# Exploring core knowledge in business intelligence research

## Abstract

**Purpose -** Although knowledge based on business intelligence (BI) is crucial, few studies have explored the core of BI knowledge; this study explores this topic.

**Design/methodology/approach** - We collected 1306 articles and 54,020 references from the Web of Science (WoS) database and performed co-citation analysis to explore the core knowledge of BI; 52 highly cited articles were identified. We also performed factor and cluster analyses to organize this core knowledge and compared the results of these analyses.

**Findings** - The factor analysis based on the co-citation matrix revealed seven key factors of the core knowledge of BI: big data analytics, BI benefits and success, organizational capabilities and performance, information technology (IT) acceptance and measurement, information and business analytics, social media text analytics, and the development of BI. The cluster analysis revealed six categories: IT acceptance and measurement, BI success and measurement, organizational capabilities and performance, big data-enabled business value, social media text analytics, and BI system (BIS) and analytics. These results suggest that numerous research topics related to big data are emerging.

**Limitations/implications** - The core knowledge of BI revealed in this study can help researchers understand BI, save time, and explore new problems. Our study has three limitations that researchers should consider: the time lag of co-citation analysis, the difference between two analytical methods, and the changing nature of research over time. Researchers should consider these limitations in future studies.

**Originality/value** - This study systematically explores the extent to which scholars of business have researched and understand BI. To the best of our knowledge, this is one of the first studies to outline the core knowledge of BI and identify emerging opportunities for research in the field.

Keywords: business intelligence, core knowledge, citation analysis, co-citation analysis, factor analysis, cluster analysis

## 1. Introduction

IT has developed rapidly and increased businesses' competitiveness in several regards (Bian *et al*., 2020; Chan *et al*., 2019). BI is closely related to IT and can increase productivity. BI consists of methodologies through which enterprises acquire useful information and products to evaluate their operations and the market environment (Jourdan *et al*., 2008). BI supports decision-making (Liang and Liu, 2018; Rouhani *et al.*, 2016) and has increasingly received attention in business and research. In addition, BI implementation focuses on holistic strategies and long-term success. The Gartner Group revealed that BI revenue was US$2.5 billion in 2006 (Gartner, 2006). A Gartner report on technical product managers predicted that the value of the BI market would exceed US$6.25 billion in 2022 (Hunter *et al.*, 2019). The key factor determining the success of enterprises is the ability to analyze data and information intelligently. For example, Coca-Cola Bottling Company, which is Coca-Cola's largest bottling partner, faced challenges in terms of its manual reporting processes and limited access to real-time operational and sales data. Coca-Cola's BI team automated the processes and thereby saved more than 260 hours of labor a year (Al Anasri *et al*., 2019).

Research has defined core knowledge as the systems of knowledge specific to a certain domain (Carey and Spelke, 1996; Hirschfeld and Gelman, 1994). This study analyzes BI as a domain-specific system of knowledge related to big data in the context of business (Brichni *et al.*, 2017; Chen *et al.*, 2012; Jin and Kim, 2018; Jourdan *et al.*, 2008). Studies have increasingly explored BI, as indicated by the journal citations in the ISI Web of Knowledge: Chen *et al.* (2012) received 2066 journal citations; Chaudhuri *et al.* (2011), 264; Elbashir *et al.* (2008), 198; Chau and Xu (2012), 159; and Jourdan *et al.* (2008), 131. Some of these highly cited studies have provided an overview of BI and related topics and identified opportunities for further research (Chaudhuri *et al*., 2011; Chen *et al*., 2012; Jourdan *et al*., 2008). Other studies have focused on the applications of BI and their effects (Chau and Xu, 2012; Elbashir *et al*., 2008). These highly cited studies have laid a solid foundation for research on BI. Jourdan *et al.* (2008) reviewed the literature on BI and employed a method of categorization that accounted for new topics and problems related to BI technology. They also suggested that researchers review studies on BI from several databases. Their results contribute to proposing an agenda for future research on BI, such as using the survey research strategy and paying attention to the benefits of BI. Chen *et al.* (2012) divided the evolution of BI and analytics (BI&A) into three stages and identified the applications and emerging research areas in each. They noted that research and development relating to BI&A offer exciting prospects for academia and the industry. Their study elucidated BI&A and demonstrated its importance as a topic of research. Webster and Watson (2002) indicated that literature reviews provide firm foundations to advance knowledge. With the rapid increase in research on BI, monitoring the literature and identifying topics for further research are crucial. López-Robles *et al.* (2019) reviewed articles on a range of topics in the field of intelligence from the WoS by using several keywords. Their results focus more on the analysis of the extensive intelligence field. Studies should analyze BI in detail to provide crucial information for researchers and practitioners. Although studies have performed literature reviews and developed classification methods to provide insight into BI (Chen *et al.*, 2012; Jourdan *et al.*, 2008; López-Robles *et al.*, 2019), few studies have explored the core knowledge of BI. Although original research is central to creating knowledge, reviewing the literature and intellectual structure of a field are equally crucial (Culnan, 1987). The purpose of this study is to explore the core knowledge of BI by identifying high-value articles. To achieve our goal, the following research questions are considered:

1. What are the highly cited (value) articles in the BI field?
2. What is the core knowledge of BI?

Bibliometric analysis (citation and co-citation) is performed on highly cited articles from the ISI Web of Knowledge database. A systematic review of the literature can outline a domain, overview the current state of knowledge, and integrate and synthesize extant knowledge (Hulland and Houston, 2020). This study outlines BI, explores its intellectual structure, and identifies the core knowledge of BI. In addition, this study explores changes in research on BI by comparing the results of studies and identifying opportunities for further research. Our results can help managers understand the elements of BI that are critical to success and acquire competitive advantages. The next section reviews BI and the co-citation analysis, Section 3 describes the research methods, Section 4 provides the results, and Section 5 presents the conclusions, implications, and limitations.

## 2. Literature review

BI involves numerous technologies, applications, and processes of collecting, storing, accessing, and analyzing data that facilitate decision-making (Wixom and Watson, 2010). Data are indispensable to BI. Ramakrishnan *et al.* (2012) examined factors affecting BI data collection strategies and noted that institutional isomorphism is an external factor that affects internal consistency. BI can help businesses achieve consistency and transformation, which depend on strategies for data collection. Understanding the relationship between the purpose of BI implementation and data collection strategies is crucial for decision-making (Ramakrishnan *et al.*, 2012). BI&A transforms raw data into meaningful information that can reduce uncertainty in decision-making (Clark *et al.*, 2007). Visinescu *et al.* (2017) indicated that information quality positively affects the perceived quality of decisions based on BI. Therefore, BI&A is crucial to improving firm performance (Torres *et al.*, 2018). Fadler and Legner (2020) described how enterprises develop BI&A capabilities by identifying four key tasks: reporting, data exploration, analytics experimentation, and analytics production. With the availability of big data, novel methods of BI-based analysis are crucial for enterprises. Paghadal *et al.* (2020) developed a conceptual model to explain how big data analytics improves firm performance through value creation. They noted that big data analytics can enhance firms' financial performance by reducing costs and improving decision-making and product quality. Anton *et al.* (2021) performed meta-analytic structural equation modeling to explore the direct effect of big data analytics capabilities on firm performance. BI can also afford competitive advantages by strengthening firms' ability to measure performance (Peters *et al.*, 2016). Moreover, BI technologies involve data warehousing, online analytical processing (OLAP), data mining, process mining, complex event processing, business performance management, benchmarking, text mining, predictive analytics, and prescriptive analytics (Chaudhuri *et al.*, 2011). For example, in addition to interviews, Lee *et al.* (2021) used text mining to collect, process, and analyze data on the Korean pop group Bangtan Boys from Twitter. They identified 10 factors based on keywords and their relationships that are crucial to the sustained popularity of Bangtan Boys.

BISs enable enterprises to combine data gathering, data storage, and knowledge management to improve decision-making (Chaudhuri *et al.*, 2011; Negash, 2004). Similarly, Wixom and Watson (2010) noted that a BIS enables business information analysis and improves businesses' operations and decision-making. Therefore, a BIS is indispensable for BI, and enterprises must implement it strategically. Yeoh and Koronios (2010) developed a framework of factors determining the success of the implementation of BISs and thereby bridged the gap between practitioners and researchers. Almusallam *et al*. (2021) compared factors affecting the adoption and use of BISs and revealed that complexity, observability, compatibility, organizational resource availability, competitive pressure, external support, and owners and managers' innovativeness and knowledge of IT are predictors of BIS adoption; these are also predictors of BIS usage, except for complexity. Watson *et al.* (2006) identified Continental Airlines as an exemplary case for organizations aiming to implement real-time BI, which requires technical, corporate, and procedural changes. BI involves gathering data into a BIS and getting data out through technology (Wixom and Watson, 2010). Data are the basis of BI, and managers invest in and use big data to determine the potential value of enterprises. They derive value from the BIS and invest in BI, thereby acquiring assets and improving organizational performance (Trieu, 2017). To determine the value and efficacy of managers' investment in BISs, Popovic *et al.* (2012) proposed a model to assess the effectiveness of BISs. They indicated that the maturity of BISs, the quality of information, accessibility to information, analytical decision-making culture, and the use of information in decision-making determine the success of a BIS. BISs have been applied in numerous fields. For example, such systems have been used to analyze problems in public schools such as poor performance and low graduation rates among students (Hopkins, 2011).

Researchers have provided overviews of the various stages of BI. Jourdan *et al.* (2008) collected, synthesized, and analyzed 167 articles on topics related to BI published between 1997 and 2006 from 10 leading journals on information systems (ISs). Their results indicated an increase in activity and a focus on exploratory research methodologies. Studies on this stage have also explored BI technology and related problems. Theories of BI have been formulated through research and literature reviews. However, in one such review by Jourdan *et al.* (2008), only the top 10 journals on ISs were considered. Because BI is multifaceted, studies from numerous databases must be reviewed. Chen *et al.* (2012) developed a framework for the evolution and applications of BI&A and new research opportunities. They identified three stages, BI&A 1.0, BI&A 2.0, and BI&A 3.0, and described the key characteristics and capabilities of these stages. BI&A 1.0 is characterized by traditional database management, with the core capabilities being ad hoc database query, online analytical processing, visual reporting, predictive modeling, and data mining. The Internet ushered in the second stage, BI&A 2.0, which involves unstructured web content analytics, opinion mining, and social media analytics. Key capabilities in BI&A 2.0 include natural language question answering, information semantic services, and text analytics. The advent of mobile and sensor-based Internet-enabled devices, which support mobile, location-based, and personalized operations, indicate the arrival of Web 3.0 and BI&A 3.0. Mobile BI is a component of BI&A 3.0 and may have a substantial influence on the BI industry. Chen *et al.* (2012) explored applications of BI such as security, healthcare, e-commerce, and market intelligence. Because research on BI is rapidly developing, tracking the literature and emerging research opportunities is crucial. López-Robles *et al.* (2019) used bibliometric techniques and tools to analyze and describe the evolution of the various definitions and main concepts relating to intelligence in the literature. They identified six sub-fields of intelligence: BI, collective intelligence, competitive intelligence, data and decision-making processes, innovation and organizational performance management, and national intelligence. Their results indicated that research on BI has high growth potential. They highlighted several key fields: business process modeling, service-oriented architecture, BISs, BI, and mobile BI. Although López-Robles *et al.* (2019) described the increasing importance of BI in the field of intelligence, focusing solely on BI and exploring emerging topics are vital. In the era of big data, BI will continue to receive attention from businesses and researchers (Chen *et al.*, 2012; Jourdan *et al.*, 2008; López-Robles *et al.*, 2019).

## 3. Methodology

We followed guidelines provided by Snyder (2019) to organize our systematic review. The first step was to design the review, which involves identifying the purpose, scope, research questions, databases, keywords, and inclusion and exclusion criteria. The second step was the review. We collected samples and documented the process. In the third step, we used a custom R-language program to identify the highly cited references by BI papers collected with a co-citation matrix. We then analyzed these highly cited references through cluster and factor analyses. Here, we present the results and describe the contributions of this review. Figure 1 presents the steps of the systematic review.

[Figure 1 is here]

The WoS is a high-quality database of approximately 12,000 leading journals (Liang and Liu, 2018; Shiau *et al.*, 2019; Zhou *et al.*, 2019). The WoS includes the Science Citation Index Expanded, the Social Science Citation Index, and the Arts and Humanities Citation Index databases (Liang and Liu, 2018; Shiau *et al.*, 2019; Zhou *et al.*, 2019), which ensures our analytic results are comprehensive and accurate. We used a balancing strategy to identify the optimal terms to employ in our search for studies. The terms indicated the subject matter and were not too general or specific. We used "business intelligent" and "business intelligence" because they are not as general as "big data" and "intelligence," which may have yielded studies from other fields. These two terms are also not too specific and can be used to locate most studies on BI. "Business intelligence" is universally used in studies on BI, and "business intelligent" is its adjectival form. According to Chen *et al.* (2012), the first stage of BI, which occurred before 2000, was based on database management systems, and few aspects of this stage have remained. The rapid development of the Internet since the early 2000s has offered new opportunities for data collection and analytical research. The second stage of BI involves web content analytics. We searched for studies published between 2000 and 2020, the period during which most relevant studies were published. To ensure the quality of the studies, we included only journal articles and excluded proceedings, conference papers, letters, and books for four reasons (Zhang and Glänzel, 2012). First, journal articles are usually more comprehensive. Second, journal articles are generally higher quality because they undergo at least two rounds of peer review. Third, journal editors require that journal articles offer considerable novelty. Finally, journal articles have less strict page limits and thus contain more information.

Citation and co-citation analyses are methods of exploring fields such as business administration, marketing, hospitality, human resources, economics, and management ISs. Citation analysis is used to create scientific knowledge maps, and to analyze cited articles in published literature, and to construct the knowledge of a field (Shiau and Dwivedi, 2013).

Frequent citation indicates recognition from other scholars and that an article covers key concepts and methods in a field (Small, 1973). Citation analysis can reveal high-value articles and their effects (Shiau *et al.*, 2017; Shiau *et al.*, 2019; Tai *et al.*, 2014). Co-citation analysis reveals the relationships among subjects (Small, 1973). Articles cited together often cover closely related topics, methods, and theories. Co-citation analysis is often used to identify the core knowledge in a field (Shiau *et al.*, 2017). It can also be used to determine the internal structure of a scientific field and the impact of group articles. Co-citation analysis is an effective method of synthesizing knowledge in various fields. We performed co-citation analysis to identify the core knowledge of BI.

We developed an R program to analyze the plain-text full records and cited reference files of the search results downloaded from the WoS. The R program outputs the list of highly cited articles, that is, the references most frequently cited in BI articles, and a co-citation matrix of the highly cited articles. We performed factor and cluster analyses in SPSS 25 by using the co-citation matrix to explore the core knowledge of a field (Shiau and Dwivedi, 2013; Shiau *et al.*, 2018). Factor analysis is used to explore the interrelationships (correlations) among numerous variables and to perform data summarization and reduction (Hair *et al.*, 2006). Cluster analysis is performed to determine internal (within-cluster) homogeneity and external (between-cluster) heterogeneity (Hair *et al.*, 2006) and to identify groups of similar research articles on the basis of their internal knowledge structure (McCain, 1990; Shiau *et al.*, 2018). Figure 2 presents the research method.

[Figure 2 is here]

## 4. Results

### *4.1 Citation analysis*

We identified 1306 journal articles and 54,020 references and analyzed their sources and the articles related to BI that they cited. The source articles were sorted by year, which revealed a steady increase in the number of published source articles on BI between 2000 and 2020 (Figure 3). Although this increase was relatively slow between 2000 and 2011, the number of articles increased considerably after 2012 because of two possible factors. First, big data have developed rapidly since 2012 and are crucial to enterprise formalization. In addition, a wave of cloud computing emerged in IT, which prompted further development of BI. Gartner (2012) indicated that big data and cloud computing were top-ranked in Gartner’s hype cycle for emerging technologies, and they are expected to be widely used. Second, the surge in 2012 may have been due to a special issue on BI research and business practitioners’ interest in BI published by Chen *et al*. (2012) in *Management Information Systems Quarterly* around that time (Trieu, 2017).

[Figure 3 is here]

The citation analysis revealed the most cited and therefore most valuable articles. The R-language program produced several co-citation matrices with various numbers of highly cited articles. We used multidimensional scaling (MDS) to determine the number of highly cited articles. MDS is used to acquire as much original data as possible and reduce that data into a few dimensions (McCain, 1990). Stress is a criterion for determining the goodness of fit between original input matrix distances and the estimated distances in low-dimensional solutions (McCain, 1990). MDS ends when stress falls below the threshold of 0.2 (Kruskal, 1964; McCain, 1990). When the number of highly cited academic papers was 52, the stress of the co-citation matrix was 0.19127 (lower than the acceptable value of 0.2). Thus, 52 highly cited academic papers were identified (Appendix).

### *4.2 Factor analysis*

Factor analysis was performed to identify the core knowledge of BI through the structure of relationships among the studies on BI. Factor analysis is commonly used in bibliometric analyses (co-citation analysis; Culnan, 1987; Leydesdorff and Vaughan, 2006; Zupic and Cater, 2015) to explore the relationships between variables and determine their underlying structure. Eigenvalues and scree plots are used for all variables to determine the number of factors (Hair *et al.*, 2006). Similar research articles often load onto the same factor, indicating subfields, the combination of which constitutes a knowledge structure (Samiee and Chabowski, 2012; Shiau *et al.*, 2019).

For factor analysis of the correlation matrix of the co-citations, principal component analysis was adopted, with eigenvalue > 1 as the criterion and the application of varimax rotation. Seven factors were extracted, and they explain 81.237% of the variance in the correlation matrix, which is higher than the recommended 70% of total variance (Hsiao and Yang, 2011; Shiau *et al.*, 2017). The seven factors were named using the cited articles in all but one (A33). Table I presents the results of the factor analysis.

[Table I is here]

Factor 1: Big data analytics

Studies in factor 1 have covered concepts, methods, and technology related to big data (Chen and Zhang, 2014; Dean and Ghemawat, 2008; Han *et al.*, 2012; Waller and Fawcett, 2013; Wamba *et al.*, 2015). "Big data" and "BI" are often used interchangeably in the literature (Trieu, 2017). McAfee and Brynjolfsson (2012) noted that big data are more powerful than traditional analytics. With big data, managers can measure and manage data more accurately than ever before and improve decision-making. Organizations that use big data focus on data flows, rely on data scientists, and use data analytics as the core of their operations (Davenport *et al.*, 2012). Sharma *et al.* (2014) recommended researchers study the effects of business analytics and decision-making processes on organizational performance. High-performing organizations are more likely to incorporate data analytics into their business practices (Lavalle *et al.*, 2011) because of their strong big data analytics capabilities (Wamba *et al.*, 2017).

Chen *et al.* (2012) divided BI&A into three stages, namely, BI&A 1.0, BI&A 2.0, and BI&A 3.0, and made definitions and descriptions according to their major features and functions. Drawing on the results of system evaluation and case study, Wamba et al. (2015) proposed a framework and analyzed the definition and applications of big data. They revealed that big data can facilitate the cocreation of knowledge, which in turn can guide evidence-based decision-making and thus maximize returns. Larson and Chang (2016) developed a framework to determine the effects of big data on BI. They also identified several opportunities for research on BI and big data analytics.

Factor 2: BI benefits and success

Studies in factor 2 have mainly covered the successful implementation of BI and its benefits. DeLone and McLean (1992) developed a model to measure the success of traditional ISs. BI is an intelligent IS that supports decision-making (Watson, 2009); researchers should focus on this effect (Jourdan *et al.*, 2008). Studies have indicated that ISs are essential to the success of implementing BI; identifying organizational problems is also key to the success of BISs (Clark *et al.*, 2007; Popovic *et al.*, 2012; Yeoh and Popovic, 2016). Organizations' absorptive capacity is crucial to their ability to utilize BI (Elbashir, 2011). In addition, the strong relationship between business processes and organizational performance positively affects BI success (Elbashir *et al.*, 2008). The practices of companies such as Harrah's Entertainment, Continental Airlines, Norfolk Southern, and Blue Cross and Blue Shield of North Carolina are examples of successful BI incorporation (Wixom and Watson, 2010). In summary, IS (e.g., BI) success is beneficial to organizations (Clark *et al.*, 2007; DeLone and McLean, 2003; Negash, 2004; Watson *et al.*, 2002; Watson *et al.*, 2006; Yeoh and Koronios, 2010).

Factor 3 - Organizational capabilities and performance

Studies in factor 3 have mainly covered organizational capabilities and performance. Teece *et al.* (1997) explored the relationship between dynamic capabilities and wealth creation. Dynamic capabilities are crucial to resource configurations (Eisenhardt and Martin, 2000). Melville *et al.* (2004) developed an IT business value model based on the resource-based view to guide research on the effects of IT on organizational performance. Bharadwaj (2000) empirically demonstrated the positive effects of strong IT capabilities on firm performance. The complex relationships among latent variables (e.g., organizational capabilities and performance) can be explored through structural equations modeling (Chin, 1998; Fornell and Larcker, 1981; Podsakoff *et al.*, 2003)

Factor 4: IT acceptance and measurement

The fourth factor is acceptance and measurement of IT. Factors affecting the efficiency of a BIS must be identified to ensure users adopt it. Davis (1989) developed and examined scales to analyze the adoption IT in terms of perceived usefulness and perceived ease of use. One study proposed a unified theory of acceptance and use of technology (UTAUT) based on the literature on the technology acceptance model to identify factors that affect cognition (Venkatesh *et al.*, 2003). Goodhue and Thompson (1995) proposed a comprehensive theoretical model and empirically tested its core. The match between technology and the tasks to which it is applied is crucial to its performance. Traditional IT theories provide a basis to examine the acceptance and measurement of BI.

Factor 5: Information and business analytics

Studies in factor 5 have mainly explored the relationship between information and business analytics. High-quality information is critical for managerial decision-making (Lonnqvist and Pirttimaki, 2006). Business analytics involves applying advanced techniques enabled by data technology to solve contextual problems (Bose, 2009; Trkman *et al.*, 2010). Organizations should use economic, social, and environmental data analytics to explore sustainability (Petrini and Pozzebon, 2009) because external information is critical to commercial activity (Cohen and Levinthal, 1990).

Factor 6: Social media text analytics

Studies in factor 6 have mainly explored social media text analytics. Scientific paradigms are often created to strengthen social capabilities with innovative technology such as social media (Hevner *et al.*, 2004). The purpose of IS design science is to develop innovative technology to strengthen humans' abilities (Hevner *et al.*, 2004). Social media is an interactive technology that facilitates the sharing of information, ideas, and opinions online, and it has strongly affected information communications. The increasing volume of opinions online provides opportunities and challenges for social media text analytics (Pang and Lee, 2008). Studies have developed frameworks and conducted investigations to help researchers and practitioners understand social media analytics (Chau and Xu, 2012; He *et al.*, 2013). Chau and Xu (2012) proposed a framework to collect text data from blogs and analyze consumers' opinions and emotions. He *et al.* (2013) studied three pizza chains and revealed the importance of social media competitive analysis. They also provided recommendations to help organizations develop competitive social media analysis strategies.

Factor 7 - The development of BI

Studies in factor 7 have covered the development of BI. Decision support systems first emerged in the early 1970s to support decision-making, and they were followed by various innovations that expanded the field (Watson and Wixom, 2007). BI was first proposed by Howard Dresner in the 1990s, and it has developed and generated interest in concepts such as real-time BI, business management, and pervasive BI (Watson and Wixom, 2007). Chaudhuri *et al.* (2011) indicated that BI can be applied to research and relevant industries. Data collection has been considerably simplified, and large databases have increased in popularity. Text data are valuable sources of information in BI. The growing demand for BI due to next-generation mobile devices offers both opportunities and challenges for the application of BI software.

### *4.3 Cluster analysis*

We performed cluster analysis to determine the structure and relationships among the studies (co-citation). Cluster analysis groups studies on the basis of their characteristics (Hair *et al.*, 2006). We performed a hierarchical, connectivity-based cluster analysis (Ward's method) and centroid-based cluster procedure (k-means) on the correlation matrix of co-citations (Hair *et al.*, 2006). Ward's method was used to determine the appropriate number of clusters and the agglomeration schedule (based on squared Euclidean distance). The cluster analysis revealed high internal (within-cluster) homogeneity and external (between-cluster) heterogeneity (Hair *et al.*, 2006) and grouped similar studies, which helped elucidate topics in their internal structures (McCain, 1990; Shiau *et al.*, 2018).

Figure 4 presents the results of the cluster analysis, and Figure 5 presents the results of MDS. The Appendix explains the coding system for the studies. Cluster 1—named IT acceptance model—included the same papers as factor 4, and cluster 3—named organizational capabilities and performance—included the same papers as factor 3. Although factor 6 included one more study (A18; Eisenhardt, 1989) than did cluster 5, because the study covered the methodologies in case studies on social media (Li *et al*., 2021), we used the same names for cluster 5 and factor 6. Thus, in this article, we only discuss clusters 2, 4, and 6.

[Figure 4 is here]

[Figure 5 is here]

Cluster 2: BI success and measurement

Whether IT will be accepted should be determined before it is applied. Studies in cluster 2 have mainly explored the key factors affecting the success of ISs (BI) how it is measured. Computer-based ISs support personal and organizational decision-making (Watson, 2009). DeLone and McLean (1992) explored a model of the success of traditional ISs comprising six dimensions: system quality, information quality, use, user satisfaction, personal effects, and organizational effects. After the advent of the Internet and electronic commerce, they adjusted the model by adding service quality, separating intention to use from use, and replacing individual and organizational effects with net benefits (DeLone and McLean, 2003). Factors affecting the success of ISs (relating to business) include strategies (Jourdan *et al.*, 2008; Wixom and Watson, 2010), the market (Negash, 2004), environmental elements (Clark *et al.*, 2007; Isik *et al*., 2013), information quality and culture (Popovic *et al.*, 2012), organizations' absorptive capacity (Elbashir, 2011), and managerial and procedural problems in organizations (Clark *et al.*, 2007; Wixom and Watson, 2001; Yeoh and Koronios, 2010). In addition to identifying factors determining success, measuring success is crucial to determine the value of and manage BI (Lonnqvist and Pirttimaki, 2006). Elbashir *et al.* (2008) developed a framework for organizations and their processes to measure the value of BISs; strong IT processes can improve organizational performance. However, the strength of this relationship differs by sector. Petrini and Pozzebon (2009) explored how BISs affect organizational sustainability and proposed a model that incorporates socioenvironmental indicators into organizational strategies for sustainable management.

Cluster 4: Big data-enabled business value

Studies in cluster 4 have mainly explored the value of big data for businesses. Big data and big data analytics have attracted much attention from researchers and practitioners (Chen *et al.*, 2012; Chen and Zhang, 2014). Big data analytics is more powerful than traditional data analytics (Davenport *et al.*, 2012; McAfee and Brynjolfsson, 2012). Big data are valuable because they can improve decision-making (Gandomi and Haider, 2015). Big data analytics provides competitive advantages by increasing efficiency for businesses (Wamba *et al.*, 2017). Therefore, organizations should prioritize data analytics (Lavalle *et al.*, 2011). Big data analytics has reduced the time required to collect data, enabling organizations to spend more time analyzing business value (Larson and Chang, 2016). Dean and Ghemawat (2008) introduced a programming model to process and generate large data sets and increase the efficiency of big data processing. Several studies have demonstrated how big data have created competitive advantages and value for businesses (Wamba *et al.,* 2015; Waller and

Fawcett, 2013).

Cluster 6: BIS and analytics

Studies in cluster 6 have mainly explored BIS and analytics. Luhn (1958) defined a BIS as a comprehensive system covering information-based problems in an organization. In BISs, data warehouses, online processing, and data mining are employed to create value (Chaudhuri *et al.*, 2011; Watson and Wixom, 2007). Trieu (2017) proposed a theoretical framework demonstrating how organizations gain value from BISs. Data mining and data analytics are crucial to intelligent systems (Han *et al.*, 2012), and organizations should develop methods for increasing competitiveness (Cohen and Levinthal 1990; Davenport, 2006). The value business analytics can create motivates organizations to invest in it (Sharma *et al.*, 2014). Technology-driven business analytics helps firms understand their operations and customers and to improve performance (Bose, 2009; Trkman *et al.*, 2010).

### *4.4 Comparison of factor and cluster analyses*

The factor analysis based on the co-citation matrix revealed seven key factors of the core knowledge of BI: big data analytics, BI benefits and success, organizational capabilities and performance, IT acceptance and measurement, information and business analytics, social media text analytics, and the development of BI. The cluster analysis revealed six categories: IT acceptance and measurement, BI success and measurement, organizational capabilities and performance, big-data-enabled business value, social media text analytics, and BIS and analytics.

[Table II is here]

A comparison of the results of the factor and cluster analyses (Table II) revealed several similarities. However, the cluster analysis yielded more concentrated results. Cluster 1, IT acceptance and measurement, overlaps factor 4 (A14, A24, and A44). This indicates that BI is an application of IT. Traditional IT theories such as the technology acceptance model and UTAUT can be used to measure the acceptance of BI. However, although BI affects both individuals and organizations, theories of the acceptance of BI do not cover the organizational level; researchers should develop theories to close this gap.

Cluster 2, BI success and measurement, overlaps partial factor 2 (A10, A16, A17, A20, A21, A28, A29, A36, A39, A49, A50, A51, and A52), and partial factor 5 (A32 and A37). This indicates that measuring the success of BI is complicated and should involve social, environmental and economic elements. Studies should empirically demonstrate the importance of indicators of the success of BI. In addition, researchers can conduct case studies to identify challenges during this process and opportunities for improvement.

Cluster 3, organizational capabilities and performance, overlaps factor 3 (A1, A2, A9, A19, A22, A35, A38, and A41). This indicates that organizational capabilities are closely related to organizational performance. BI strengthens organizations' dynamic capabilities and facilitates decision-making, which can improve performance. Organizations should thus incorporate BI into their strategies. Because each industry requires different capabilities, studies should explore the industry-specific capabilities that optimize performance.

Cluster 4, big data-enabled business value, covers partial factor 1 (A7, A8, A13, A15, A23, A30, A31, A34, A45, A46, and A47). This finding means that big data- enabled business value is part of big data analytics. Large sets of various types of data can be analyzed to identify patterns, correlations, trends, customers' preferences, and other useful information. Enterprises utilize big data to obtain valuable information that can benefit their business. Big data-enabled business value refers to the value businesses derive from using big data. It focuses on technology, organizations, and data; emphasizes the combination of technology and business; and realizes business value. Organizations can benefit from mining big data and understanding their value. Technologies such as mobile devices facilitate the collection of terabytes or more of data. Therefore, researchers and practitioners should focus on both the traditional uses of data and data from social media, digital images, and the Internet of Things, which contain valuable information for businesses.

Cluster 5, social media text analytics, overlaps partial factor 6 (A3, A5, A26, and A27). This indicates that social media text analytics is an emerging research topic. Social media generate large amounts of online data that can be analyzed to create competitive advantages for organizations. Organizations should incorporate social media analytics into their business strategies to understand their customers and competitors. Researchers should also identify the effects of social media on organizational decision-making.

Cluster 6, BIS and analytics, overlaps partial factor 1 (A12, A25, A40, and A42), partial factor 5 (A4, A11, and A43), factor 7 (A6 and A48). This result indicates that BIS and analytics relate to numerous other concepts. The BIS is an IS that uses data warehouse technology, OLAP, and data mining technology to realize business value. BISs collect not only internal operation data but also external information such as social media data. Big data analytics is the main purpose of BISs. With the development of BI, novel functions are continually added to BISs for specific purposes; thus, researchers should carefully and accurately define BISs before they initiate context-specific BIS studies.

## 5. Implications

### *5.1 Implications for research*

This study describes the core concepts of research on BI, which can help researchers save time, and explore new problems in the BI field. Our study expands on other literature reviews by applying cluster and factor analyses and comparing the results of these analyses. The factor analysis revealed seven factors that focus on various areas of BI, ranging from studies on big data analytics to studies identifying the development of BI. The cluster analysis revealed six clusters of BI, ranging from IT acceptance and measurement to BIS and analytics. Researchers should focus on the intraorganizational acceptance and use of BI and big data analytics capabilities. Our study also expands on others (Chen *et al.*, 2012; Jourdan *et al.*, 2008; López-Robles *et al.*, 2019) by identifying emerging topics for research, such as social media text analytics, the importance of which has been explored in various conference papers (Basyal *et al.*, 2021; Nasralah *et al.*, 2019). Most relevant studies have explored BI in relation to firms; studies should also explore how it relates to industries and countries. The characteristics of each industry determine how BI evolves and its effects on organizational performance. Studies can explore factors related to technological change and industry-specific

BI standards. In addition, studies should explore how countries' cultures, education systems, infrastructure, legal systems, and technological regulations affect the use of BI (Trieu, 2017) and its value.

### *5.2 Implications for practice*

This study also offers opportunities for practitioners who are involved in adopting, implementing, and using BI. BI facilitates organizational learning and decision-making, thereby increasing operational efficiency (Bozic and Dimovski, 2019; Trieu, 2017). Because of the complexity of BI, its implementation is challenging and entails high risk and costs. Therefore, most organizations have not derived the expected benefits from BI. Practitioners must understand the factors critical to successful BI implementation (Gaardboe and Svarre, 2018). The factor and cluster analyses in this study can help managers understand the core aspects of BI and improve their performance by investing in BI. In addition to the results of this study, IT such as artificial intelligence and machine learning can increase efficiency for enterprises (López-Robles *et al.*, 2019). The cluster and factor analyses also demonstrated the importance of BI analytics, which is consistent with the results of Gartner (2019), who noted that augmented analytics encourages the purchase of analytics and BI platforms. Data from social media and apps can create both challenges and opportunities for managers. For example, analyzing social media text can help managers understand public opinion (Chen *et al.*, 2020). COVID-19 has demonstrated the value of modeling and predicting how the pandemic would spread. Companies, governments, and even countries should utilize BI-based predictive analytics to strengthen their dynamic capabilities.

## 6. Limitations and future research

Our study has several limitations. First, co-citation analysis entails time lag, which means that articles published after the search were not included; studies should therefore continue to review newly published studies on this topic. Second, we employed factor and cluster analyses in our study; because the method adopted can affect the results, studies should use other methods and compare their results with ours. Third, we concentrated on research articles. Studies can also investigate industry reports and interviews with experts on BI. Finally, research changes over time, and new BI-based technology such as mobile BI has emerged. Studies should compare the various stages of research on BI to demonstrate how the core knowledge changes over time.

## 7. Conclusions

BI involves methodologies, processes, architecture, and technology that transform raw data into meaningful and useful information that can be used to identify new opportunities and develop effective strategies to gain competitive advantages. BI has become increasingly important for research and business (Chen *et al.*, 2012; Jin and Kim, 2018; Jourdan *et al.*, 2008). Therefore, understanding BI is crucial. We outlined the core knowledge of BI by examining 1306 journal articles published between 2000 and 2020 through citation analysis, which yielded 52 highly cited articles. We then performed factor analysis to group the articles into seven core factors: big data analytics, BI benefits and success, organizational capabilities and performance, IT acceptance and measurement, information and business analytics, social media text analytics, and the development of BI. The results of cluster analysis are as follows:

IT acceptance and measurement, BI success and measurement, organizational capabilities and performance, big data-enabled business value, and social media text analytics, and BIS and analytics. This information can help researchers save time as they seek out new opportunities for research. This information can also help managers understand the key aspects of BI, use BI to manage their enterprises, improve decision-making, and gain competitive advantages. BI will continue to be a crucial topic in various areas as technology continues to advance.

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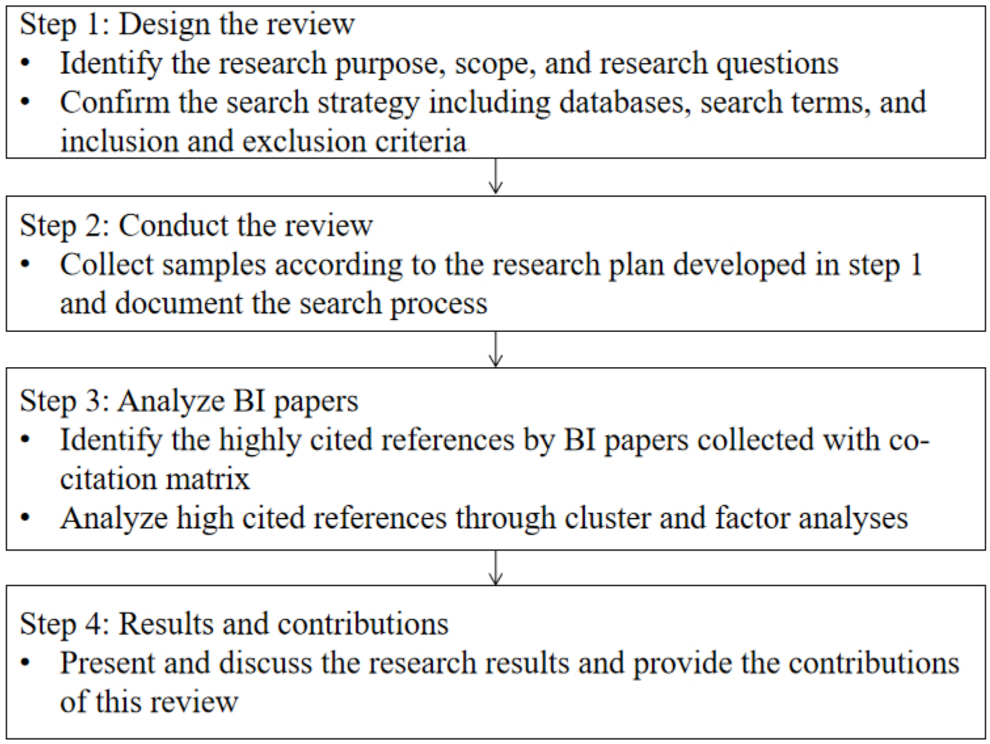


Figure 1. The steps of systematic review

510x387mm (38 x 38 DPI)

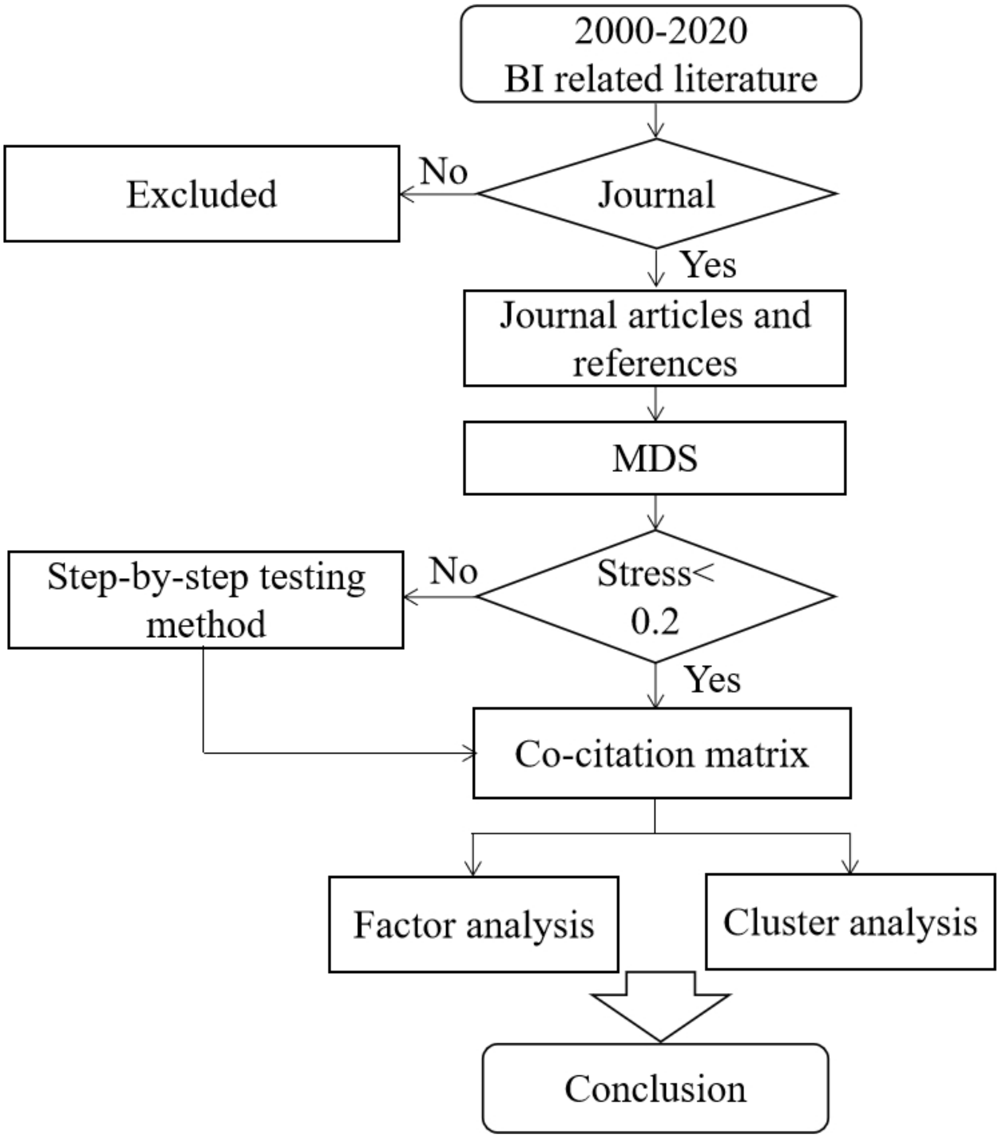


Figure 2. The steps of research method

263x310mm (72 x 72 DPI)

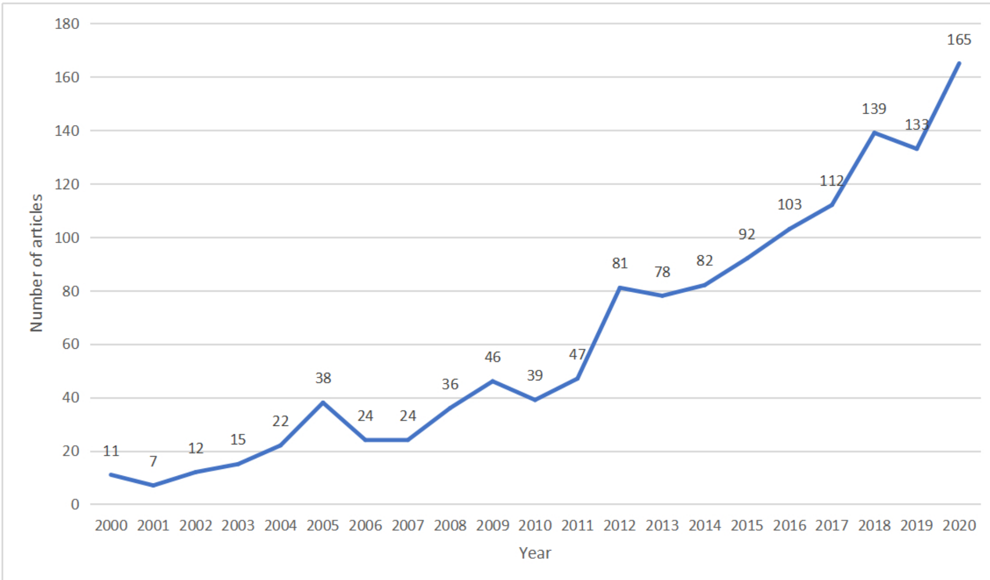


Figure 3. The distributions of business intelligence

490x287mm (59 x 59 DPI)

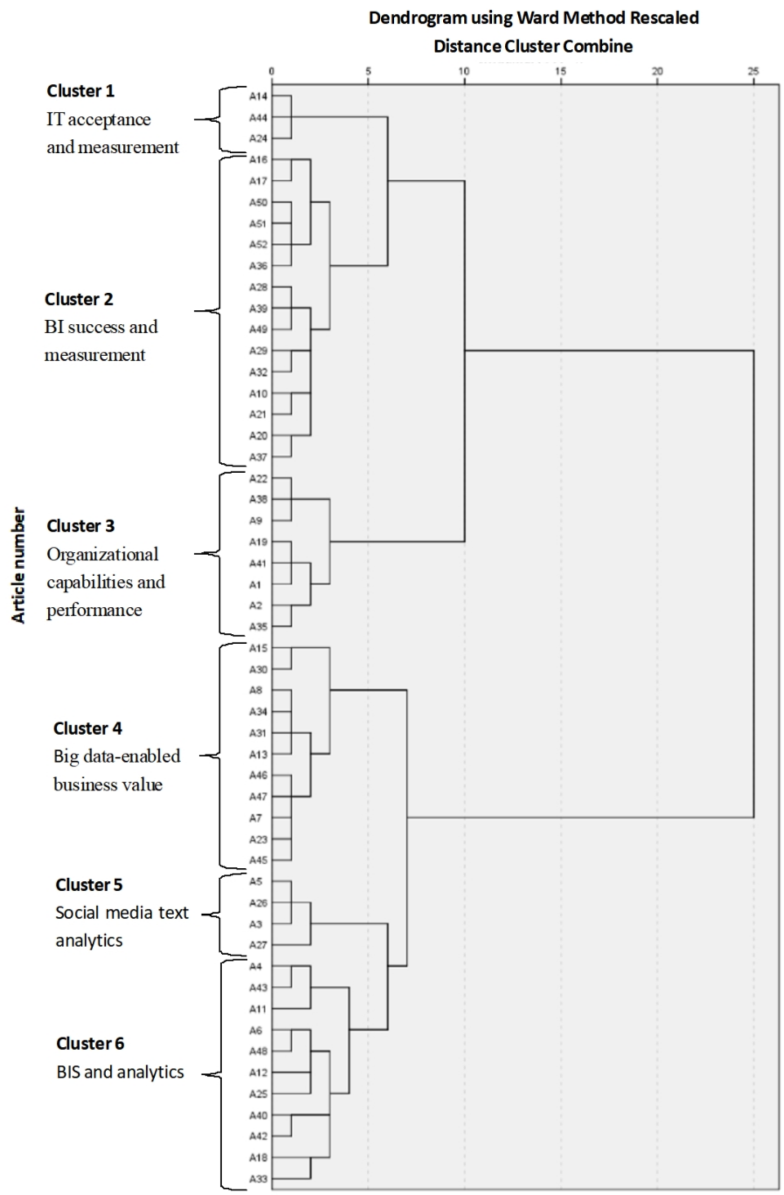


Figure 4. Results of cluster analysis

385x579mm (72 x 72 DPI)

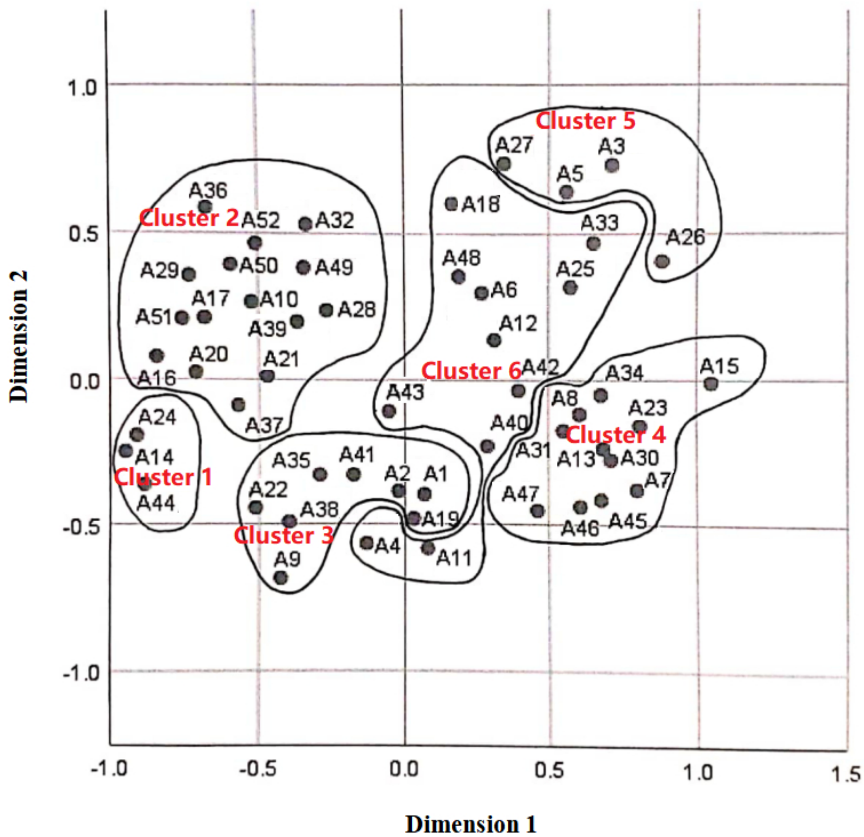


Figure 5. Results of multi-dimensional scaling analysis

308x271mm (72 x 72 DPI)

**Table I.** Results of factor analysis

| Factor | Conceptual theme | No. of article | VE% |
|---|---|---|---|
| 1 | Big data analytics | A7, A8, A12, A13, A15, A23, A25, A30, A31, A34, A40, A42, A45, A46, A47 | 31.605 |
| 2 | BI benefits and success | A10, A16, A17, A20, A21, A28, A29, A36, A39, A49, A50, A51, A52 | 22.020 |
| 3 | Organizational capabilities and performance | A1, A2, A9, A19, A22, A35, A38, A41 | 9.500 |
| 4 | IT acceptance and measurement | A14, A24, A44 | 6.156 |
| 5 | Information and business analytics | A4, A11, A32, A37, A43 | 4.575 |
| 6 | Social media text analytics | A3, A5, A18, A26, A27 | 4.397 |
| 7 | The development of BI | A6, A48 | 2.983 |

Note: factors only containing one article were ignored.

**Table II.** Comparison of cluster and factor analyses

| Cluster | Factor | Conceptual theme |
|---|---|---|
| 1 | 4 | IT acceptance and measurement |
| 2 | Partial 2, Partial 5 | BI success and measurement |
| 3 | 3 | Organizational capabilities and performance |
| 4 | Partial 1 | Big data-enabled business value |
| 5 | Partial 6 | Social media text analytics |
| 6 | 7, Partial 1, Partial 5 | BIS and analytics |

Note: factors only containing one article were ignored.

**Appendix.** Highly cited articles

| No. | Articles |
|---|---|
| A1 | Barney, J. (1991), "Firm resources and sustained competitive advantage", *Journal of Management*, Vol. 17 No. 1, pp. 99-120. |
| A2 | Bharadwaj, A. S. (2000), "A resource-based perspective on information technology capability and firm performance: an empirical investigation", *MIS Quarterly*, Vol. 24 No.1, pp. 169-196. |
| A3 | Pang, B. and Lee, L. (2008), "Opinion mining and sentiment analysis", *Foundations and Trends in Information Retrieval*, Vol. 2 No.1-2, pp. 1-135. |
| A4 | Bose, R. (2009), "Advanced analytics: opportunities and challenges", *Industrial Management and Data Systems*, Vol. 109 No. 2, pp. 155-172. |
| A5 | Chau, M. and Xu, J. (2012), "Business intelligence in blogs: understanding consumer interactions and communities", *MIS Quarterly*, Vol. 36 No. 4, pp. 1189-1216. |
| A6 | Chaudhuri, S., Dayal, U. and Narasayya, V. (2011), "An overview of business intelligence technology", *Communications of the ACM*, Vol. 54 No. 8, pp. 88-98. |
| A7 | Chen, C.L.P. and Zhang, C.Y. (2014), "Data-intensive applications, challenges, techniques and technologies: a survey on big data", *Information Sciences*, Vol. 275, pp. 314-347. |
| A8 | Chen, H.C., Chiang, R.H.L. and Storey, V.C. (2012), "Business intelligence and analytics: from big data to big impact", *MIS Quarterly*, Vol. 36 No. 4, pp. 1165-1188. |
| A9 | Chin, W.W. (1998), "The Partial Least Squares Approach to Structural Equation Modeling", *Modern Methods for Business Research*, Vol. 295 No.2, pp. 295–336. |
| A10 | Clark Jr., T.D., Jones, M.C. and Armstrong, C.P. (2007), "The dynamic structure of management support systems: theory development, research focus, and direction", *MIS Quarterly*, Vol. 31 No. 3, pp. 579-615. |
| A11 | Cohen, W. M. and Levinthal, D. A. (1990), "Absorptive capacity: a new perspective on learning and innovation", *Administrative Science Quarterly*, Vol. 35 No. 1, pp. 128-152. |
| A12 | Davenport, T.H. (2006), "Competing on analytics", *Harvard Business Review*, Vol. 84 No. 1, pp. 98-107. |
| A13 | Davenport, T. H., Barth, P. and Bean, R. (2012), "How 'big data' is different", *MIT Sloan Management Review*, Vol. 54 No. 1, pp. 22-24. |
| A14 | Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319-340. |
| A15 | Dean, J. and Ghemawat, S. (2008), "MapReduce: simplified data processing on large clusters", *Communications of the ACM*, Vol. 51 No. 1, pp. 107-113. |

| No. | Articles |
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| A16 | DeLone, W.H. and McLean, E.R. (1992), "Information systems success: the quest for the dependent variable", *Information Systems Research*, Vol. 3 No. 1, pp. 60-95. |
| A17 | DeLone, W.H. and McLean, E.R. (2003), "The Delone and Mclean model of information systems success: a ten-year update", *Journal of Management Information Systems*, Vol. 19 No. 4, pp. 9-30. |
| A18 | Eisenhardt, K.M. (1989), "Building theories from case study research", *Academy of Management Review*, Vol. 14 No. 4, pp. 532-550. |
| A19 | Eisenhardt, K. M. and Martin, J. A. (2000), "Dynamic capabilities: what are they?", *Strategic Management Journal*, Vol. 21 No. 10-11, pp. 1105-1121. |
| A20 | Elbashir, M.Z., Collier, P.A. and Davern, M.J. (2008), "Measuring the effects of business intelligence systems: the relationship between business process and organizational performance", *International Journal of Accounting Information Systems*, Vol. 9 No. 3, pp. 135-153. |
| A21 | Elbashir, M. Z., Collier, P. A. and Sutton, S. G. (2011), "The role of organizational absorptive capacity in strategic use of business intelligence to support integrated management control systems", *The Accounting Review*, Vol. 86 No. 1, pp. 155-184. |
| A22 | Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50. |
| A23 | Gandomi, A. and Haider, M. (2015), "Beyond the hype: big data concepts, methods, and analytics", *International Journal of Information Management*, Vol. 35 No. 2, pp. 137-144. |
| A24 | Goodhue, D.L. and Thompson, R.L. (1995), "Task-technology fit and individual performance", *MIS Quarterly*, Vol. 19 No. 2, pp. 213-236. |
| A25 | Han, J., Kamber, M. and Pei, J. (2012), *Data Mining Concepts and Techniques* (3rd ed.). Waltham, MA: Morgan Kaufman. |
| A26 | He, W., Zha, S. and Li, L. (2013), "Social media competitive analysis and text mining: a case study in the pizza industry. International journal of information management", Vol. 33 No.3, pp. 464-472. |
| A27 | Hevner, A.R., March, S.T., Park, J. and Ram, S. (2004), "Design science in information systems research", *MIS Quarterly*, Vol. 28 No. 1, pp. 75-105. |
| A28 | Isik, O., Jones, M.C. and Sidorova, A. (2013), "Business intelligence success: the roles of bi capabilities and decision environments", *Information and Management*, Vol. 50 No. 1, pp. 13-23. |
| A29 | Jourdan, Z., Rainer, R.K. and Marshall, T.E. (2008), "Business intelligence: an analysis of the literature", *Information Systems Management,* Vol. 25 No. 2, pp. 121-131. |
| A30 | Larson, D. and Chang, V. (2016), "A review and future direction of agile, business intelligence, analytics and data science", *International Journal of Information Management*, Vol. 36 No. 5, 700-710. |

| No. | Articles |
|---|---|
| A31 | Lavalle, S., Lesser, E., Shockley, R., Hopkins, M.S. and Kruschwitz, N. (2011), “Big data, analytics and the path from insights to value”, *MIT Sloan Management Review*, Vol. 52 No. 2, pp. 21-32. |
| A32 | Lonnqvist, A. and Pirttimaki, V. (2006), “The measurement of business intelligence”, *Information Systems Management*, Vol. 23 No. 1, pp. 32-40. |
| A33 | Luhn, H.P. (1958), “A business intelligence system”, *IBM Journal of Research and Development*, Vol. 2 No. 4, pp. 314-319. |
| A34 | McAfee, A. and Brynjolfsson, E. (2012), “Strategy and competition big data: the management revolution”, *Harvard Business Review*, Vol. 90 No. 10, pp. 60-66. |
| A35 | Melville, N., Kraemer, K. and Gurbaxani, V. (2004), “Review: information technology and organizational performance: an integrative model of IT business value”, *MIS Quarterly*, Vol. 28 No. 2, pp. 283-322. |
| A36 | Negash, S. (2004), “Business intelligence”, *Communications of the Association for Information Systems*, Vol. 13, pp. 177-195. |
| A37 | Petrini, M. and Pozzebon, M. (2009), “Managing sustainability with the support of business intelligence: integrating socio-environmental indicators and organisational context”, *Journal of Strategic Information Systems*, Vol. 18 No. 4, pp. 178-191. |
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| A39 | Popovic, A., Hackney, R., Coelho, P.S. and Jaklic, J. (2012), “Towards business intelligence systems success: effects of maturity and culture on analytical decision making”, *Decision Support Systems*, Vol. 54 No. 1, pp. 729-739. |
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| A41 | Teece, D.J., Pisano, G. and Shuen, A. (1997), “Dynamic capabilities and strategic management”, *Strategic Management Journal*, Vol. 18 No. 7, pp. 509-533. |
| A42 | Trieu, V. H. (2017), “Getting value from business intelligence systems: a review and research agenda”, *Decision Support Systems*, Vol. 93, pp. 111-124. |
| A43 | Trkman, P., McCormack, K., De Oliveira, M. P. V. and Ladeira, M. B. (2010), “The impact of business analytics on supply chain performance”, *Decision Support Systems*, Vol. 49 No. 3, pp. 318-327. |
| A44 | Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), “User acceptance of information technology: toward a unified view”, *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478. |