteria, is synthesized in Figure 2. The final sample was then analyzed in Excel.

As cognitive analytics is the only type of analytics using ML (a subfield of AI), we also built a second independent search query based on "machine learning" and "deep learning" that was used as a robustness check for the SLR. More specifically, we conducted a query using a combination of the keywords "machine learning" or "deep learning" on one hand, with the hospitality and tourism words "*hospitality", "hotel", "touris*", "travel*", "leisure"* in the title, abstract, and keywords. As in the previous main query focused on "analytics", we retained only articles written in English and pertaining to the domains of business and management, decision sciences, and social sciences. After dropping articles that did not directly pertain to analytics and were not published in hospitality and tourism journals, the second query generated a sample of 159 articles whose analysis was used as a robustness check to enrich the interpretation of the findings of the main SLR.

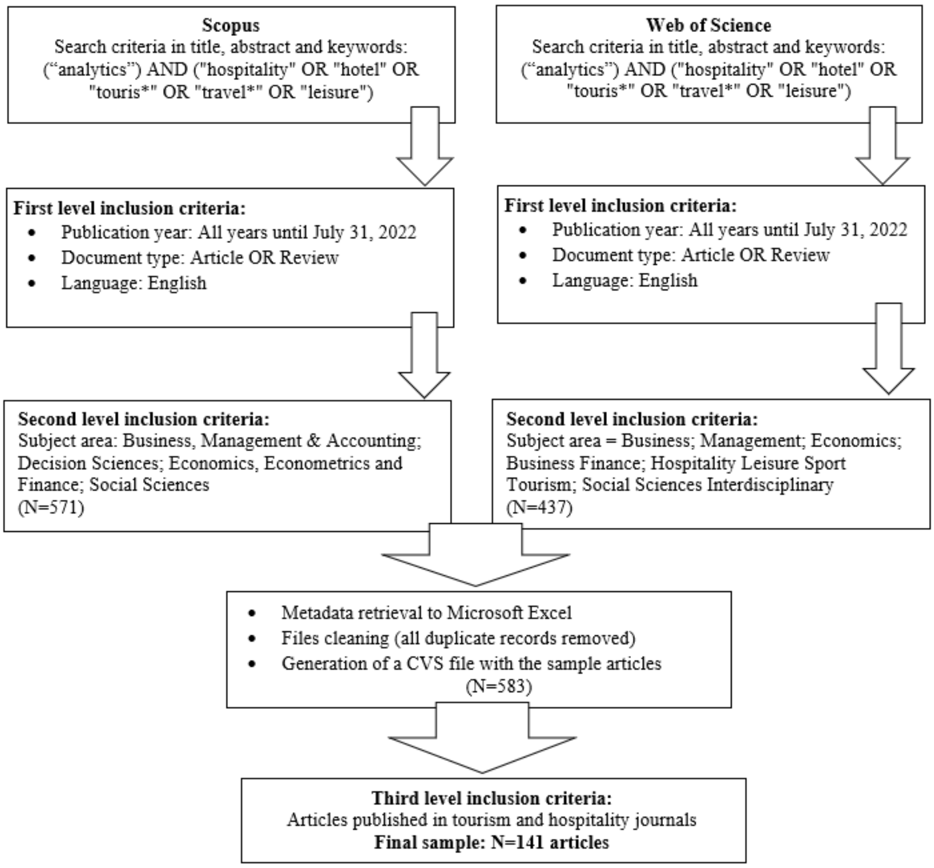

Fig. 2 – Search protocol and sampling process for the SLR (main query related to "analytics")

4. Results and discussion

Our analysis shows that there is an exponential growth of articles published in hospitality and tourism academic journals on the topic of "analytics". The number of articles published grew by 12 times from 2015 to 2022 with an acceleration in 2019 (see Figure 3).

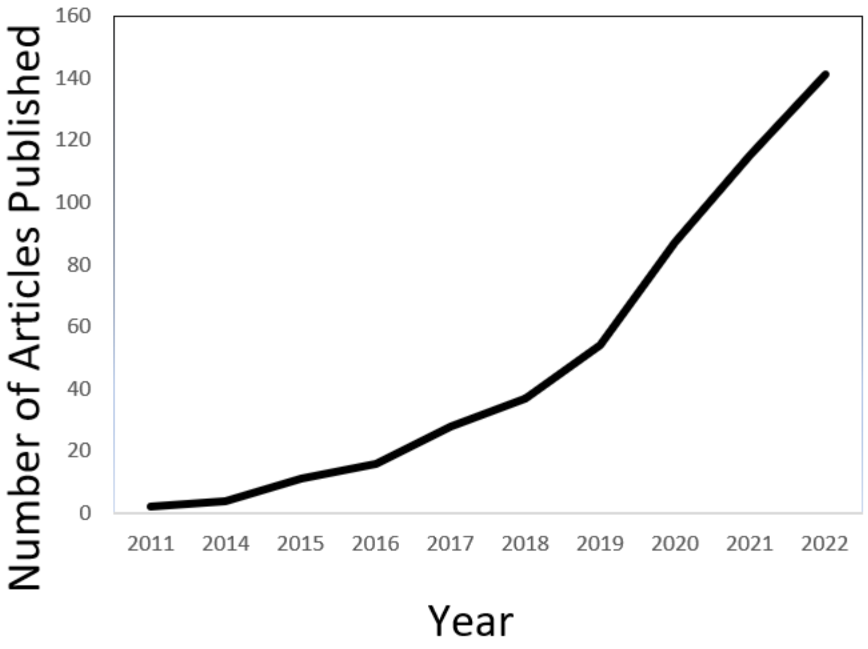

Figure 3. Cumulative distribution of the number of articles on “analytics”

The journals with the highest share of articles (see Table 2) are, as expected, the leading journals in the field with the top three positions held by *Tourism Management*, *International Journal of Contemporary Hospitality Management*, and *International Journal of Hospitality Management*.

Table 2. Journals with the highest number of publications on analytics

Rank	Journal	N
1	*Tourism Management*	16
2	*International Journal of Contemporary Hospitality Management*	14
3	*International Journal of Hospitality Management*	10
4	*Current Issues in Tourism*	9
5	*Tourism Review*	8
6	*Annals of Tourism Research*	6
7	*Journal of Travel and Tourism Marketing*	6
8	*Journal of Travel Research*	5
9	*Journal of Destination Marketing and Management*	5
10	*African Journal of Hospitality, Tourism and Leisure*	5

Following past research, we examined the titles, abstracts and keywords before reading the articles in depth (Mariani *et al.*, 2022). This approach is considered effective for extrapolating the dominant topics and issues covered in a body of literature (e.g., Mariani *et al*., 2018). A list of the 20 most frequent terms (single words and 2-grams) contained in the corpus is reported in Table 3.

Table 3 - Most frequently used words and 2-grams in the title, abstract and key words, and mentions

	Keywords			2-grams		
Rank	**Term**	**N**	**Ave per article**	**Term**	**N**	**Ave per article**
1	data	317	2.3	big - data	98	0.7
2	tourism	278	2.0	social - media	94	0.7
3	study	202	1.4	data - analytics	52	0.4
4	research	183	1.3	online - reviews	42	0.3
5	analytics	170	1.2	design - methodology	38	0.3
6	analysis	128	0.9	methodology - approach	38	0.3
7	destination	122	0.9	originality - value	38	0.3
8	online	120	0.9	hospitality - tourism	34	0.2
9	reviews	116	0.8	media - analytics	27	0.2
10	social	116	0.8	tourism - industry	22	0.2
11	hospitality	109	0.8	practical - implications	22	0.2
12	big	104	0.7	user - generated	21	0.1
13	media	98	0.7	machine - learning	21	0.1
14	findings	96	0.7	destination - management	19	0.1
15	hotel	96	0.7	purpose - paper	18	0.1
16	paper	82	0.6	relationship - between	17	0.1
17	using	78	0.6	study - aims	17	0.1
18	approach	77	0.5	customer - satisfaction	17	0.1
19	tourists	74	0.5	destination - image	17	0.1
20	customer	74	0.5	business - intelligence	15	0.1

Note: N refers to the number of times a keyword or 2-gram was mentioned. Ave per article refers to the average times a keyword or 2-gram was mentioned in the title, abstract, and keywords of the articles. For instance, the keyword "data" is mentioned on average 2.3 times in each paper belonging to the final sample.

As can be seen in Table 3, "data" play a key role in analytics research; it is mentioned on average 2.3 times in the title, abstract, and keywords of each article. This finding is consistent with the INFORMS definition of analytics as "the scientific process of transforming data into insight for making better decisions" (Boyd, 2012, p. 1). Interestingly, the most common 2-grams include "big data", "social media", "data analytics," and "online reviews". These findings suggest that sources of analytics studies include big data, especially related to social media and online reviews, which is consistent with recent research. For example, Liu and Beldona (2021) found that social media are a main source of data, and Mariani and Baggio (2022) emphasized that user generated content (UGC) is the dominant type of data in big data and analytics studies. Furthermore, cognitive analytics did not emerge as a 2-gram in the analysis, suggesting that this term is not used in articles dealing with analytics.

Next, we read the full texts of the articles. We found that only a few articles explicitly defined their interpretation of analytics and the specific type of analytics used (i.e., labelled the type of analytics examined as descriptive, exploratory, predictive, prescriptive, or cognitive analysis). This was the case even when an article clearly referred to a specific type such as "descriptive" (e.g., Lee et al., 2021).

Next, we searched for the term 'cognitive analytics' and did not find a single mention of it in any of the articles. However, in 19 articles (13.5% of the sample) the authors mentioned that they used some forms of ML in the analysis (e.g., Gur et al., 2021). As a robustness check, to determine if scholars working with ML simply omitted to define and use the term 'analytics', we developed a further query using the keywords "machine learning" OR "deep learning" matched with the hospitality and tourism words "*hospitality", "hotel", "touris*",* "*travel*", and "leisure"* in the title, abstract, and keywords and identified 159 articles (some of them overlapping with the articles generated by our main query represented in Figure 1). Those articles deploy some form of ML to obtain their results, but do not use the term "analytics" explicitly (e.g., Li et al., 2022) and in most of the cases (85.5%) they do not even use the term artificial intelligence (e.g., Huang et al., 2022). This suggests that scholars generating ML- and AI-based analytics in hospitality and tourism either do not mention the word "analytics" at all or do not label them as "cognitive analytics" and, in most of the cases, they do not even use the term "artificial intelligence". There might be two different reasons why hospitality and tourism management scholars deploying ML methods and techniques do not use the term "cognitive analytics": they ignore the term, or they take it for granted. Either way, they do not make explicit if and how ML – which is a subfield of AI – can power analytics to generate an advanced form of analytics such as cognitive analytics.

5. Conclusions and implications

5.1 Conclusions

This study yielded the following key findings. First, there is a growing body of hospitality and tourism management research on analytics, which has further accelerated from 2019 onwards. Second, we found that very rarely scholars provide a scientific based definition of analytics examined in their research. Specifically, analytics are seldom labelled with reference to their type examined in an article (e.g., whether it is descriptive, exploratory, predictive, prescriptive, or cognitive analytics). Third, cognitive analytics is missing in the terminology deployed by hospitality and tourism management scholars. However, there is a growing body of research that leverages ML to analyze data and therefore it seems that several scholars (e.g., Li et al., 2022) are working *de facto* in the field of cognitive analytics but do not use the label 'cognitive', or simply are not aware of this terminology. Fourth, neither AI nor ML are explicitly linked to analytics. The reasons might be that: (1) cognitive analytics represents a frontier in AI research (Hair et al., 2022; Rousopoulou et al., 2020) and has not yet been on the radar of tourism and hospitality management researchers; or, more likely, (2) that scholars take for granted that the outcome of ML is some form of analytics without further labelling it. Overall, and in response to our research questions, (1) analytics has not been accurately and consistently defined in hospitality and tourism management research; and (2) *cognitive analytics*, the most advanced type of analytics, has not been examined explicitly in hospitality and tourism management research.

5.2 Theoretical implications

Several research implications originate from this study. First, compared to a recent literature review (Mariani and Baggio, 2022) that showed that a growing number of hospitality and tourism management scholars were dealing with both big data and data analytics until 2020, our study clarifies that there is a discernible growth also in the narrower area of data analytics. By extending recent reviews on big data in hospitality and tourism (Mariani and Baggio, 2022; Stylos et al, 2021; Zarezadeh et al., 2022), this finding suggests that data analytics is and will be of interest, regardless of developments in big data as analytics pertain to any size of data.

Second, despite the concept of analytics is rooted in logic and mathematics (Smith, 2018) and in computer and data science (Boyd, 2012), and has been defined and discussed in depth in those disciplines, hospitality and tourism management scholars rarely put forward the definition of analytics they use in their studies. Consequently, we encourage those scholars to adopt the definition developed by Andrew Boyd (2012) that was later endorsed by INFORMS. Accordingly, analytics should be defined as “the scientific process of transforming data into insight for making better decisions” (Boyd, 2012, p. 1). We suggest that authors who want to deviate from this definition might want to clarify their definition explicitly and back it with appropriate reasoning and literature. This would translate into a more consistent use of terminology and should be conducive to a more integrated and connected body of knowledge on analytics.

Third, our study corroborates the findings of a recent literature review on big data and analytics which found that “authors themselves seldom label the analytics in their study” (Mariani and Baggio, 2022, p. 267). This issue seems worrying as it prevents readers and scholars to get the definitional clarity needed to position their study in the ongoing debate on analytics. Therefore, we encourage hospitality and tourism management scholars to specify the type of analytics they refer to in their work by relying on the typology proposed in the recent analytics literature (e.g., Hair et al., 2022). Specifically, it recognizes at least five types of analytics: descriptive, exploratory, predictive, prescriptive, and cognitive analytics. For instance, the growing number of scholars using sentiment analysis (for a recent review see Mehraliyev et al., 2022) might want to define the type of sentiment analytics they deploy in their method section.

Fourth, ‘cognitive analytics’ seems missing in the terminology deployed by hospitality and tourism management scholars. Cognitive analytics is ML-based analytics, but hospitality and tourism literature leveraging on ML has not linked it back explicitly to cognitive analytics. Therefore, the term ‘cognitive analytics’ is not used probably because scholars take it for granted or because they ignore it. It is likely that they ignore it as cognitive analytics is an emerging term and represents an advanced frontier of research that has received attention only in the last few years (Hair et al., 2022). Regardless of the reason, we encourage scholars to embrace the term (Hair et al., 2022) and specify clearly if the analytics they are dealing with are ML-based and, if possible, to label them as ‘cognitive analytics’ or at least ‘ML-based analytics’ or ‘AI-based analytics’. This might be useful as it would convey the idea that a superior level of data management maturity was required to generate such analytics.

Fifth, as cognitive analytics is the only type of analytics relying on ML, it is also the only type of analytics whose sole purpose is feeding cognitive systems. Despite recent work that has reviewed advanced AI methods used in hospitality and tourism (i.e., ML, artificial neural networks, and deep learning algorithms, and ML applications), the nexus between cognitive analytics and ML is still largely unexplored and not made explicit. For example, a recent review article (Doborjeh et al., 2022) mentions the term ‘analytics’ only in passing in the introduction and is not further linked to ML methods and applications in the rest of the article. It would be worthwhile to see a growing number of hospitality and tourism scholars who use ML in their empirical research to make clear a connection between the ML methods and techniques they use and the specific type of analytics they examine. A more precise and accurate way of labelling ML-based analytics and ML techniques might clarify their work also for analytics-uninitiated readers. From a theoretical point of view, to conceptualize more thoroughly the relationship between analytics and AI (namely analytics and ML) in hospitality and tourism settings, scholars might draw on information management and information systems frameworks and theories for further theory development. It also helps empirical researchers to clarify the theoretical assumptions that guide their analyses, and also when the use of data analytics is linked to a specific theory (the only study linking analytics to a specific theory was developed by Berente *et al*., 2018). In a nutshell, we encourage scholars to discuss more critically key challenges and opportunities related to the symbiotic relationship between analytics and AI.

Sixth, hospitality and tourism management scholars tend to associate cognitive systems mainly to robots. However, robots are only one of the possible forms of cognitive systems since ML, deep learning, natural language processing (NLP), and computer vision can take place also in other AI applications. Since cognitive analytics stems from a combination of ML, deep learning, natural language processing (NLP), and computer vision that allow cognitive systems to learn, make decisions, and communicate them (in natural language) to humans, a more fruitful dialogue should be fostered between computer and data scientists on the one hand, and hospitality and tourism management scholars on the other, to give the letter a broader understanding of cognitive analytics. In synthesis, cognitive analytics are not only confined to robots. Accordingly, we suggest that academic circles should draw more precise distinctions when they use terms such as analytics, big data, AI, and robots to more accurately reflect the terminology used in information systems and information management research.

Seventh, while hospitality and tourism firms increasingly use cognitive systems, there is a dearth of information system management research within hospitality and tourism management on the analytics that feed those cognitive systems. This is something that should be tackled as scholars need to cross pollinate information systems and management research if they want to gain a better understanding of how analytics can enhance human-cognitive systems interactions (c.f. Wirtz et al., 2022).

Last, it seems that basic definitions of established and emerging digital technologies are not clear and well understood by hospitality and tourism management scholars (Mariani et al., 2021). More specifically, it is not clear: (1) how hospitality and tourism management scholars define analytics; (2) what types of analytics they refer to; and (3) the extent to which the analytics produced or discussed are related to ML. The inconsistent use of terms and definitions might generate confusion and ultimately prevent from building a shared scientific language and a consistent, meaningful, and linked up body of knowledge. To address this issue, inter- and multi-disciplinary cooperation might be effective. We therefore recommend academic departmental subject leaders in hospitality and tourism management to forge partnerships with scholars in data and computer science departments to encourage their teams to absorb the key notions and concepts and gain a flavor of the technical features of important and emerging digital technologies.

5.3 Practical implications

This study generates several practical implications. First, hyper competition between hospitality and tourism firms is urging them to adopt AI and all types of analytics to achieve efficiency while pursuing effectiveness (Wirtz and Zeithaml, 2018). However, this trend is more visible in large hospitality and travel firms that have set up specific organizational and functional roles dealing with analytics and AI (e.g., Chief Data Officers, Head of Analytics and Data, and Head of AI solutions; Bornet et al. 2021). However, SMEs in hospitality and tourism lag behind and often do not exploit the full potential of cognitive analytics to empower their AI applications and extract the most out of their investments in digital technology. We recommend SMEs to explore the adoption of third-party solutions of AI and cognitive analytics that increasingly become democratized, that is, they become cheaper (often freeware) and increasingly easy to implement with the promise of plug and play.

Second, a common issue hospitality and tourism organizations face when embarking on analytics and AI investments is that they tend to think in a monadic way and ignore other stakeholders at the destination level. For this reason, analytics and AI vendors tend to sell stand-alone solutions that are typically not integrated into larger destination ecosystems. This represents a limitation as hospitality and tourism firms miss the opportunity to leverage on data and analytics of other organizations and learn from them to improve their own applications and services. We recommend destination management organizations (DMOs) that increasingly invest in destination management systems should lobby with the local professional associations to convince these individual players to participate in the wider ecosystems. For instance, the Italian region of Lombardy launched the Digital Ecosystem E015 that allows destination stakeholders to share data and analytics through APIs and learn from each other. Specifically, participating firms use cloud-based software as a service (SaaS) that is fed data by all the stakeholders in the ecosystem. Ultimately, pooled cognitive analytics should develop their business models and ensure that their analytics and AI-empowered value propositions complement each other and enlarge the overall value created and captured by the ecosystem.

Finally, while there is a number of specialized firms (such as Savioke/Relay for AI, and robotics solutions and STR for business intelligence and analytics) that are supporting digitized operations and analytics-based decision making at the sector level, it seems that not all big tech companies that have competence in the area of cognitive systems and analytics (e.g., Alphabet, Microsoft, and Apple) are as active as some of their competitors (e.g. IBM) in developing cognitive systems for hospitality and tourism client firms. More intense cooperation between big tech companies and hospitality and tourism client firms should be encouraged as it could generate positive outcomes for hospitality and tourism industries.

5.4 Limitations and future research

This work is not without limitations. First, our SLR was limited to the Scopus and WoS databases. Future work might want to extend the coverage to Google Scholar to explore whether conference proceedings, book chapters and other publications that are not indexed in Scopus and WoS can identify more emerging work. Second, we did not look at the level of analysis (e.g., individual, organizational, industry) adopted across all the articles of the sample. This might be performed in future research, by carrying out a more granular analysis of the articles. It might help understand the challenges and opportunities pertaining to cognitive analytics at different levels.

Our study offers a number of avenues for further research. First, we encourage hospitality and tourism scholars to use consistently technical terminology and draw more precise distinctions when they use terms such analytics, ML, and AI to better map their research to information systems, information management, and high-quality industrial research. Second, a more fruitful dialogue should be fostered between computer and data scientists on one the hand, and hospitality and tourism management scholars on the other to ensure that cognitive systems are not thought as a mere synonym of robots. Third, there is a dearth of information system management research within hospitality and tourism management. Here, scholars should work more closely with information systems researchers if they want to gain a better understanding of cognitive systems.

In conclusion, we hope that this critical reflection study will help hospitality and tourism management scholars become aware of the terminological inconsistencies and inaccuracies that has characterized this field. By shedding light on the inconsistent use of terms and definitions, and by pointing to a few key definitions (e.g., analytics, cognitive analytics), we hope that our study allows scholars to build a more precise shared scientific language and a more consistent, meaningful, and connected body of knowledge.

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