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Analytical evaluation of big data applications in E-commerce: A mixed method approach

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A B S T R A C T

E-commerce is one of the industries most affected by big data, from collection to analytics in the highly competitive market. Previous research on big data analytics in E-commerce focused only on particular applications, and there is still a gap in presenting a framework to evaluate big data applications from a challenges-values point of view. This study employs a three-phase methodology to evaluate big data applications in E-commerce with respect to big data challenges and values using a hybrid multi-criteria decision-making technique that combines BWM and fuzzy TOPSIS. The results showed process challenge and the strategic value obtained the highest weight for challenges and values criteria. Financial fraud detection is relatively the most challenging, and online review analytics is the most valuable application of big data in E-commerce among identified applications. Evaluating big data applications based on cost and benefit criteria is practical for E-commerce managers and experts to make decisions on implementation priorities to overcome the challenges and make the most of values. Moreover, the proposed approach is not only limited to big data analytics in E-commerce and can also be applied in other industries to evaluate emerging technology applications.

1. Introduction

With the development of the internet and flourishing information technology, people's consumption patterns have changed since the whole purchase process can be completed through the internet, from ordering to delivery. Many traditional manufacturers expanded online retail channels to organized channels with third parties to complement traditional channels (Han et al., 2018). Our lives have changed significantly by the quarter of 2020 due to the COVID-19 pandemic. Subsequently, customer's demand to buy products and services via the internet and e-commerce platform increased significantly and became an integral part of people's daily lives. E-commerce is going to be the central part of business activity (Hua, 2016), and its market sales worldwide are estimated to grow 20.4 percent in 2022 to $ 5.424 trillion (Flood, 2021). Compared to traditional selling methods, online shopping has several advantages, such as being more flexible, faster, and more convenient for both customers and sellers. Sellers need to increase trust, understand customers' needs, and find ways to convert one-time customers into repeat buyers (Oliveira, 2017). Over the past few years, e-commerce has thrived and attracted significant attention in both industry and academia, with a number of research topics related to e-commerce (Yuan et al., 2018).

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E-commerce has experienced dramatic changes since the beginning of the 21st century due to the rapid reduction of network costs and enhancement of network infrastructure (Uzoka et al., 2017). As e-commerce has expanded around the world over the past decade and competes globally, how to attract new customers and retain existing ones for repurchase are more important concerns than ever before for e-commerce platforms (Fang, 2014). Information and communication technology allows organizations to conduct business activities as quickly as possible. In the late twentieth century, advances led to the formation of e-commerce, which revolutionized commerce and dramatically changed people's lifestyles (MacGregor & Vrazalic, 2005). With the high internet penetration rate in people's lives around the world, people can use devices such as computers, laptops, smartphones, etc., to purchase anywhere and anytime. Online sellers have shifted their attention from persuading consumers to adopt their online channels in order to motivate them to purchase repeatedly, and this electronic version of interactions has made companies reach their customers quickly and continually (Behl, 2019). The growth in e-commerce and the evolution of its activity is beneficial for both customers and vendors. Vendors spend much less on infrastructure and labor force than the traditional business model, and customers' accessibility to a wide variety of products and proper level of service is enhanced (Hurtado et al., 2019).

The advent of the internet and the rise of connected technology has transformed e-commerce from a traditional trading model to a new business model that will eventually lead to a change in the consumer's lifestyle and a constant change in their needs; hence immediate actions and cooperation between production and the market are crucial (Li, 2018). Today, e-commerce operates in a dynamic and competitive environment, and vendors compete with other vendors by reducing production costs and providing better quality. Giving better quality products at low cost is challenging decision-making for sellers in the competitive market. Due to advancements in technologies and data science, sellers need to extract actionable insight by predicting customer needs through big data analytics (Chong, 2017). Organizations use business analytics tools, technology, and process, including predictive and prescriptive analytics, to integrate a large volume of data from multiple internal and external sources to recommend the best solutions (D.Q. Chen et al., 2015; Zineb et al., 2021). This technology is rapidly gaining popularity due to its ability to manage and process large amounts of data, especially in e-commerce (Raguseo & Vitari, 2018). Big data analytics capabilities have affected every discipline, including engineering, economics, medicine, marketing, psychology, human resource management, and environmental sciences (Fosso Wamba et al., 2018), moreover attracting e-commerce companies to invest in and apply tools to gain core competency over their competitors (Behl, 2019). E-commerce is one of the industries that has been most affected by big data, from collection to analytics (Zineb et al., 2021), and data generation is on the scale of petabytes daily due to increased website visits (Malhotra & Rishi, 2021). Today's success of e-commerce companies depends mainly on their capability to capture, store, and efficiently use data (Zheng, 2020), and e-commerce that apply big data analytics in their activities obtain 5 to 6 percent higher productivity than their competitors. Using data more efficiently, having a higher conversion rate, decision-making improvement, and empowering customers are the impacts of big data analytics in e-commerce (Akter, 2016; McAfee, 2012). Enormous data from clicking through the marketing advertisement, logging on platforms to purchase and receive the final product; online reviews, customer profiles, and generated activities can be used to analyze customers and make influential customer forecasts (Li, 2018; Zhu, 2021). Social media plays an important role in developing e-commerce because it increases the ability to reach a larger group. Many studies have confirmed that social media helps promote brand and product awareness and improve user experiences (Makki & Chang, 2016). Social media and e-commerce are critical issues for organizations in different domains. Social media changes people's lifestyles considerably and enables e-commerce by targeting a real audience. Frequent shopping and use of e-commerce platforms generate a large amount of browsing and logging data that are valuable if big data development strategies are applied to mine hidden patterns (Xie et al., 2020). The internet and social media development have brought challenges and opportunities for big data into the big data e-commerce era (See-To & Ngai, 2018). Although big data analytics in e-commerce and market intelligence is one of the emerging research opportunities (Chen et al., 2012; Qi et al., 2016; Wamba, 2015), there is still a gap in comprehensive research devoted to big data applications evaluation in e-commerce considering big data challenges and values brings for e-commerce. Previous research related to big data analytics in e-commerce focused on the particular applications in domains such as operations (Hu, 2019; Mishra, 2018), marketing (Alojail & Bhatia, 2020; Mach-Król & Hadasik, 2021), and finance (Carta et al., 2019) in order to optimize the efficiency of the related e-commerce process. Therefore, this study aims to identify and rank big data analytics in e-commerce with respect to challenges and values of big data by exploring the following two questions:

RQ1: What are the rankings of big data applications in e-commerce based on big data challenges?
RQ2: What are the rankings of big data applications in e-commerce based on big data value creation?

The rest of the study is structured as follows. Section 2 is about the theoretical background of the research. The third section explains the methodology and proposed framework for evaluating big data applications in detail. Section four illustrates numerical findings and results analysis, and finally, the last section deals with conclusions and future research.

2. Theoretical background

2.1 Big data

The development of big data has been identified as one of the most critical areas of future information technology, and it is evolving at a rapid pace, driven by multiple data sources. Recently, big data has gained popularity and is considered a critical need for modern organizations (Lee, 2017; Olszak & Zurada, 2020). Big data is defined by its characteristics; Laney

(2001) stated that big data is generally defined by three characteristics known as 3Vs: volume, velocity, and variety. Volume refers to the size and quantity of data generated. Velocity is the measure of speed at which data is available and captured. Variety represents data types that could be structured, unstructured, or semi-structured and generated from various sources. Fosso Wamba et al. (2015) formulated big data by adding the Vs of value and veracity. The value refers to valuable knowledge extraction from data employing big data analytics, and veracity represents how accurate and trustful data is from the data governance view.

Big data analytics is currently a trendy topic in both academia and industry, from concepts to applications. Big data analytics comprises two parts: big data and analytics. As stated above, big data is defined based on its characteristics. The term analytics helps discover what makes a significant change for the business. Therefore big data analytics is an advanced analytical technique that refers to processes, tools, techniques, and technology that makes the most of big data advantage for decision-making in different business issues (Wamba et al., 2017; Zineb et al., 2021). Recent advancements have made big data analytics more valuable to companies as a way to capture vast amounts of data and analyze it with more powerful analytical techniques. The ability to collect and analyze big data enables companies to automate highly complex decisions typically made by humans (D. Q Chen et al., 2015).

2.2 Big data values and challenges

While big data analytics brings e-commerce with valuable insight, there are challenges and issues with big data implementation. Accordingly, we consider big data values and challenges as two criteria for prioritizing big data applications in e-commerce. E-commerce is developing rapidly as a digital platform that faces large volumes of structured and unstructured data. The growth in data generation involves data security in different stages of collection, storage, and analysis, which should be solved in e-commerce (Zhang et al., 2021). Privacy, data-driven culture, managerial issues, and the use of new technology are the main challenges in capturing and analyzing data in the big data environment (Vassakis et al., 2018). Organizations encounter new challenges and need to apply new techniques due to big data characteristics in volume, speed, and variety (Fan, 2013). Analyzing and synthesizing research on big data analytics, Sivarajah et al. (2017) explored the challenges associated with big data. These proposed challenges are comprehensive, and we adopt them as the big data challenges for this research. They grouped the broad challenges of big data into three groups: data, process, and management challenges.

- Data challenges are rooted in the characteristics of the data itself, as explained in the big data definition.
- Process challenges are related to a series of techniques for capturing, integrating, transforming, modeling, and analyzing data.
- Management challenges include issues such as privacy, security, governance, and ethics.

Big data analytics create values by reducing market, managerial, and time transaction costs within the e-commerce context. Furthermore, it enables the seller to track and analyze user behavior in order to discover the impactful way of converting one-time customers into loyal ones (Le & Liaw, 2017). Côrte-Real et al. (2016) proposed a conceptual model to assess big data analytics value chain in European firms. They indicated that big data analytics improve organizational agility through knowledge management, process, and competitive advantages. Popovič et al. (2018) investigated the impact of big data analytics on high value business performance in the manufacturing sector. Big data applications in manufacturing enhance decision-making through planning, operation process, and quality assurance. Since the data itself does not automatically add value to firms, Zeng and Glaister (2018) used a theoretical framework to show the value creation process from big data. Their research revealed that analysis of internal data and additional external data with partners consequently as a transaction and relational driven are both require for creating value from big data. Ghasemaghaei and Calic (2020) explored that big data utilization improves firm innovation and significantly impacts financial returns, customer perspective, and operational excellence. Elia et al. (2020) proposed a comprehensive framework as a way to assist organizations in exploiting the value of big data applications. They identified the multiple values of big data that organizations can derive, such as informational, transactional, strategic, and infrastructural values. Besides integrating evidence from the literature review, the proposed model was also applied to organizations in various industries (e-commerce, FMCG, and banking), highlighting its usefulness. Therefore, this research considers these dimensions as the initial criteria for big data value creation.

2.3 E-commerce and big data

E-commerce involves a variety of computer network-based business arrangements for electronic interaction and is considered as a proper strategy for marketing, sales, and integration of online services, which plays a vital role in identifying, acquiring, and retaining customers. Applying and benefiting from information technology is one of the essential factors in growing the efficiency of e-commerce since it optimizes and strengthens relationships between organizations, manufacturers, distributors, and customers. Organizations in various industries should utilize information and communication technology development to maintain and enhance their competitive advantages (Awa, 2015; Choshin, 2017; Li, 2018). Big data analytics is a combination of techniques and technologies that e-commerce applies to analyze large volumes of data that could be complex and diverse. This analysis provides a clear understanding of the current and future company status to make decisions and gain competitive advantages over others (Kwon O, 2014). Large amounts of unstructured, semi-structured, and structured data are generated on the e-commerce website through customer interaction per second. Enterprises seek to use big data mining to translate data into customer knowledge in order to improve overall operational efficiency (Hu, 2019; Zhao, 2019).

The use of big data has become increasingly important in the field of e-commerce (Liu et al., 2019; Wamba et al., 2017), and data such as customer behavior, market trend, demand characteristics, transaction, supply chain processes, etc., are required for accurate analytics in the big data environment (Weiqing, 2021). Social media, user-generated content, information diffusion via an e-commerce platform, financial transactions, and information searches are the multiple sources of big data in e-commerce (Blazquez & Domenech, 2018). E-commerce platforms have collected large amounts of consumer data over the years that are considered valuable business resources. Big data technology and analytics enable the e-commerce platform to obtain more accurate information from these data to obtain a better understanding of the consumers (Zhan et al., 2018). Analyzing big data generated in e-commerce activities helps managers and departments enhance business strategy, increase customer values and discover new opportunities (Hadwan, 2021). Marketing strategies in e-commerce change from product-centric to customer-centric since they can benefit from the transaction, observation, interaction, and user information data that customers generate (Rao et al., 2018). The aspect of big data analytics used for marketing in e-commerce is called big data marketing. Collecting and analyzing large volumes of data from different sources to help marketers target audiences, advertise content, manage marketing time and resources, and understand customer behavior are examples of this aspect of analytics (Xu et al., 2017). Big data e-commerce mainly consists of determining how to extract value and insights from big data in real time to make more intelligent and more profitable business decisions. The idea of big data e-commerce is to use large volumes of data to derive real-time insights, which requires understanding how to extract value from big data (Qi et al., 2016). Although comprehensive studies addressed big data values and challenges, no comprehensive research has enumerated big data applications in e-commerce since each study only addressed particular aspects of big data analytics in e-commerce. Therefore before ranking big data applications in e-commerce, we need to identify them by reviewing related works.

3. Methodology

As shown in Fig. 1, a three-phase methodology is proposed to evaluate big data applications in e-commerce based on big data challenges and values. Phase 1 involves identifying experts, literature reviews, and discussing with experts to finalize criteria and applications through the Delphi method. As stated in the previous section, the initial criteria for big data challenges and values are based on Sivarajah et al. (2017) and Elia et al. (2020) research. Since there is no comprehensive study for enumerating big data applications in e-commerce, we need to conduct a detailed overview of the previous works to identify the big data applications. To accomplish this, we use various databases such as Emerald, Proquest, Google Scholar, Science Direct, IEEE Xplore, and Scopus in order to search articles with different formats of keywords of "big data" and "E-commerce" included in the title or abstract. Inclusion and exclusion criteria for the process of searching are presented in Table 1. After investigating records, 47 articles were obtained to extract the big data application in e-commerce. Delphi method with five experts is used to finalize criteria and big data applications in e-commerce. Experts 1 and 2 are data scientists with more than six years of experience in e-commerce. Expert 3 is a senior data engineer in e-commerce with a background in industries such as telecommunication and baking. Expert 4 is a chief data officer in a leading e-commerce company with an experience of more than ten years in data-related positions. Finally, expert 5 is a general manager of e-commerce with a background in management of more than fifteen years. After a series of discussions and deliberation with five experts, the big data challenges, values, and applications in e-commerce were finalized, as shown in Tables 2 and 3. Phase 2 involves ranking big data challenges and values for e-commerce using the best-worst method given by Rezaei (2015). The BWM, based on pairwise comparisons, was developed to solve multi-criteria decision-making problems. It has two key advantages over other MCDM methods: it requires fewer pairwise comparisons and produces more consistent results than other MCDM methods (Ahmadi et al., 2017). Finally, in the third phase of this study, big data applications in e-commerce are ranked using fuzzy Technique for Order Preferences by Similarity to an Ideal Solution (TOPSIS). The details of each phase are discussed in the following subsections.

Table 1
Inclusion and exclution criteria for selecting articles

Criteria	Decision
Language of research is not English	Exclusion
Paper published online from 2000 to 2021	Inclusion
The research keywords exists in title or abstract	Inclusion
Papers focus on big data analytics in e-commerce	Inclusion

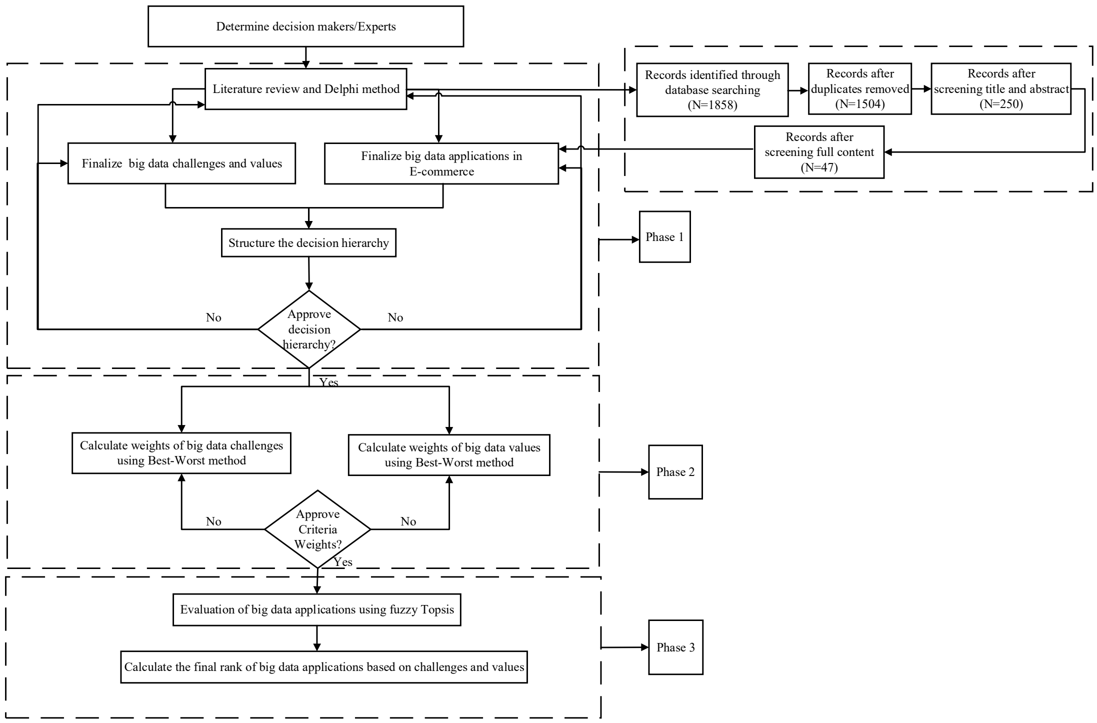

Fig. 1. Proposed approach to evaluate big data applications in e-commerce

Table 2
Big data challenges and values in e-commerce

Main challenge	Sub-challenge	Main value	Sub-value
Data Challenge (DC)	Volume	Informational value (IV)	Decision making support
	Velocity		Transform operation activity
	Variety		Knowledge discovery
	Variability	Transactional value (TV)	Revenue growth
	Veracity		Productivity gain
Process Challenge (PC)	Data acquisition and warehousing		Cost efficiency and savings
	Data mining and cleansing	Strategic value (SV)	Market positioning
	Data aggregation and integration		Market responsiveness
	Analysis and modeling		Customer loyalty enhancement
Management Challenge (MC)	Privacy		Skill development
	Security		
	Data governance		
	Data and information sharing		
	Operational expenditures		

Table 3
Big data applications in e-commerce

	Application	Research
A1	Analyze and extract customer need	Akter (2016); Qi et al. (2016); Salehan and Kim (2016); Hou et al. (2017); Chen and Xu (2017); Li (2018); Lehrer et al. (2018); Katarya and Verma (2018); Yuan et al. (2018); Chiang and Yang (2018); Atta-ur-Rahman et al. (2019); Huang et al. (2019); Moorthi (2020); Alojail and Bhatia (2020); Zineb et al. (2021); Pal et al. (2021); Pan and Yang (2021); Mach-Król and Hadasik (2021); Ehikioya and Zeng (2021)
A2	Coordinate and monitor supply chain process	Akter (2016); Hou et al. (2017); Li (2018); See-To and Ngai (2018); Han et al. (2018); Wu and Lin (2018); Hu (2019); Zheng (2020); Wang et al. (2021)
A3	Create new product and service	Qi et al. (2016); Lehrer et al. (2018); Zhang et al. (2019); Mariani and Fosso Wamba (2020); Alojail and Bhatia (2020)
A4	Improve customer experience	Salehan and Kim (2016); Lehrer et al. (2018); Zhao et al. (2019); Mariani and Fosso Wamba (2020); Xie et al. (2020); Zheng (2020; Elia et al. (2020); Pal et al. (2021); Mach-Król and Hadasik (2021); Yang et al. (2021)

Table 3
Big data applications in e-commerce (Continued)

	Application	Research
A5	Customer segmentation	Zhang et al. (2015); Akter (2016); Lehrer et al. (2018); Katarya and Verma (2018); Chiang and Yang (2018); Huang et al. (2019); Mariani and Fosso Wamba (2020); Elia et al. (2020); Zineb et al. (2021); Li and Zhang (2021); Pal et al. (2021); Mach-Król and Hadasik (2021); Ehikioya and Zeng (2021)
A6	Customized advertisement	Li et al. (2016); See-To and Ngai (2018); Chiang and Yang (2018); Huang et al. (2019); Alojail and Bhatia (2020); Mach-Król and Hadasik (2021); Ehikioya and Zeng (2021)
A7	Customized marketing promotion	Akter (2016); Li et al. (2016); Lehrer et al. (2018); Yuan et al. (2018); Chiang and Yang (2018); Atta-ur-Rahman et al. (2019); Hu (2019); Huang et al. (2019); Elia et al. (2020); Malhotra and Rishi (2021); Zineb et al. (2021); He (2021); Li and Zhang (2021); Mach-Król and Hadasik (2021); Ehikioya and Zeng (2021)
A8	Demand forecasting	Hou et al. (2017); See-To and Ngai (2018); Yuan et al. (2018); Hu (2019); Huang et al. (2019); Mariani and Fosso Wamba (2020); Moorthi (2020); Wang et al. (2021)
A9	Detect fake and deceptive review	Zhang et al. (2014); Salehan and Kim (2016); Dong et al. (2018)
A10	Dynamic pricing	Akter (2016); Han et al. (2018); Yuan et al. (2018)
A11	Financial fraud detection	Zhang et al. (2015); Akter (2016); Carcillo et al. (2018); Zhou et al. (2019); Carta et al. (2019); He (2021)
A12	Innovate product, process, and business model	Li (2018); Lehrer et al. (2018); Wu and Lin (2018); Hu (2019); Mariani and Fosso Wamba (2020); Moorthi (2020); Yi and Liu (2020); Yang et al. (2021)
A13	Inventory management	Akter (2016); Verma and Singh (2017); See-To and Ngai (2018); Yuan et al. (2018); Zheng (2020); Malhotra and Rishi (2021); Li and Zhang (2021)
A14	Market basket anlaysis	Verma and Singh (2017); Moorthi (2020); Malhotra and Rishi (2021); Pal et al. (2021); Pan and Yang (2021); Mach-Król and Hadasik (2021); Ehikioya and Zeng (2021)
A15	Online customer review analytics	Qi et al. (2016); Li et al. (2016); Salehan and Kim (2016); Singh et al. (2017); Hou et al. (2017); Chen and Xu (2017); See-To and Ngai (2018); Yuan et al. (2018); Mariani and Fosso Wamba (2020); Zhao et al. (2019); ;Choi and Leon (2020); Yi and Liu (2020); Filieri and Mariani (2021); Yang et al. (2021)
A16	Predict the next to buy (upselling and cross-selling)	Hou et al. (2017); Verma and Singh (2017); Lehrer et al. (2018); Katarya and Verma (2018); Chiang and Yang (2018); Pal et al. (2021); Pan and Yang (2021)
A17	Product categeroziation	Li et al. (2016); Choi and Leon (2020); Yi and Liu (2020); Yang et al. (2021);
A18	Recommend personalized service	Zhang et al. (2015); Chen and Xu (2017); Dong et al. (2018); Li (2018); Lehrer et al. (2018); Han et al. (2018); Chiang and Yang (2018); Huang et al. (2019); Xie et al. (2020); Zheng (2020); Moorthi (2020); Elia et al. (2020); Malhotra and Rishi (2021); He (2021); Pal et al. (2021); Mach-Król and Hadasik (2021); Ehikioya and Zeng (2021)
A19	Redesign and improve service and product feature	Qi et al. (2016); Salehan and Kim (2016); Singh et al. (2017); Dong et al. (2018); Li (2018); Han et al. (2018); Zhang et al. (2019); Zhao et al. (2019); Yang et al. (2021)
A20	Revenue management	Akter (2016); See-To and Ngai (2018); Han et al. (2018); Mariani and Fosso Wamba (2020); Moorthi (2020); Zineb et al. (2021); Ehikioya and Zeng (2021)
A21	Risk management	Zhang et al. (2015); Li (2018); Han et al. (2018); Han et al. (2018); Zhou et al. (2019); Zhang et al. (2019); Wang et al. (2021)
A22	Service and product sales analytics	Li et al. (2016); See-To and Ngai (2018); Yuan et al. (2018); Moorthi (2020); Elia et al. (2020); Filieri and Mariani (2021); Pan and Yang (2021)
A23	Social network analysis	Zhang et al. (2014); Salehan and Kim (2016); Verma and Singh (2017); Katarya and Verma (2018); Atta-ur-Rahman et al. (2019); Mariani and Fosso Wamba (2020); Xie et al. (2020); Mach-Król and Hadasik (2021)

3.1 Obtaining weights of challenges and values using BWM

We use BWM to rank big data challenges and values in e-commerce. The BWM is a strong and widely used MCDM technique for calculating the weights of the criteria and has been extensively utilized in analyzing various topics such as ranking big data analytics barriers for manufacturing (Sharma et al., 2021) and smart cities (Khan, 2021), service quality evaluation (Gupta, 2018), evaluating risks and strategies of big data implementation in supply chain (Kusi-Sarpong et al., 2021). Here are the steps as given by (Rezaei, 2015; Rezaei, 2016):

Step1: Determine and finalize criteria through literature review and expert opinion.

Step2: The expert selects the best and the worst attribute for each main criteria and subcriteria among the criteria determined in step 1.

Step3: Experts are asked to provide a preference rating from 1 to 9 for the best criteria selected over all other criteria.

Step 4: After this, provide preferences of all the other criteria over the worst criterion based on a scale of 1 to 9.

Step 5: The optimized weights ($w_1^*, w_2^*, \ldots, w_n^*$) for all criteria are calculated next. The objective is to obtain weight of the criteria so that the maximum absolute differences for all j can be minimized for $\{|w_B - a_{Bj} w_j|, |w_j - a_{jw} w_w|\}$. The following minimax model will be obtained:

$$\begin{aligned} &\min \max \{|w_B - a_{Bj} w_j|, |w_j - a_{jw} w_w|\} \\ &\text{subject to} \\ &\textstyle\sum_j w_j = 1 \\ &w_j \geq 0, \text{ for all } j \end{aligned} \tag{1}$$

When this model is transformed into the following linear model gives better results:

$$\begin{aligned} &\min \xi^L \\ &\text{subject to} \\ &|w_B - a_{Bj} w_j| \leq \xi^L, \text{for all } j \\ &|w_j - a_{jw} w_w| \leq \xi^L, \text{ for all } j \\ &\textstyle\sum_j w_j = 1 \\ &w_j \geq 0, \text{ for all } j \end{aligned} \tag{2}$$

The optimal weights ($w_1^*, w_2^*, \ldots, w_n^*$) and optimal value of ξ^L are obtained by solving problem (2).

3.2 Ranking big data applications through Fuzzy Topsis

Technique for order performance by similarity to ideal solution (Topsis) is a multi-criteria decision-making method widely used for evaluating and ranking alternatives in domains such as e-commerce (Hana & Trimib, 2018), energy (Solangi et al., 2021), banking (Roy & Shaw, 2022), manufacturing (Azizi et al., 2015), healthcare (Khambhati et al., 2021), etc. In the Topsis method, the main idea is to choose the best alternative which is nearest to the positive ideal solution and has the farthest distance from the negative ideal solution. It is more realistic and intuitive to use linguistic evaluations instead of numerical evaluations when dealing with inexact and ambiguous information, such as human judgments. Since TOPSIS requires alternative preferences to be rated by experts, it is often difficult for them to provide precise alternative ratings. Therefore Fuzzy TOPSIS is proposed as a solution, in which fuzzy numbers are used to give preferences by experts (Gupta & Barua, 2018; Walczak & Rutkowska, 2017). The steps of the Fuzzy Topsis methodology are defined as follows:

Step1: Construct evaluation matrix K based on the linguistic scale presented in Table 4. This matrix consists of comparisons of big data applications in e-commerce with respect to big data challenges and values.

$$K = [k_{ij}]_{m \times n} \text{ where } i=1,2,3,\ldots,m \text{ and } j=1,2,3,\ldots,n \tag{3}$$

Step 2: Once the pair-wise comparison matrix is obtained, it is transformed into a weighted normalized matrix as shown below:

$$V = [v_{ij}]_{m \times n} \text{where } i=1,2,3,\ldots,m \text{ and } j=1,2,3,\ldots,n \text{ and } v_{ij} = w_j k_{ij} \tag{4}$$

Step 3: The next step is to obtain fuzzy positive ideal (FPIS)and fuzzy negative ideal solution (FNIS):

$$\begin{aligned} &A^+ = \{v_1^+, \ldots, v_n^+\} \text{ where } v_j^+ = \{\max(v_{ij}) \text{ if } j \in J; \min(v_{ij}) \text{ if } j \in J'\} \\ &A^- = \{v_1^-, \ldots, v_n^-\} \text{ where } v_j^- = \{\min(v_{ij}) \text{ if } j \in J; \max(v_{ij}) \text{ if } j \in J'\} \end{aligned} \tag{5}$$

Step 4: Calculate the distance of each alternative from FPIS and FNIS using the equation below:

$$d_i^+ = \{\textstyle\sum_{j=1}^{n} (v_{ij} - v_{ij}^+)^2\}^{\frac{1}{2}}, \ i=1,\ldots,m \tag{6}$$

$$d_i^- = \left\{\sum_{j=1}^{n} (v_{ij} - v_{ij}^-)^2\right\}^{\frac{1}{2}},\ i=1,\ldots,m$$

Step 5: The Closeness coefficient (CCi) for each solution is obtained by using the equation below:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+}\ ,\ i=1,\ldots,m \tag{7}$$

Table 4
Linguistic scale for alternatives selection

Linguistic terms	Corresponding fuzzy numbers
Very Low (VL)	(0,0,0.2)
Low (L)	(0,0.2,0.4)
Medium (M)	(0.2,0.4,0.6)
High (H)	(0.4,0.6,0.8)
Very High (VH)	(0.6,0.8,1)
Excellent (E)	(0.8,1,1)

4. Results and findings

This section explains the numerical findings of the proposed framework for evaluating big data applications in e-commerce with respect to big data challenges and values. In the first part of this section, the weights of the main challenges, sub-challenges, main values, and sub-values of big data in e-commerce are obtained, which are then used to rank big data applications separately.

4.1 Calculation of criteria weights using BWM

After the finalization of big data challenges and values through literature review and Delphi method, the weights of these criteria are calculated using steps presented in section 3.1. The pairwise comparison questionnaire for BWM, based on a 1 to 9 rating, is used separately for challenges and values, answered by ten experts in big data analytics e-commerce. As explained earlier, experts select the best and the worst criterion for main challenges and main values among the determined criteria and then express the preference of the best criterion over all the other criteria and the preference of all the other criteria over the worst by rating between 1 and 9. Similar to the main challenges and values, the pairwise comparison matrix for sub-challenges and sub-values are obtained through experts' opinions. Tables 1-16 in the appendix show the pairwise comparison of BWM method for main and sub-criteria. The next step is finding the weights of criteria and sub-criteria using linear programming in equation 2. Tables 5 and 6 show the final average of weights for challenges and values criteria and consistency ratios. The calculated consistency values are relatively close to zero, indicating high consistency for pairwise comparisons.

4.2 Ranking big data applications using Fuzzy Topsis

After calculating the weights of all main challenges, sub-challenges, main values, and sub-values, the next step is to obtain the ranking of big data applications in e-commerce. Fuzzy TOPSIS methodology is used to rank big data applications with respect to challenges and values separately. A panel of experts explained in section 3 was formed, and they were asked to rate the big data application using the linguistic scale as shown in Table 4. The obtained comparison matrices based on corresponding fuzzy values of linguistic variables for big data values and challenges are presented in Tables 17 and 18 of the appendix, respectively. After obtaining comparison matrices, the next step is calculating the weighted normalized matrix using Eq.4. FPIS and FNIS are defined as $v_1^+ = (1,1,1)$ and $v_1^- = (0,0,0)$ for values in terms of benefit criteria and as $v_1^+ = (0,0,0)$ and $v_1^- = (1,1,1)$ for challenges as cost criteria in this study. In order to rank big data applications, the final step is to obtain the closeness coefficient value using Eqs. 6 and 7. The corresponding CCi and ranks of big data applications in e-commerce based on big data challenges and value creation are presented in Tables 7 and 8.

Table 5
Aggregate weights of Main values and sub-values

Main values	Weights of main values	Main CR	Sub-values	Weights of sub-values	Sub CR	Global weights	Ranking
Informational value	0.283	0.054	IV1	0.440	0.049	0.125	2
			IV2	0.291		0.082	6
			IV3	0.269		0.076	7
Transactional value	0.231		TV1	0.492	0.048	0.114	4
			TV2	0.302		0.070	8
			TV3	0.205		0.047	10
Strategic value	0.486		SV1	0.216	0.062	0.105	5
			SV2	0.249		0.121	3
			SV3	0.399		0.194	1
			SV4	0.136		0.066	9

4.3 Analysis of findings

The values and challenges weights of big data analytics in e-commerce are obtained through BWM and are presented in Tables 5 and 6. Among the main values of big data, the strategic value is ranked first with a criteria weight of 0.486. Realizing the strategic value of big data that firms and managers can bring to the business is the main reason for big data analytics adoption in emerging economies (Verma & Bhattacharyya, 2017). As big data analytics projects are most successful when they achieve strategic business value, which gives firms a competitive advantage, the sellers in e-commerce must evaluate the strategic role of big data analytics (Grover et al., 2018). The strategic value of big data makes e-commerce more consumer-centric, agile, and faster to change, better equipped to forecast customer needs and behavior to have an effective customer relationship, more tightly aligned between information technology and e-commerce strategies, enhancing capabilities and skills, and eventually strengthening competitive advantage (Elia et al., 2020; Urbinatia et al., 2019). The sub-value customer loyalty enhancement with a global weight of 0.194 is ranked first among the strategic value and also all other sub-values. Customer loyalty is increasingly highlighted by academic and business managers in e-commerce to counter the competitive pressures in electronic commerce. They seek to achieve the behavioral and attitudinal e-loyalty of the consumers behavioral and attitudinal e-loyalty (Cachero-Martínez & Vazquez-Casielles, 2021; Kim & Peterson, 2017). Hence customer loyalty enhancement in e-commerce is the critical value for long-term profitability resulting in repeat buying behavior (Swaminathana et al., 2019).

Table 6
Aggregate weights of main challenges and sub-challenges

Main challenges	Weights of main challenges	Main CR	Sub- challenges	Weights of sub-challenges	Sub CR	Global weights	Ranking
Data Challenges	0.295	0.053	DC1	0.352	0.068	0.104	3
			DC2	0.151		0.044	11
			DC3	0.236		0.070	8
			DC4	0.113		0.034	14
			DC5	0.148		0.044	12
Process Challenges	0.355		PC1	0.203	0.056	0.072	6
			PC2	0.230		0.082	5
			PC3	0.245		0.087	4
			PC4	0.323		0.114	2
Management Challenges	0.350		MC1	0.205	0.066	0.072	7
			MC2	0.181		0.063	9
			MC3	0.368		0.129	1
			MC4	0.127		0.044	10
			MC5	0.119		0.042	13

Table 7
Final rankings of big data applications based on values

Applications	D+	D-	CCj	Ranking
Analyze and extract customer need	9.376	0.632	0.063	3
Coordinate and monitor supply chain process	9.378	0.630	0.063	5
Create new product and service	9.479	0.534	0.053	11
Improve customer experience	9.376	0.631	0.063	4
Customer segmentation	9.877	0.157	0.016	21
Customized advertisement	9.587	0.431	0.043	15
Customized marketing promotion	9.462	0.550	0.055	10
Demand forecasting	9.595	0.424	0.042	16
Detect fake and deceptive review	9.575	0.443	0.044	14
Dynamic pricing	9.779	0.253	0.025	18
Financial fraud detection	9.504	0.510	0.051	12
Innovate product, process, and business model	9.388	0.621	0.062	6
Inventory management	9.877	0.160	0.016	20
Market basket anlaysis	9.882	0.154	0.015	22
Online customer review analytics	9.360	0.646	0.065	1
Predict the next to buy (upselling and cross-selling)	9.409	0.602	0.060	7
Product categeroziation	9.891	0.145	0.014	23
Recommend personalized service	9.368	0.639	0.064	2
Redesign and improve service and product feature	9.556	0.461	0.046	13
Revenue management	9.419	0.591	0.059	8
Risk management	9.802	0.230	0.023	19
Service and product sales analytics	9.744	0.284	0.028	17
Social network analysis	9.443	0.569	0.057	9

The findings revealed that process challenge with the criteria weight of 0.355 is the most significant big data challenge in e-commerce. Furthermore, data governance as one of the management challenges is ranked first among the sub-challenges with a weight of 0.129. As big data is continuously growing organizations consider data governance to ensure the quality of data mined from a pool of large data in order to maintain data values as a vital organizational asset for generating actionable business insights (Sivarajah et al., 2017). Data governance focuses on the data management activities from collection to interpretation and analytics. Implementing data governance brings critical challenges for organizations since the data acquired by the business department are often untested, inconsistent, poorly defined, and not following the organization's structure. The appropriate data governance needs sufficient managerial and technical skills to produce reliable information for optimal decision-making (Janssen et al., 2020; Wang et al., 2019). Tables 7 and 8 show the final ranking of big data applications in e-commerce with respect to big data challenges and values using Fuzzy Topsis. The results indicate that financial fraud detection is the most challenging application of big data in e-commerce among the identified applications in this study. While using transactional data in e-commerce can uncover customer interests, habits, and behavior, fraud detection for online e-commerce transactions has become increasingly challenging, requiring real-time responsiveness and high accuracy models (Zhou et al., 2019). Due to the features of online e-commerce transactions, fraud detection is required to achieve high accuracy and real-time responsiveness, as fraudulent transactions are more covertly scattered with authentic transactions. Class imbalance, data heterogeneity, concept drift, model stacitiy, stream processing, and cold start are the most critical challenges affecting financial fraud detection in e-commerce (Carcillo et al., 2018; Carta et al., 2019).

Similar to ranking applications on challenges, the same approach is used to rank them based on big data value creation criteria. Evaluating big data applications in e-commerce according to values shows that online customer review analytics is ranked first. Various studies have illustrated this application has big value for sellers in e-commerce (Li et al., 2016; Singh et al., 2017; Dong et al., 2018; Zhao et al., 2019; Zhang et al., 2019; Filieri & Mariani, 2021). Online customer reviews on e-commerce platforms provide valuable insight into how customers perceive a product or service (Liu et al., 2020; Qi et al., 2016) and are considered the second most trusted source of product information after recommendations from family and friends (Salehan & Kim, 2016).

Table 8

Final rankings of big data applications based on challenges

Applications	D+	D-	CCj	Ranking
Analyze and extract customer need	0.681	13.340	0.951	19
Coordinate and monitor supply chain process	0.847	13.165	0.940	22
Create new product and service	0.658	13.365	0.953	16
Improve customer experience	0.836	13.177	0.940	21
Customer segmentation	0.274	13.774	0.981	3
Customized advertisement	0.273	13.773	0.981	2
Customized marketing promotion	0.489	13.545	0.965	8
Demand forecasting	0.496	13.537	0.965	9
Detect fake and deceptive review	0.698	13.323	0.950	20
Dynamic pricing	0.678	13.344	0.952	18
Financial fraud detection	0.881	13.128	0.937	23
Innovate product, process, and business model	0.613	13.411	0.956	15
Inventory management	0.379	13.662	0.973	5
Market basket anlaysis	0.335	13.710	0.976	4
Online customer review analytics	0.574	13.452	0.959	11
Predict the next to buy (upselling and cross-selling)	0.397	13.643	0.972	7
Product categeroziation	0.669	13.354	0.952	17
Recommend personalized service	0.578	13.447	0.959	12
Redesign and improve service and product feature	0.572	13.454	0.959	10
Revenue management	0.380	13.664	0.973	6
Risk management	0.599	13.426	0.957	14
Service and product sales analytics	0.247	13.797	0.982	1
Social network analysis	0.582	13.444	0.958	13

Recommending personalized services and products is ranked the second most valuable application of big data analytics in e-commerce. Recommending individualized products and services helps users make better decisions and choose relevant products from many choices. Furthermore, it helps e-commerce get to know their customer more in depth, such as their behaviors, attitudes, and purchases (Isinkaye et al., 2015; Katarya & Verma, 2018). This application of big data enables sellers to tailor products and services cost-effectively instead of mass customization, creating new value propositions, increasing sales by 10% or more, and providing a five to eight time return on investment on marketing expenditure (Akter, 2016; Lehrer et al., 2018). Implementing all big data applications at the same time is difficult due to limited accessible sources. The idea of ranking these applications based on cost and benefit criteria help managers to exploit appropriate policy based on the company's and market's current status. The relative categorization of big data applications originated from the intersection of values and challenges, resulting in four application segments:

1. Low Challenge-High Value: These applications are the first priority of implementation and should be planned for immediate execution. If firms ignore these groups, they won't survive in the highly competitive market of e-commerce since these are critical applications of big data analytics in e-commerce.

2. High Challenge-Low Value: The general strategy associated with these applications is to deprioritize and postpone in order to enable resources to focus on other applications in other big data analytics.
3. Low Challenge-Low Value: These applications can be implemented if there are extra capabilities and resources. The important point about this category of applications is that instead of abandoning them, their value and latest development should be constantly checked to give them a higher priority if they are beneficial.
4. High Challenge-High Value: Since the origin challenge of each application varies, firstly, the cause of the challenge should be identified based on firm capability. The next step is to make an appropriate plan to overcome barriers and develop the required abilities. Analyzing and investigating the challenges of this application are crucial due to their value creation for e-commerce.

5. Conclusion and future works

In recent decades, information and communication technology advancements have changed many processes in many fields, such as commerce, economics, banking, etc. Nowadays, the internet plays a crucial role in all aspects of people's lives and has led to opportunities and changes in commerce. Traditional commerce will not be able to meet the demands of modern consumer needs since the technology, internet, and commerce have been intertwined. Using information technology in commercial and economic processes has led to the development of the new interdisciplinary field known as e-commerce. Different domains benefit from big data, and the current state of e-commerce has entered the era of big data to gain valuable insights due to the generation of large amounts of behavioral and transactional data. Various applications of big data analytics in e-commerce have been focused by previous studies separately on one aspect of e-commerce. Neither studies related to the big data applications in e-commerce are present, nor a framework to evaluate these applications from a challenges-values point of view is given anywhere in the literature. To address this gap, the present study has identified and ranked big data applications in e-commerce using a hybrid multi-criteria decision-making technique that combines BWM and fuzzy TOPSIS.

While using big data analytics in each business process drives value creation for e-commerce, there are different types of challenges in implementing big data applications. Therefore, considering challenges and values for ranking applications provides managers with more insights and clear ideas about its importance. A total of twenty-three applications of big data in e-commerce were identified and finalized through the extensive literature and experts ' opinions. BWM was used to get the weights of big data challenges and values in e-commerce and Fuzzy Topsis was utilized to rank applications. The results showed the process challenge and strategic value obtained the highest weight for challenges and values, respectively. Further, financial fraud detection is relatively the most challenging, and online review analytics is the most valuable application of big data in e-commerce among all applications. The proposed method is practical for e-commerce managers, experts, and practitioners for ranking the application of big data to decide their implementation priorities to overcome the challenges and make the most of values. Apart from identifying and ranking big data applications on challenges and values, this study takes a step further to help managers to exploit appropriate policies for big data analytics. Since it is challenging to implement all big data applications simultaneously due to various constraints; therefore, making decisions is essential to the stepwise implementation. Implementing immediately, managing challenges, implementing if there are extra resources and deportirise are four policies about big data application according to challenge and value.

Although the current study is the initial attempt of its kind, which aims at proposing a scientific method for big data analytics evaluation in e-commerce, it still has limitations that can be extended in future studies. This study did not consider the possible interactions and impact of each of the criteria. Future studies can focus on the impact of each challenge and value and also expand the number of e-commerce experts. Challenges of financial fraud detection and benefits from customer review analytics are topics that future research can shed much more light on since they are in priority for e-commerce. The proposed method of ranking applications is not limited to the specific application or industry, and it is flexible to evaluate the application of other emerging technologies such as blockchain and the internet of things. Although this study generally involves ranking big data analytics in e-commerce, the presented framework is practical for e-commerce to customize big data applications prioritization due to their business strategy, market status, and capabilities. Furthermore, the prioritization of big data applications was based on challenges and values; future studies can focus on ranking based on sustainability development, other values, and challenges dimensions. Finally, the present study employed BWM and Fuzzy method in the proposed methodology to rank applications based on determined criteria; however other multi-criteria techniques like AHP, VIKOR, SMART, ELECTRE, etc., can also be explored to compare the results with the current study.

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Appendix

Table A1
Main value preferences (Best to others)

Expert	BO	IV	TV	SV
1	SV	3	2	1
2	SV	4	2	1
3	SV	2	4	1
4	SV	4	2	1
5	IV	1	4	2
6	TV	3	1	2
7	SV	2	3	1
8	SV	2	4	1
9	IV	1	3	2
10	SV	3	4	1

Table A2
Main value preferences (Others to worst)

Expert	1	2	3	4	5	6	7	8	9	10
OW	IV	IV	TV	IV	TV	IV	TV	TV	TV	TV
IV	1	1	3	1	4	1	2	3	3	2
IV	2	3	1	3	1	3	1	1	1	1
SV	3	4	4	4	3	2	3	4	2	4

Table A3
Informational value preferences (Best to others)

Expert	BO	IV1	IV2	IV3
1	IV1	1	2	3
2	IV2	2	1	3
3	IV2	2	1	3
4	IV3	4	3	1
5	IV1	1	3	4
6	IV1	1	2	4
7	IV3	4	5	1
8	IV1	1	4	2
9	IV1	1	3	5
10	IV1	1	2	3

Table A4
Informational value preferences (Others to worst)

Expert	1	2	3	4	5	6	7	8	9	10
OW	IV3	IV3	IV3	IV1	IV3	IV3	IV2	IV2	IV3	IV3
IV1	3	2	2	1	4	4	2	4	5	3
IV2	2	3	3	2	2	3	1	1	2	2
IV3	1	1	1	4	1	1	5	3	1	1

Table A5
Transactional value preferences (Best to others)

Expert	BO	TV1	TV2	TV3
1	TV1	1	2	3
2	TV2	2	1	3
3	TV1	1	2	3
4	TV1	1	4	5
5	TV1	1	3	2
6	TV3	2	3	1
7	TV1	1	3	4
8	TV2	3	1	4
9	TV1	1	2	3
10	TV1	1	3	4

Table A6
Transactional value preferences (Others to worst)

Expert	1	2	3	4	5	6	7	8	9	10
OW	TV3	TV3	TV3	TV3	TV2	TV2	TV3	TV3	TV3	TV3
TV1	3	2	3	5	3	2	4	2	3	4
TV2	2	3	2	2	1	1	2	4	2	2
TV3	1	1	1	1	2	3	1	1	1	1

Table A7
Strategic value preferences (Best to others)

Expert	BO	SV1	SV2	SV3	SV4
1	SV3	3	2	1	4
2	SV2	2	1	2	5
3	SV2	3	1	2	2
4	SV3	4	3	1	5
5	SV1	1	3	2	4
6	SV3	2	2	1	5
7	SV3	2	3	1	4
8	SV3	4	3	1	3
9	SV3	3	2	1	2
10	SV3	2	4	1	3

Table A8
Strategic value preferences (Others to worst)

Expert	1	2	3	4	5	6	7	8	9	10
OW	SV4	SV4	SV1	SV4	SV4	SV4	SV4	SV1	SV1	SV2
SV1	2	3	1	3	4	3	4	1	1	2
SV2	3	5	3	3	3	4	3	2	3	1
SV3	4	2	2	5	3	5	4	4	3	4
SV4	1	1	2	1	1	1	1	2	3	2

Table A9
Main challenge preferences (Best to others)

Expert	BO	DC	PC	MC
E1	DC	1	3	4
E2	DC	1	4	2
E3	MC	3	2	1
E4	MC	2	3	1
E5	MC	2	4	1
E6	MC	4	2	1
E7	PC	2	1	6
E8	PC	2	1	4
E9	PC	4	1	2
E10	PC	5	1	2

Table A10
Main challenge preferences (Others to worst)

Expert	1	2	3	4	5	6	7	8	9	10
OW	PC	DC	PC	PC	DC	MC	MC	DC	DC	DC
DC	4	1	2	3	1	4	3	1	1	1
PC	1	2	1	1	3	6	4	4	5	4
MC	3	3	3	4	4	1	1	3	3	3

Table A11
Data challenge preferences (Best to others)

Expert	BO	DC1	DC2	DC3	DC4	DC5
E1	DC1	1	4	2	7	4
E2	DC3	2	3	1	4	3
E3	DC1	1	5	3	4	3
E4	DC1	1	3	6	4	4
E5	DC3	2	3	1	4	3
E6	DC1	1	5	4	3	3
E7	DC2	2	1	3	4	3
E8	DC1	1	6	3	3	3
E9	DC3	3	6	1	3	4
E10	DC1	1	2	3	5	4

Table A12
Data challenge preferences (Others to worst)

Expert	1	2	3	4	5	6	7	8	9	10
OW	DC4	DC4	DC2	DC3	DC4	DC2	DC4	DC2	DC2	DC4
DC1	7	3	5	6	3	5	3	6	4	5
DC2	4	2	1	2	3	1	4	1	1	4
DC3	5	4	3	1	4	3	2	3	6	4
DC4	1	1	2	2	1	3	1	4	4	1
DC5	2	2	3	2	2	3	3	3	3	3

Table A13
Process challenge preferences (Best to others)

Expert	BO	PC1	PC2	PC3	PC4
E1	PC4	4	2	2	1
E2	PC4	2	5	3	1
E3	PC3	2	3	1	4
E4	PC4	4	2	2	1
E5	PC4	4	3	3	1
E6	PC4	2	5	3	1
E7	PC3	5	4	1	3
E8	PC2	2	1	5	3
E9	PC2	6	1	4	4
E10	PC1	1	5	3	2

Table A14
Process challenge preferences (Others to worst)

Expert	1	2	3	4	5	6	7	8	9	10
OW	PC1	PC2	PC4	PC1	PC1	PC2	PC1	PC3	PC1	PC2
PC1	1	3	3	1	1	3	1	4	1	5
PC2	2	1	2	3	2	1	2	5	6	1
PC3	3	3	4	2	2	3	5	1	2	3
PC4	4	5	1	4	4	5	3	3	2	3

Table A15
Managment challenge preferences (Best to others)

Exper	BO	MC	MC	MC	MC	MC
E2	MC	1	3	4	3	5
E3	MC	4	4	1	5	8
E4	MC	3	3	1	4	6
E5	MC	2	3	1	2	2
E6	MC	4	3	1	3	3
E7	MC	1	2	2	5	4
E8	MC	4	4	1	6	7
E9	MC	3	2	1	4	3
E10	MC	4	6	1	3	3

Table A16
Managment challenge preferences (Others to worst)

Exper	1	2	3	4	5	6	7	8	9	10
OW	MC	MC	MC	MC	MC	MC	MC	MC	MC	MC
MC1	2	5	4	4	2	1	5	3	3	3
MC2	4	2	4	4	1	3	3	3	2	1
MC3	3	3	8	6	3	4	4	7	4	6
MC4	1	3	2	3	2	3	1	2	1	2
MC5	2	1	1	1	2	2	3	1	3	2

Table A17
Fuzzy comparison matrix for big data values

App	IV1	IV2	IV3	TV1	TV2	TV3	SV1	SV2	SV3	SV4
A1	0.8,1,1	0.8,1,1	0.8,1,1	0.6,0.8,1	0.8,1,1	0.6,0.8,1	0.6,0.8,1	0.8,1,1	0.6,0.8,1	0.6,0.8,1
A2	0.8,1,1	0.8,1,1	0.8,1,1	0.6,0.8,1	0.8,1,1	0.8,1,1	0.6,0.8,1	0.6,0.8,1	0.6,0.8,1	0.6,0.8,1
A3	0.6,0.8,1	0.4,0.6,0.8	0.6,0.8,1	0.6,0.8,1	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1	0.8,1,1
A4	0.8,1,1	0.8,1,1	0.8,1,1	0.6,0.8,1	0.6,0.8,1	0.8,1,1	0.8,1,1	0.8,1,1	0.6,0.8,1	0.4,0.6,0.8
A5	0.2,0.4,0.6	0,0,0.2	0.2,0.4,0.6	0,0,0.2	0,0.2,0.4	0,0,0.2	0,0,0.2	0,0.2,0.4	0,0,0.2	0,0,0.2
A6	0.2,0.4,0.6	0.2,0.4,0.6	0.2,0.4,0.6	0.2,0.4,0.6	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1
A7	0.6,0.8,1	0.6,0.8,1	0.4,0.6,0.8	0.6,0.8,1	0.4,0.6,0.8	0.6,0.8,1	0.6,0.8,1	0.4,0.6,0.8	0.8,1,1	0.4,0.6,0.8
A8	0.2,0.4,0.6	0.4,0.6,0.8	0.6,0.8,1	0,0.2,0.4	0.4,0.6,0.8	0.2,0.4,0.6	0.2,0.4,0.6	0.4,0.6,0.8	0.4,0.6,0.8	0.8,1,1
A9	0.4,0.6,0.8	0.2,0.4,0.6	0.6,0.8,1	0.2,0.4,0.6	0.2,0.4,0.6	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1	0.4,0.6,0.8	0.2,0.4,0.6
A10	0.2,0.4,0.6	0.2,0.4,0.6	0.2,0.4,0.6	0,0.2,0.4	0.2,0.4,0.6	0,0,0.2	0,0.2,0.4	0.4,0.6,0.8	0,0.2,0.4	0,0.2,0.4
A11	0.8,1,1	0.4,0.6,0.8	0.8,1,1	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1	0.4,0.6,0.8	0.4,0.6,0.8	0.2,0.4,0.6	0.6,0.8,1
A12	0.8,1,1	0.8,1,1	0.8,1,1	0.6,0.8,1	0.6,0.8,1	0.8,1,1	0.8,1,1	0.6,0.8,1	0.6,0.8,1	0.4,0.6,0.8
A13	0.2,0.4,0.6	0,0.2,0.4	0,0.2,0.4	0,0.2,0.4	0,0,0.2	0,0,0.2	0,0,0.2	0,0.2,0.4	0,0,0.2	0,0.2,0.4
A14	0.2,0.4,0.6	0,0,0.2	0,0.2,0.4	0,0,0.2	0,0.2,0.4	0,0.2,0.4	0,0.2,0.4	0,0,0.2	0,0,0.2	0,0,0.2
A15	0.8,1,1	0.8,1,1	0.8,1,1	0.8,1,1	0.8,1,1	0.6,0.8,1	0.8,1,1	0.8,1,1	0.8,1,1	0.4,0.6,0.8
A16	0.8,1,1	0.6,0.8,1	0.8,1,1	0.6,0.8,1	0.4,0.6,0.8	0.6,0.8,1	0.6,0.8,1	0.6,0.8,1	0.6,0.8,1	0.6,0.8,1
A17	0.2,0.4,0.6	0,0,0.2	0,0.2,0.4	0,0,0.2	0,0.2,0.4	0,0,0.2	0,0,0.2	0,0.2,0.4	0,0,0.2	0,0,0.2
A18	0.8,1,1	0.8,1,1	0.8,1,1	0.8,1,1	0.8,1,1	0.6,0.8,1	0.6,0.8,1	0.6,0.8,1	0.8,1,1	0.6,0.8,1
A19	0.6,0.8,1	0.6,0.8,1	0.6,0.8,1	0.2,0.4,0.6	0.2,0.4,0.6	0.4,0.6,0.8	0.2,0.4,0.6	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8
A20	0.8,1,1	0.6,0.8,1	0.6,0.8,1	0.8,1,1	0.6,0.8,1	0.8,1,1	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1	0.8,1,1
A21	0.6,0.8,1	0.2,0.4,0.6	0.2,0.4,0.6	0.2,0.4,0.6	0,0.2,0.4	0,0.2,0.4	0,0,0.2	0,0,0.2	0,0,0.2	0,0.2,0.4
A22	0.2,0.4,0.6	0.2,0.4,0.6	0.4,0.6,0.8	0,0.2,0.4	0,0.2,0.4	0.2,0.4,0.6	0,0.2,0.4	0,0,0.2	0.2,0.4,0.6	0.4,0.6,0.8
A23	0.6,0.8,1	0.6,0.8,1	0.8,1,1	0.4,0.6,0.8	0.6,0.8,1	0.4,0.6,0.8	0.6,0.8,1	0.4,0.6,0.8	0.6,0.8,1	0.8,1,1

Table A18
Fuzzy comparison matrix for big data challenges

App	DC1	DC2	DC3	DC4	DC5	PC1	PC2	PC3	PC4
A1	0.6,0.8,1	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1	0.6,0.8,1	0.4,0.6,0.8
A2	0.6,0.8,1	0.6,0.8,1	0.8,1,1	0.6,0.8,1	0.6,0.8,1	0.8,1,1	0.8,1,1	0.6,0.8,1	0.8,1,1
A3	0.2,0.4,0.6	0.4,0.6,0.8	0.2,0.4,0.6	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1	0.6,0.8,1	0.4,0.6,0.8	0.6,0.8,1
A4	0.6,0.8,1	0.6,0.8,1	0.8,1,1	0.6,0.8,1	0.6,0.8,1	0.8,1,1	0.8,1,1	0.6,0.8,1	0.8,1,1
A5	0.2,0.4,0.6	0,0.2,0.4	0,0,0.2	0.2,0.4,0.6	0,0,0.2	0,0.2,0.4	0,0.2,0.4	0,0.2,0.4	0.2,0.4,0.6
A6	0.2,0.4,0.6	0,0.2,0.4	0,0.2,0.4	0.2,0.4,0.6	0,0.2,0.4	0,0,0.2	0,0,0.2	0,0,0.2	0.2,0.4,0.6
A7	0.4,0.6,0.8	0.4,0.6,0.8	0.2,0.4,0.6	0.4,0.6,0.8	0.4,0.6,0.8	0,0.2,0.4	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8
A8	0.4,0.6,0.8	0.2,0.4,0.6	0.2,0.4,0.6	0.4,0.6,0.8	0.4,0.6,0.8	0.2,0.4,0.6	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8
A9	0.6,0.8,1	0.6,0.8,1	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1	0.6,0.8,1	0.6,0.8,1
A10	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1	0.4,0.6,0.8	0.6,0.8,1	0.6,0.8,1
A11	0.8,1,1	0.8,1,1	0.4,0.6,0.8	0.8,1,1	0.8,1,1	0.8,1,1	0.8,1,1	0.8,1,1	0.8,1,1
A12	0.2,0.4,0.6	0.4,0.6,0.8	0.2,0.4,0.6	0.2,0.4,0.6	0.4,0.6,0.8	0.6,0.8,1	0.4,0.6,0.8	0.6,0.8,1	0.4,0.6,0.8
A13	0.2,0.4,0.6	0.2,0.4,0.6	0.2,0.4,0.6	0,0.2,0.4	0,0.2,0.4	0,0.2,0.4	0,0.2,0.4	0.2,0.4,0.6	0.2,0.4,0.6
A14	0.2,0.4,0.6	0.4,0.6,0.8	0.2,0.4,0.6	0.2,0.4,0.6	0.4,0.6,0.8	0,0.2,0.4	0,0.2,0.4	0,0.2,0.4	0.2,0.4,0.6
A15	0.8,1,1	0.4,0.6,0.8	0.4,0.6,0.8	0.2,0.4,0.6	0.2,0.4,0.6	0.2,0.4,0.6	0.6,0.8,1	0.2,0.4,0.6	0.4,0.6,0.8
A16	0.4,0.6,0.8	0.2,0.4,0.6	0.2,0.4,0.6	0.2,0.4,0.6	0.2,0.4,0.6	0,0.2,0.4	0.2,0.4,0.6	0.2,0.4,0.6	0.2,0.4,0.6
A17	0.2,0.4,0.6	0.2,0.4,0.6	0.8,1,1	0.6,0.8,1	0.4,0.6,0.8	0.6,0.8,1	0.6,0.8,1	0.6,0.8,1	0.4,0.6,0.8
A18	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.2,0.4,0.6
A19	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.2,0.4,0.6	0.2,0.4,0.6
A20	0.2,0.4,0.6	0,0.2,0.4	0,0.2,0.4	0.2,0.4,0.6	0.2,0.4,0.6	0,0.2,0.4	0,0.2,0.4	0.2,0.4,0.6	0,0.2,0.4
A21	0.4,0.6,0.8	0.2,0.4,0.6	0.4,0.6,0.8	0.2,0.4,0.6	0.6,0.8,1	0.6,0.8,1	0.4,0.6,0.8	0.2,0.4,0.6	0.4,0.6,0.8
A22	0.2,0.4,0.6	0,0.2,0.4	0,0,0.2	0.2,0.4,0.6	0,0,0.2	0,0.2,0.4	0,0,0.2	0,0,0.2	0.2,0.4,0.6
A23	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1	0.4,0.6,0.8	0.4,0.6,0.8	0.2,0.4,0.6	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8

Table 18 (continued)

App	MC1	MC2	MC3	MC4	MC5
A1	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8
A2	0.4,0.6,0.8	0.4,0.6,0.8	0.8,1,1	0.6,0.8,1	0.6,0.8,1
A3	0.4,0.6,0.8	0.4,0.6,0.8	0.6,0.8,1	0.4,0.6,0.8	0.2,0.4,0.6
A4	0.6,0.8,1	0.4,0.6,0.8	0.8,1,1	0.2,0.4,0.6	0.4,0.6,0.8
A5	0,0.2,0.4	0,0,0.2	0,0,0.2	0,0.2,0.4	0.4,0.6,0.8
A6	0.2,0.4,0.6	0.2,0.4,0.6	0,0,0.2	0,0.2,0.4	0,0.2,0.4
A7	0,0.2,0.4	0.2,0.4,0.6	0,0.2,0.4	0.4,0.6,0.8	0.2,0.4,0.6
A8	0.2,0.4,0.6	0,0.2,0.4	0,0.2,0.4	0.4,0.6,0.8	0.2,0.4,0.6
A9	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.2,0.4,0.6
A10	0.2,0.4,0.6	0.4,0.6,0.8	0.6,0.8,1	0.2,0.4,0.6	0.4,0.6,0.8
A11	0.8,1,1	0.8,1,1	0.6,0.8,1	0.4,0.6,0.8	0.6,0.8,1
A12	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8
A13	0,0.2,0.4	0.2,0.4,0.6	0.2,0.4,0.6	0.2,0.4,0.6	0.2,0.4,0.6
A14	0,0.2,0.4	0,0.2,0.4	0,0,0.2	0,0.2,0.4	0.2,0.4,0.6
A15	0.4,0.6,0.8	0.2,0.4,0.6	0.2,0.4,0.6	0.4,0.6,0.8	0,0.2,0.4
A16	0,0.2,0.4	0.2,0.4,0.6	0,0.2,0.4	0.2,0.4,0.6	0,0.2,0.4
A17	0.2,0.4,0.6	0.2,0.4,0.6	0.6,0.8,1	0.4,0.6,0.8	0.4,0.6,0.8
A18	0.2,0.4,0.6	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.2,0.4,0.6
A19	0.4,0.6,0.8	0.2,0.4,0.6	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8
A20	0.4,0.6,0.8	0.2,0.4,0.6	0.2,0.4,0.6	0,0.2,0.4	0.4,0.6,0.8
A21	0.2,0.4,0.6	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8	0.4,0.6,0.8
A22	0,0,0.2	0,0,0.2	0,0,0.2	0.2,0.4,0.6	0.4,0.6,0.8
A23	0.4,0.6,0.8	0.4,0.6,0.8	0.2,0.4,0.6	0.4,0.6,0.8	0,0.2,0.4