Big Data Analytics in E-commerce for the U.S. and China Through Literature Reviewing

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Abstract Big data analytics (BDA) in e-commerce, which is an emerging field that started in 2006, deeply affects the development of global e-commerce, especially its layout and performance in the U.S. and China. This paper seeks to examine the relative influence of theoretical research of BDA in e-commerce to explain the differences between the U.S. and China by adopting a statistical analysis method on the basis of samples collected from two main literature databases, Web of Science and CNKI, aimed at the U.S. and China. The results of this study help clarify doubts regarding the development of China’s e-commerce, which exceeds that of the U.S. today, in view of the theoretical comparison of BDA in e-commerce between them.

Keywords big data analytics; e-commerce; U.S. and China; literature review

1 Introduction

With the increasing cooperation and competition between the United States and China, especially considering the outbreak of S&T and trade war, increasingly more attention has been paid to comparison between the United States and China’s big data analytics (BDA) in

Received May 11, 2020, accepted June 25, 2020

Supported by the Ministry of Education’s Humanities and Social Sciences Research Project (18YJAZH153); Fujian Natural Science Foundation (2018J01648); Fujian Social Sciences Federation Planning Project (FJ2018B032); Development Fund of Scientific Research from Fujian University of Technology (GY-S18109)

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application. It comprehensively and systematically compares the relevant literature for BDA in e-commerce between U.S. and China, collected by two main literature databases, Web of Science and CNKI respectively aim at U.S. and China, during the period from 1990 to 2017. Before analyzing, the overall academic research of U.S. and China in related subjects of big data and e-commerce need to be introduced first, and as the foundation of BDA, comparison of research situation in business intelligence and analytics, and models and algorithms of BDA, are also presented between U.S. and China; Next, BDA in e-commerce is discussed around trends in e-commerce research, online consumer behavior, internet of things in e-commerce, mobile technology in e-commerce, cloud computing in e-commerce, and artificial intelligence in e-commerce; Finally, a brief prospect is given.

2 Overall Research in the U.S. and China

As a whole, we present the results of three stages of searching for subject terms classified by title¹ from several literature databases in Table A1. The first stage retrieves the term ‘Electronic Commerce’ or ‘Electronic Business’ from databases, including the Web of Science (abbr. WoS), ProQuest, EBSCOhost, JSTOR, EI Engineering Village, and ACM Digital Library from the U.S. and CNKI from China. The second stage is retrieval of the term ‘big data’ so that searching for ‘Electronic Commerce’ or ‘Electronic Business’ retrieve the term ‘Big Data Analytics’. Then, if the comparison of some of the U.S. literature databases with China’s CNKI is not very different, then it is concluded that China, similar to the U.S., has shown great interest and paid great attention to Electronic Commerce. For instance, searching ‘e-commerce’ and ‘Big Data’ in CNKI (All) retrieves 85 documents that concentrate on e-commerce and Big Data from a group of 13,072 papers, and the proportion is 0.65 percent, which is higher than that of the WoS, 0.59 percent, and others. However, this search finds that WoS at 0.61 percent is higher than CNKI (All), 0.54 percent, as shown in Table A2. Compared with more similar literature databases, CNKI (All) and EI Engineering Village, in four cases of searching for the subject terms, the proportion of retrieve papers that concentrate on e-commerce and big data from CNKI (All) is 0.52 percent, higher than that from EI Engineering Village, 0.28 percent. According to Master’s and doctoral dissertations, it is obvious that China puts more effort into e-commerce using BDA research as well.

To further observe the change of the quantity of the literature from the U.S. and China’s databases yearly, different characteristics of research activities on e-commerce using BDA between the U.S. and China are described in Table A2, Figure 1, and Figure 2. The study of e-commerce dates back to 1995; after four years, it developed very rapidly to approximately 7000 papers published every year and during the year of 1999 to 2000 according to the ProQuest database; however, the study output from 2001 to 2010 showed a downward trend until 2011, when it returned to previous levels of growth. In short, research on e-commerce in the U.S. has not drawn extensive attention, which was also found from the WoS database. However, in China, the development of research on e-commerce has been slightly different than that of the

¹Searching subject terms classified by title in the literature in this article is performed because there are a number of papers that are not directly related to count if searching by subject/title/abstract, which would reduce the accuracy of the study.

U.S., with almost the same starting time of research; however, this research has continuously increased in output, much like the trend of the growth of Alibaba, a company founded in 1999 that has constantly and swiftly grown. This process of past research in China may be verified by the development of e-commerce in practice, which is likely somewhat of a correlation of theory and practice and will be analyzed in the next section. The goal of this paper is to explain why China's electronic commerce trade is much more active than that of the U.S. Furthermore, retrieving the terms 'e-commerce' and 'Big Data' from CNKI, regardless of being limited to periodicals or not, shows that there are slightly more papers than in the WoS (Core Collection) and ProQuest. This discrepancy is a serious problem that needs to be faced and resolved in the U.S.

Figure 1 (a) Literature quantity retrieved with the 'e-commerce' subject term from U.S. and China databases; (b) Literature quantity retrieved for the 'e-commerce' and 'Big Data' subject terms from U.S. and China databases

Figure 2 (a) Comparison of the literature quantity retrieved with the "e-commerce" subject term from U.S. and China databases; (b) Comparison of the literature quantity retrieved for the "e-commerce" and "Big Data" subject terms from U.S. and China databases

3 Business Intelligence and Analytics

Business intelligence and analytics (BI&A) and the related field of big data analytics have become increasingly important in both the academic and the business communities over the past two decades^[1]. Sun, et al.^[2] surveyed data analysis and showed that the proposed big data analytics service-oriented architecture (BASOA) is viable for enhancing BI and enterprise information systems. In the late 2000s, business analytics was introduced to represent the key analytical component in BI^[1, 3], and then, in 2005, Andreas, et al.^[4] proposed an architecture for enhanced business intelligence that was composed of two infrastructure types, information integration and business integration; this architecture was a real-time analytics technique with the aim of reducing the action time and increasing the value. Successively, several articles^[5-13] were published in conference proceedings and so on that were valuable for promoting the correlation of BI&A and BDA; of course, the data warehouse of BI&A was not constructed and equipped with the infrastructure of big data that Hadoop has hardened for enterprises^[14]. Escobedo, et al.^[15] used business intelligence and data analytics (BI&DA) to support the operation of the smart grid, and a combination of BI&A and BDA and some of the enabling technologies for the future development of such fields have appeared.

Danyel, et al.^[16] introduce business intelligence analytics to help users understand and act on widely disparate types of data in a special issue of IEEE CG&A. Hence, the development

of big data analytics can be followed and described by the evolution of BI&A. Until now, the evolution of BI&A has gone through four phrases: BI&A 1.0, where data are mostly structured and DBMS-Based; BI&A 2.0, for unstructured and web-based approaches; BI&A 3.0, which presented a new era of mobile and sensor-based approaches^[1]; and BI&A 4.0, which is ultraintelligent and allows optimal decisions to be made automatically as well as combines physical and virtual data; BI&A 4.0 can be referred to as an artificial intelligence-based approach^[17]. In addition, business analytics can be divided into three main components: Descriptive analytics, predictive analytics and prescriptive analytics^[18]. While some organizations recognize and exploit the benefits of business intelligence and analytics use^[19], others fail to capitalize on their potential^[20] because their deployment is complex, expensive, time consuming and laden with risk^[21–23]. Therefore, research on analytics and big data is still in its nascent stage, and academics and practitioners are involved in developing new algorithms as well as applying existing algorithms to solve new problems^[18].

Regarded as one framework and analysis tool of BDA in e-commerce, the integration of BI and BDA is a necessity to assist decision makers in increasing the efficiency of public services^[24]. Therefore, a dramatic comparison between on the selected ‘WoS (Core Collection)’ and ‘CNKI (Periodical)’ literature databases from the U.S. and China, respectively, shows that in researching business intelligence and analytics, the academic research in this field can be ascertained for the two countries; how much this research has contributed to enterprises that specialize in BDA in e-commerce will be discussed below in this article. The results, as shown in Table A3, present the definite difference of research achievements in BI&A between the U.S. and China. Until 28 May 2018, there was a total number of 63 papers in the WoS, in which the direct research work started in 2005 and proceeded indifferently afterwards, but since 2014, this research has shown a large increase, from a few papers to over a dozen papers per year, which implies that not only academic research but also applications of BI&A have been widely considered as important in the U.S. over the past three years. However, in China, this research proceeded inconspicuously from the past to the present, even though it began early in 2001.

More specifically, following the comparison presented in Table A4, the U.S. pays more attention to creating a new theoretical framework of the combination of BI and BDA^[25–27] than China, and the technical exploitation and discussion of BI also surpass those in China. Apparently, this result clearly indicates that the U.S. goes further in using BDA to support business intelligence in e-commerce both in theory and application.

4 Models and Algorithms of Big Data Analytics

Over the past decade, we have witnessed the unfolding of the Internet of Things, advancements in machine learning, and technological breakthroughs in areas including robotics, artificial intelligence, virtual reality, autonomous vehicles, facial recognition, medical diagnostics, and fraud detection^[47]. The potential advantages of utilizing these data have been broadly recognized^[48], and the exponential creation of data by new data generating sources has gained attention from businesses, governments, and academia through efforts to harness and analyze big data^[49]. In the book with the refereed conference proceedings of the Fourth International Conference on Big Data Analytics (BDA 2015)^[50], some of the representative papers introduce a

wide range of algorithms for BDA, including Raj's^[51] completely new rethink of the MapReduce paradigm, Masashi's^[52] mobility big data analysis and visualization, Kiran's^[53] periodic pattern mining in analyzing e-commerce behaviors, Surbhi's^[54] VDMR-DBSCAN (varied density MapReduce DBSCAN), Goel's^[55] formal concept analysis (FCA), Astha's^[56] α -miner algorithm, and Arpita's^[57] proposed algorithm, etc. To understand the models and algorithms of BDA well, the big data characteristics defined by V's should be made certain.

The first attempt at defining the big data phenomenon was by Laney from the META Group (now Gartner) in 2001^[58]. Without mentioning the term explicitly, Laney^[59] introduced the concept of the '3Vs', underpinning the increase in data volume, velocity, and variety. Volume refers to the quantity of data generated at an exponential rate, with data sets ranging from terabytes to zettabytes in size. Velocity relates to the increased speed at which data are available and requires near real-time processing to maximize the value of data. Variety refers to the multiplicity of data types generated from a range of sources, including social networks, mobile phones, traffic cameras, and various sensors^[60]. However, data are simply raw symbols with no significance beyond their existence, while information is data that have been processed and attributed substantive meaning. Hence, later studies have noted that these data characteristics are insufficient to explain the multifaceted nature of big data^[61]. Duygu^[62] extends the concept to '6Vs', including other factors such as veracity, which points to the trustworthiness of data; vocabulary, which involves schema, models, and ontologies that describe the data's structure; and value, which refers to insight and cost. Several authors have added features such as veracity^[63, 64], value^[65-67], variability^[66], and visualization^[1] for a total of '8Vs'. Consequently, big data has become a volatile term that has led to different interpretations^[58].

To realize the objectives and functions of these 'Vs', some efficient and effective models and algorithms are needed to handle and analyze big data from various angles, involving the architecture of Hadoop^[68-72]; approaches to collect, store, process, and clean big data^[73-75]; big data techniques and applications^[76, 77]; and big data security and privacy^[78], etc. Concretely, some key subject terms of big data models and algorithms can be retrieved using the field of 'title' separately in the WoS (U.S.) and CNKI (China). As shown in Table A5 and Figure 3, there are only a few differences between the U.S. and China in carrying out research on big data models or algorithms, with the exception of 'MapReduce', 'Apriori', and 'Cloud and Big Data', etc. These models or algorithms, such as 'k-means', 'SVM', 'machine learning', 'deep learning', 'clustering algorithm', 'cloud', 'regression', 'decision analytics', 'optimization', 'genetic algorithm', 'neural networks', 'text analysis', 'association rules', 'classifier', 'social network', and 'prediction model', were applied to big data shortly after 2010 and will undoubtedly propel prospective applications of big data analytics in the coming years. In Figure 4, a dramatic increase of researchers involved in the models and algorithms of big data analytics in both the U.S. and China is shown, which started around 2010, and the quantity of China's research outputs in some fields has even exceeded that of the U.S. For example, the combination of 'cloud' and big data has grown faster in China than in the the U.S. over the past years, which can be verified by the development status of the 'cloud' and big data industry.

Figure 3 Comparison of the literature from the U.S. and China in terms of the total quantity of big data models and algorithms

Figure 4 Comparison of the literature from the U.S. and China in terms of the quantity of some big data models and algorithms per year

Whether used in the U.S. or China, big data learning algorithms that can select suitable techniques to manage and analyze dynamically growing massive data sets efficiently and extract useful information^[79] represent a continued vital breakthrough area for both countries. To improve big data learning algorithms in the future, for instance, by addressing the remarkable progress of the quantum computing architecture that will perform computations beyond the capabilities of any classical computer (Von Neumann architecture)^[34], the framework of big data learning models and algorithms must be explained using the characteristics of the data domain^[79] under the classical computing architecture first. Big data learning deals with an environment where the given data are known^[79] through various deep learning models and algorithms^[80, 81], which are made up of the following components: The big data processing system, outlier detection system, feedback mechanism and continuous learning, and the supervised learning module^[82], with their corresponding responses shown in Figure 5.

Figure 5 Schematic of big data learning

5 Big Data Analytics in E-Commerce

A report from Statista shows that retail e-commerce sales worldwide amounted to 2.3 trillion US dollars in 2017 and that e-retail revenues are projected to grow to 4.88 trillion US dollars in 2021². In 2017, in Pacific Asia, e-retail sales accounted for 14.9 percent of retail sales³, of which the U.S. accounted for 9 percent⁴ and China accounted for 23.8 percent⁵. With the global e-commerce market continuing to flourish, e-commerce trends, market discipline, trading behaviors, and demand characteristics, etc. are required to have sets of complex technical measures for accurate analyses and predictions in the big data environment. Thus, BDA in e-commerce is becoming a hot issue in academic research but remains poorly-explored as a concept, which obstructs its theoretical and practical development^[83]. As illustrated in Table A6, it is shown that combining BDA and e-commerce has only started in recent years and there is handful of direct literature in the U.S. and China.

5.1 Trends in E-Commerce Research

With its increasing sales and share of market, e-commerce research transforms into how to innovate new products and services to draw participants and create new operation modes. However, the key point is to examine participants' attitudes and preferences regarding the use of electronic commerce^[84] and use data analysis technologies to examine them^[84]. For instance, academic research often focuses on the capability of recommender systems that adopt data analysis approaches, such as a learning-based approach, to help judge users by their long-term preference profiles^[85]. Another aspect of this research is investigating patterns in e-commerce activities and their impact on the economy; this type of research also utilizes statistical analysis approaches^[86]. As a consequence, it is believed that the research trends of the e-commerce domain are linked to other disciplines, such as computer science, engineering, information science,

²Data come from the Statista website, <https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/>.

³Data come from the Statista website, <https://www.statista.com/statistics/534114/e-commerce-share-of-retail-sales-in-APAC/>.

⁴Data come from the Statista website, <https://www.statista.com/statistics/379112/e-commerce-share-of-retail-sales-in-US/>.

⁵Data come from the Statista website, <https://www.statista.com/statistics/379087/e-commerce-share-of-retail-sales-in-China/>.

telecommunications, psychology, social sciences, and mathematics, which are^[87] involved with the most cutting-edge scientific and technological methods. For the U.S. and China, Tsai^[87] explores e-commerce research trends through an analysis of the SSCI database in the past and forecasts that both countries will produce more e-commerce literature in the future.

5.2 Online Consumer Behavior

As a focal research trend of e-commerce activities and participants' preferences, online consumer behavior has attached importance in the U.S. and China, not only in research but also in practice. However, studies that help to understand consumers' views and their behavior towards applications of BDA are lacking^[88]. Articles on big data initiatives in statistical and artificial intelligence are popular among relative periodicals^[89]. The theoretical framework of online consumer behavior usually integrates information systems (technology acceptance model), marketing (consumer behavior), and psychology (flow and environmental psychology)^[90] and then statistically analyzes the large amount of data. In particular, these dynamic irregular unexpected behaviors require key determinants determined through BDA, such as online impulse buying regardless of website quality^[91], helping merchants adapt their website content in real time to capture the current preferences of online customers, and using data mining and other clickstream analysis techniques^[92]. With the help of social media, e-commerce presents new social characteristics and interactive behaviors^[93] that can integrate qualitative interaction content data and consumer transactions data to assemble a unique data set using content analysis methods^[94]. In addition, Ghose^[95] study the effects of search engine rankings on consumer behavior using archival data analysis that unravels the economic impact of ranking (including search engine ranking, product rating, and personalized ranking) and its interaction with social media on product search engines.

In short, e-commerce issues concerning transaction behavior will increasingly consider data analysis techniques and tools to process and learn data and then obtain valuable information to support decision-making. Considering the retrieval consequence presented in Table A7, the U.S. and China are mainly consistent in academic research, where the search subject term 'Online Consumer Behavior' classified by the field of 'title' occurs several times in the WoS (Core Collection) and CNKI (All), whereas they differ in the search subject terms 'Online Consumer Behavior' and 'Big Data' simultaneously classified by the field of 'topic'. Barely any papers are found in the CNKI database. Obviously, China's academic discussion of online consumer behavior has not started to adopt BDA, which is inappropriate considering its great achievements in e-commerce industrialization, particularly in retail web sales, which totaled 7.18 trillion yuan (\$1.149 trillion) in 2017⁶. One possible reason for the lack of adoption of BDA is that the contribution of academic research on e-commerce in China is limited to industry or applications, and this point will be examined and verified below.

5.3 Internet of Things in E-Commerce

The Internet of Things (IoT) is gaining increasing popularity in every field, including e-commerce^[96], as shown by Google results for the 'Internet of Things in e-commerce' on July-

⁶Data come from the Digital Commerce 360 website, <https://www.digitalcommerce360.com/2018/02/08/online-retail-sales-china-soar-past-1-trillion-2017/>.

2-2018, which included approximately 180 million entries; Baidu was included in at 3.9 million entries. Accordingly, the academic research trends in both the U.S. and China present rapid growth, as shown in Table A8, especially that of China, which shows a more significant increase in this field than the U.S. As a vital technique of connecting interorganizational operations and processes, RFID is used to build the IoT such that a network would allow companies to track goods^[97–99] and close some of the information gaps in e-commerce^[100]. Moreover, Samuel^[101] proposes a ‘Living Laboratory’ strategy approach that properly fills the gap identified in the current RFID literature. Hsu^[102] considers the newest information technology that will change the e-commerce module and then provides a framework for creating e-commerce models for IoT applications. The growth of the number of intelligent devices will create a network rich with information and allow data to be seamlessly transferred to the Internet via the IoT^[103], which obviously presents unprecedented business opportunities and profoundly impacts the existing concept of e-commerce. For example, a system based on beacon technology that can detect the location and experience information of customers inside shops will send data to a server for processing to provide the customers with better service^[104]; in addition, for data applied to e-commerce, the innovative application of the Internet of Things in e-commerce is faster and wider^[105–107], even in rural China^[108]. Undoubtedly, future technologies, such as the Internet of Things, big data analytics, and cloud computing, will be widely adopted to enhance e-commerce logistics at the system level, operational level, and decision-making level and may function in real time and be intelligent in the next decade^[109].

5.4 Mobile Technology in E-Commerce

Mobile devices and social media have led to a profound revolution of modern society, obliging many companies to reorient their sales systems toward more successful commercial formats (mobile commerce and social commerce)^[110]. The literature on mobile commerce was started early and can be placed into five distinct categories: mobile commerce theory and research, wireless network infrastructure, mobile middleware, wireless user infrastructure, and mobile commerce applications and cases^[111]. On account of the differences of age, trust, social influence, etc., which affect consumer intention and behavior in mobile commerce^[112], the U.S. has focused less than China on mobile technology in e-commerce in practice but has more positive discussion than China in academic research, as shown in Table A8. China’s booming mobile commerce benefits from its mobile payment technology, which can be defined as any payment transaction involving the purchase of goods or services completed with wireless devices^[113]. Nevertheless, e-commerce, especially mobile commerce, is being taken not only as a technical difficulty but also as a great opportunity in areas such as those that exist in the least developed countries^[114]. In addition, SMEs from the least developed countries have indicated that it is not necessary to invest in transactive web-based e-commerce because mobile technology, especially mobile payment services, is already fulfilling their transactional needs^[114]. For mobile technology innovation in e-commerce, Spott is an innovative second screen mobile multimedia application that offers viewers relevant information on goods they see and like on their television screens^[115]. Other applications of mobile devices and social media networks, such as Facebook and WeChat, have revolutionized the e-commerce adoption process in SMEs^[116]. The prevalent consumption channel with portable devices has led to an emerging pattern of online-to-offline (O2O)

purchasing behavior using quick response codes (QR codes)^[117].

In short, the role of mobile devices is growing in importance among society, with increasingly more mobile applications compared with traditional devices (laptop, desktop computer) being used to communicate with the Internet every year^[118]. Of course, there are also many trends of mobile technology in e-commerce that should be discussed^[12]. Although the new mobile payment service can provide users and stores with various benefits, it also introduces new security concerns and vulnerabilities^[119], and a lack of in-depth user and resources information has become the main bottleneck restricting the predictive analytics of recommendation systems in mobile commerce^[120].

5.5 Cloud Computing in E-Commerce

E-commerce contributions to developing countries' economies may face a challenge due to the lack of telecommunications infrastructure; fortunately, cloud computing offers a solution to most of these challenges, providing access to a low-cost, reliable and flexible internet-based infrastructure^[121]. The e-commerce applications of cloud computing enable businesses to rapidly respond to market changes, and the increasing usage of cloud computing and mobile devices is reshaping the regular methods of computing and storing information, which improve e-commerce businesses' technical architecture^[122]. The combination of cloud computing and e-commerce can reliably and validly predict the benefits of e-commerce^[123, 124] and is extensively applied in the logistics industry^[125–127] and financial services^[128]. Together with the explosive growth of mobile applications and the emergence cloud computing, mobile cloud computing in e-commerce^[129] has been introduced to mobile commerce, mobile learning, mobile healthcare, mobile gaming, etc.^[130]. In addition, the architectures and models for adoption of cloud computing in e-commerce^[131–137] are both discussed in U.S. and Chinese literature databases, but China focuses more on issues in this domain, as shown in Table A8.

5.6 Artificial Intelligence in E-Commerce

The research domain of artificial intelligence in e-commerce tends to study micropblems of e-commerce, of which users' attitudes and preferences, transaction characteristics and behaviors are studied and solved using many techniques. In 2007, a knowledge-based intelligent e-commerce system^[138] was presented for decision-making and provided feasible solutions or actions based on the results of rule-based reasoning via the Internet. Then, Hu^[139] solved the key technical problem of real-time intelligent order processing in B2C e-commerce. In recent years, recommender systems have been developed, which typically produce a list of recommendations to precisely predict users' preference for items^[140], as well as online consumer reviews^[141], and are good for helping customers learn about the strengths and weaknesses of different products and to find those that best suit their needs^[142]; moreover these systems can discover the underlying sentiments toward different aspects in review texts and associate the rating scores with these sentiments^[109, 143]. A number of research methodologies and intelligence technologies have been used to investigate e-commerce issues, for example, a computational intelligence system architecture integrated the techniques of singular value decomposition and dimensionality reduction, fuzzy c-means and the adaptive neuro-fuzzy inference system for rating prediction, as described by Georgina^[144]; biometric methods for predicting dynamic behaviors^[145]; and

applications in the context of time series forecasting using k NN regression^[146]. Therefore, understanding consumer perceptions and influential factors through online customer reviews^[147] to predict and analyze in practical industries^[148] are prevalent in research. In 2018, more pure and mature artificial intelligence technologies were using e-commerce while producing large volumes of data every day in the era of big data. Ali^[149] proposed a robust semisupervised growing self-organizing map for online classification with partial labeled data and extracted knowledge, and Rafailidis^[150] proposed a multilient transition model to identify the correlation between users' recent and past preferences to generate accurate recommendations. With the increasing default in e-commerce, Leonardo^[151] implemented risk management in an artificial intelligence system that is in the process of genetic programming. Likewise, Thambo^[152] built automated designed genetic programming classifiers for data and then contrasted them with manually designed GP classifiers. Thus, artificial intelligence in e-commerce is a new and burgeoning research field in both the U.S. and China, as shown in Table A8.

6 Prospects

Regardless of whether the U.S. or China is considered, the theoretical research work is deeply impressing and has propelled practical application of BDA in e-commerce. And the next research work is going to find out the theoretical achievements how to promote the actual economic activity on BDA in e-commerce, and the different of this two between U.S. and China.

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Table A1 Quantity of literature from databases from the U.S. and China when searching for specific subject terms

Literature Databases	Searching Subject Terms					
	Electronic Commerce/Electronic Business			e-commerce/ E-Business		
	Big Data			Big Data		
	Big Data Analytics			Big Data Analytics		
	U.S.					
WoS (Core Collection)	2036/571	3/0	0/0	6225/2237	37/3	5/0
ProQuest	8192/3496	6/2	0/0	45366/13475	36/2	5/0
EBSCOhost	18384/10487	2/6	0/0	32245/9222	33/2	4/0
JSTOR	173/72	0/0	0/0	782/879	0/0	0/0
Ei Engineering Village	4114/1201	6/0	0/0	12661/4515	50/7	9/0
ACM Digital Library	1554/195	1/0	0/0	5170/6249	21/30	1/3
	China					
CNKI (All)	4599/1119	17/5	0/0	13072/2381	85/3	1/0
CNKI (Periodical)	3027/774	15/3	0/0	8212/1607	57/2	0/0
CNKI (Master's & Doctoral Dissertations)	1422/296	2/2	0/0	3961/517	18/1	0/0

Notes: The date of the search was May-10-2018; all the searched subject terms are classified by the field of 'title'.

Table A2 Quantity of literature from databases from the U.S. and China sorted by year when searching for specific subject terms

Year	Searching Subject Term 'e-commerce'					Searching Subject Terms 'e-commerce' and then 'Big data'				
	ProQuest	WoS (Core Collection)	CNKI (All)	CNKI (Periodical)	CNKI (Master's & Doctoral Dissertations)	ProQuest	WoS (Core Collection)	CNKI (All)	CNKI (Periodical)	CNKI (Master's & Doctoral Dissertations)
2018	1171	56	309	288	9	2	2	10	9	0
2017	3988	481	1638	948	465	9	15	23	15	3
2016	3698	448	1645	823	560	3	8	26	21	3
2015	3521	451	1528	807	470	6	9	16	5	9
2014	2752	338	1367	620	439	11	3	9	5	2
2013	1667	313	1073	535	304	3	1	4	2	—
2012	1299	266	1018	479	272	3	—	—	—	—
2011	1253	324	1026	476	206	1	—	—	—	—
2010	971	328	860	418	193	0	—	—	—	—
2009	746	483	682	385	177	0	—	—	—	—
2008	660	434	714	404	146	0	—	—	—	—
2007	597	310	727	380	128	0	—	—	—	—
2006	648	247	603	350	121	1	—	—	—	—
2005	605	281	550	292	74	0	—	—	—	—
2004	656	235	449	249	47	0	—	—	—	—
2003	763	235	411	221	28	0	—	—	—	—
2002	1151	252	653	213	32	0	—	—	—	—
2001	2485	296	668	221	15	0	—	—	—	—
2000	7737	297	205	85	2	0	—	—	—	—
1999	6901	111	23	15	—	0	—	—	—	—
1998	1722	22	2	2	—	0	—	—	—	—
1997	288	10	0	0	—	0	—	—	—	—
1996	82	9	1	1	—	0	—	—	—	—
1995	11	—	—	—	—	1	—	—	—	—

Notes: The date of the search was May-13-2018; all the searched subject terms are classified by the field of 'title'.

Table A3 Quantity of literature when searching for the subject term of ‘Business Intelligence Analytics’

Year	Searching Subject Term ‘Business Intelligence Analytics’	
	WoS (Core Collection)	CNKI(Periodical)
2018	2	3
2017	14	3
2016	13	0
2015	14	6
2014	4	2
2013	3	1
2012	4	2
2011	3	3
2010	3	4
2009	1	4
2008	1	1
2007	0	3
2006	0	4
2005	1	1
2004	–	1
2003	–	0
2002	–	1
2001	–	1
Total	63	40

Notes: The date of the search was May-13-2018; all the searched subject terms are classified by the field of ‘title’.

Table A4 Summary of papers within the BI&A research framework

Field	Issue	Resolved Issues	Unresolved & Future Research Issues	Authors	Database Source
In Theory	Architecture for enhancing BI and real-time business analytics	Extended a traditional BI architecture with S&R system and analytical services to transform business events into performance indicators and intelligent business actions	Develop a service-oriented business intelligence platform	[4]	WoS (Core Collection)
	Visual analytics for converging-business-ecosystem intelligence	Propose business ecosystem intelligence in applying visual analytics	Deep knowledge of domain-specific entities, attributes, characteristics, and culture of business-ecosystem intelligence	[9]	
	Video analytics for business intelligence	Various algorithms and techniques in video analytics of business intelligence	Not mentioned	[28]	
	BI&A solutions in storage and computing	Outline a novel design of BIA solutions	Evaluate a full-fledged solution that spans all layers	[29]	
	Analytics-as-a-consumer-service of BI&A	Extend organizational BI&A environment to a wide range of consumers	Reconsider the framework of a BI environment, data quality, consumer-focused analytics environments	[30]	
	Social business intelligence	Present the technical architecture of a prototype tool for social business intelligence (SBI)	IT artifact empirically tested toward facilitating SBI	[31]	
	Business intelligence and data analytics (BI&DA)	Propose a framework for the development of BI&DA techniques applied to the different issues	Cloud computing, Near Real-Time BI, enterprise search, distributed data mining, data stream mining, time series data mining, information security and BI&DA	[15]	
	Deploying BDA in the cloud for BI	Outline the benefits and challenges involved in deploying big data analytics through cloud computing	The privacy and security of BDA deployed through cloud computing for BI	[32]	

In Application	Business intelligence and big data analytics in evidence-based medicine	The EBM Process & how BI&A support various evidence-based medicine processes	Broadening the practice of evidence-based medicine through the applications of business intelligence and big data analytics.	[33]
	Evaluating business intelligence and analytics effectiveness	Develop a comprehensive BIA effectiveness diagnostic (BIAED) framework	Continue to refine and deploy the BIAED framework to be effective in different geographies and cultures	[34]
	The implications of big data analytics on business intelligence	BDA of data collected from Chinese social media enhance BI greatly	Seek more insights on the drivers and inhibitors of use of BDA for BI	[35]
	Literature review of BI&A in small and medium-sized enterprises	Basic research situation of BI&A's components, solutions, application, adoption, implementation and mobile BI&A, cloud BI&A, etc.	The factors that influence adoption and implementation of BI&A for SMEs, cloud-based and mobile-based BI&A solutions for SMEs	[36]
	Factors influencing business intelligence and analytics usage	Data-related infrastructure capabilities, top management, market, data management challenges, etc. influence BI&A usage	The relation of organizational performance and factors of BI&A usage	[20]
	Agile practices for data warehousing and business intelligence (DW/BI) projects	Agile values place less emphasis on tools to individuals, but DW/BI is a sociotechnical role of methodological, organizational, and technological issues	Not mentioned	[37]
	Mode of data analysis agent (DAA) in business intelligence	The architecture of DAA, describe the differences between conventional mode and agent mode of data analysis in BI	Not mentioned	[38]
	Introduce the concept of business ecosystem	Employ the concepts of information communion and competitive intelligence and discuss the way of establishing a new business ecosystem	Not mentioned	[39]
				CNKI (Periodical)

In Application	BI analysis and report publish system within.NET framework	Refers to a high-level system structure of BI that is mainly in regard to front-analysis within Microsoft.NET framework	Application of the system structure BI that this paper presents	[40]
	Framework of real-time BI	Introduce the defects of traditional BI system, and put forward a future framework of real-time BI system	Future research and practice in real-time BI	[41]
	BI search engines	The advantages of BI search engine compared with traditional search engines	Research more BI search engines	[42]
	Spatial business intelligence	Online multisource data integration and interactive geovisual analytics in spatial business intelligence	Integration of industrial geovisual analysis and social media data in BI	[43]
	Analysis of mainstream business intelligence software	BI software divides into ROLAP, which is apt to conduct massive data, and MOLAP that is more likely to analyze real-time data	Such factors of individual demands and features that affect the adoption of BI software	[44]
	Use BI to support decision-making in Insurance	Design and implementation in insurance data analyzing and decision-making based on BI	Business application and value of BI	[45]
	Application of BI in power dispatching and controlling	Use BI to solve the massive data statistical analysis problem as an example of the D5000 system	The function of data mining of BI should perform a deep research in power systems	[46]

Year	Searching Subject Terms																							
	T11		T12		T13		T14		T15		T16		T17		T18		T19		T20		T21			
	WoS (Core)	CNKI (Periodical)	WoS (Core)	CNKI (Periodical)	WoS (Core)	CNKI (Periodical)	WoS (Core)	CNKI (Periodical)	WoS (Core)	CNKI (Periodical)	WoS (Core)	CNKI (Periodical)	WoS (Core)	CNKI (Periodical)	WoS (Core)	CNKI (Periodical)	WoS (Core)	CNKI (Periodical)	WoS (Core)	CNKI (Periodical)	WoS (Core)	CNKI (Periodical)		
2018	36	180	2	1	2	4	9	21	0	0	2	2	2	1	3	5	5	2	0	6	2	2	5	
2017	153	392	10	5	11	5	41	43	3	1	14	4	4	3	2	5	8	7	1	26	11	10	15	
2016	188	337	12	6	5	6	65	46	8	3	14	7	6	1	3	5	7	1	26	5	6	9		
2015	165	258	10	10	3	1	31	15	2	1	5	3	3	2	2	5	2	6	13	3	6	4		
2014	80	169	1	1	5	1	14	12	1		8		0	1	2	1	2	1	9	6	3	6		
2013	38	76	0		3	0	4	1			1		3		3	1		3	6	2	1			
2012	9	20	1				1	1			0							1	1					
2011	1	2									0													
2010		0									0													
2009		0									0													
2008		0									1													
2007		0																						
2006		1																						
Total	670	1435	36	23	29	18	165	139	14	5	45	16	16	16	8	20	22	27	2	87	29	28	39	

Notes: (1) The date of the search was June-11-2018; all of the searched subject terms are classified by the field of 'title'; (2) T01 refers to "Big Data Model"; T02: "Big Data Algorithm"; T03: "Hadoop"; T04: "MapReduce"; T05: "Apriori"; T06: "k-means" and "Big Data"; T07: "SVM" and "Big Data"; T08: "Machine Learning" and "Big Data"; T09: "Deep Learning" and "Big Data"; T10: "Clustering Algorithm" and "Big Data"; T11: "Cloud" and "Big Data"; T12: "Regression" and "Big Data"; T13: "Decision Analytics" and "Big Data"; T14: "Optimization" and "Big Data"; T15: "Genetic Algorithm" and "Big Data"; T16: "Neural Networks" and "Big Data"; T17: "Text Analysis" and "Big Data"; T18: "Association Rules" and "Big Data"; T19: "Classifier" and "Big Data"; T20: "Social Network" and "Big Data"; T21: "Prediction Model" and "Big Data".

Table A6 Quantity of literature when searching for the subject term of ‘E-commerce & Big Data Analytics’

Year	Searching Subject Terms “E-commerce & Big Data Analytics”	
	WoS (Core Collection)	CNKI (Periodical)
2018	9	0
2017	24	12
2016	12	8
2015	10	6
2014	2	6
2013	3	1
2012	1	1
Total	60	34

Notes: The date of the search was June-18-2018; all of the searched subject terms are classified by the field of ‘title’.

Table A7 Quantity of literature when searching for the subject term of ‘Online Consumer Behavior’

Year	Searching Subject Term “Online Consumer Behavior” classified by the field of “title”		Searching Subject Terms “Online Consumer Behavior & Big Data” classified by the field of “topic”	
	WoS (Core Collection)	CNKI (All)	WoS (Core Collection)	CNKI (All)
2018	9	4	8	0
2017	26	31	31	1
2016	34	36	20	1
2015	23	23	16	0
2014	15	26	7	0
2013	13	19	2	0
2012	12	25	1	0
2011	19	17	0	0
2010	9	16	1	0
2009	12	14	1	0
2008	8	11	1	0
2007	5	3	0	0
2006	8	5	0	0
2005	5	4	0	0
2004	2	0	0	0
2003	4	2	1	0
2002	6	0	0	0
2001	1	1	0	0
2000	4	0	0	0
1999	0	0	1	0
1998	1	0	0	0
Total	216	238	90	2

Notes: The date of the search was June-21-2018.

Table A8 Quantity of literature when searching for several relative subject terms of Big Data Analytics in e-commerce

Year	Searching Subject Term “Internet of Things & e-commerce”		Searching Subject Terms “Mobile Technology & e-commerce”		Searching Subject Term “Cloud Computing & e-commerce”		Searching Subject Terms “Artificial Intelligence & Big Data & e-commerce”		Searching Subject Terms “Quantum Computing”	
	WoS (Core Collection)	CNKI (Periodical)	WoS (Core Collection)	CNKI (Periodical)	WoS (Core Collection)	CNKI (Periodical)	WoS (Core Collection)	CNKI (Periodical)	WoS (Core Collection)	CNKI (Periodical)
2018	10	28	21	3	16	31	3	17	57	10
2017	26	120	73	12	39	78	6	31	93	26
2016	23	136	66	17	43	99	11	17	106	19
2015	16	162	54	23	32	151	0	24	69	16
2014	5	86	44	19	29	98	0	11	87	19
2013	6	92	41	17	31	86	3	8	76	5
2012	3	53	22	10	14	80	4	2	58	7
2011	5	59	34	11	9	72	3	6	85	13
2010	0	33	25	9	5	31	0	5	72	9
2009	1	2	37	11	5	6	0	7	71	18
2008	3	0	37	14	0	3	0	7	83	11
2007	1	1	23	14	0	0	5	9	89	13
2006	2	1	21	10	0	0	8	5	63	10
2005	2	0	20	10	0	0	4	5	95	9
2004	1	0	24	7	0	0	0	8	72	13
2003	2	0	20	6	0	0	5	5	113	14
2002	4	0	25	6	0	0	8	3	84	9
2001	2	0	17	8	0	0	3	4	72	6
2000	0	0	11	0	0	0	0	4	63	5
1999	0	0	3	0	0	0	0	0	32	3
1998	0	0	2	0	0	0	0	0	41	6
1997	0	0	0	0	0	0	0	0	18	1
1996	0	0	0	0	0	0	0	0	13	0
1995	0	0	0	0	0	0	0	0	10	1
1994	0	0	0	0	0	0	0	0	6	0
1993	0	0	0	0	0	0	0	3	4	0
1992	0	0	0	0	0	0	0	0	4	0
1991	0	0	0	0	0	0	0	0	3	0
1990	0	0	0	0	0	0	0	0	5	0
Total	112	773	620	207	223	735	92	181	1644	243

Notes: Except for “Quantum Computing” (the search was performed on July-30-2018 classified by the field of “title”); for others, the date of the search was June-21-2018, and the searching subject terms are classified by the field of “topic”.