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Framework of Data Analytics and Integrating Knowledge Management

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ABSTRACT

Big data is significantly dependent on technologies such as cloud computing, machine learning and statistical models. However, its significance is becoming more dependent on human qualities e.g. judgment, value, intuition and experience. Therefore, the human knowledge presents a basis for knowledge management and big data, which are a major element of data analytics. This research contribution applies the process of Data, Information, Knowledge and Perception hierarchy as a structure to evaluate the end-users' process. The framework in incorporating data analytics and display a conceptual data analytics process (with three phases) evaluated as knowledge management, including the creation, discovery and application of knowledge. Knowledge conversion theories are applicable in data analytics to emphasize on the typically overlooked organizational and human aspects, which are critical to the efficiency of data analytics. The synergy and alignment between knowledge management and data analytics is fundamental in fostering innovations and collaboration.

1. Introduction

Knowledge Management has been in existence for more than two decades now. M. Edenius and J. Borgerson in Ref. [1] have evaluated the need to manage knowledge focusing on the ideology that most firms as knowledge intensive. Knowledge is considered a valuable resource, which provides meaning to most of enterprises' operations. If you evaluate the value of the market of a public enterprise, it is normally five to ten times more than the business assets (physical assets that are predominant) capital in the balance sheet. Knowledge management can be easier to create a practical methodology for education. The most present educational frameworks are abstract by nature. Education is purposed to create learning; however, it does not indicate the manner in which learning operates. The abstract format it forms is necessarily ineffective and has been in existence for many years; however, it has not worked all that time. Knowledge management is useful in creating alternative education schemes by providing similar alternative educational schemes by providing similar learning opportunities to users.

The R. Bosua and K. Venkitachalam in Ref. [2] added that the process of learning can be utilized at five dimensions of knowledge management. These integrate knowledge development, teaching knowledge and personalizing knowledge. The most fundamental segment of utilizing knowledge management in education is based on learning, which is purposed to comprehend knowledge itself. Learning is considered an interactive, integrated, multidimensional and dynamic process and knowledge is typically managed effectively and efficiently in university, college and high schools, in workplaces, personal lives and in the society. These findings and facts do not necessitate any additional proofs for us to focus on what we need to provide additional categories of big data within the data system curriculum. It should be noted that outputs of most big data systems are based on knowledge other than data. Comprehending the condition of knowledge and the way it can be turned into action is fundamental. After evaluating the present literature in depth, there are minimal proofs concerning how data and knowledge management can be mixed for use during the process of making decisions.

Knowledge is not fad; instead, it is a valuable asset in the present society and even in the past. Without this, we might not have safeguarded civilization [3]. The ideology that "Knowledge is power" is real. Countries with more knowledge in their economy and fabric are the leaders in the globe. It is clearly disadvantaged to disregard to significance of knowledge management. Educators of knowledge management are obliged to identify the themes, which have to be integrated to formulate maximum effects on the future of knowledge management around the globe. If educators and analysts do not react to this, it might be needful to invest more additional online classes, seminars and training to cope up with the rapidly advancing technological competition. There is critical proof that big data has been integrated in educational sectors; however, less has been considered to connect this to knowledge management.

Various similar terminologies have been utilized to illustrate the procedure of identifying different patterns and attaining insights from

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raw information and data to inform the process of making decisions and supporting the solving of problems. Data science and data mining are two terminologies commonly utilized in technical fields. Business intelligence and business analytics are two terms normally used in management fields. In academia, Knowledge Discovery in Database (KDD) is normally used. Whereas these terms can different in their mechanics, they all have the same meaning. This research focuses on the generic terminology data analytics for its balanced scope of both business and technology. We shall adopt the meaning of data analytics as the expansive application of data, quantitative and statistical evaluation, predictive and explanatory framework and fact-oriented management to develop actions and enhance the process of decision making.

Different from data analytics, knowledge management is not known with synonyms. Nonetheless, it certainly integrates no limitation of diversified definitions. D. Hislop in Ref. [5] have made a compilation of fifty definitions, and some of them are classified as either process-based or management-based. Based on the perspective of management, knowledge management represents the conscious efforts that have been directed by the firm's management. Contrary to that, the process perspectives classify the knowledge management as a procedure of human interaction and human activities, either control by the organization or done autonomously by individuals. A frequently referenced, management-based definition from the Gartner group us that knowledge management is a segment, which promotes an integrated methodology to identify, capture, evaluate, retrieve and share all the firm's data assets.

Data assets may integrate procedures, policies, documents, databases and previously uncaptured experiences and expertise in individual workers. The definitions define the different types of knowledge assets that integrate both the tangibles e.g. human experience and human expertise. S. Ponis and E. Koronis in Ref. [4] provides a process-based definition that explains knowledge management as any practice or process that creates, acquires, captures, shares and uses knowledge, whenever it resides, to develop performance and learning practices within the firm. The definition focuses on the value of knowledge management that is to develop business performance and learning.

This research posits that intangible business learning and human experience, and processes of knowledge management are fundamental ingredients for the successful efforts in data analytics; despite the fact that knowledge management and data analytics are two different segments with varied approaches, and share similar goals of enhancing organizational performance and effectiveness. With reference to the ontological perspective, knowledge and data re two inseparable and related constructs classified on similar spectrums of the human experience. A gold ore represents a source of gold, and gold is normally a refined type of ore; therefore, gold ore is a single entity that assumes a different format at varied lifecycle phases. Similar dual aspect can be ascribed to knowledge and data.

This paper will begin with an analysis of literature sources, before focusing on the methodology and analyzing of the Data, Information, Knowledge and Intelligence hierarchy and the concepts of explicit and tacit knowledge. These two constructs provide a theoretical basis for the evaluation of the end-to-end data integration and data analytics process with the management of knowledge. In addition, the paper will propose a concept model for data analytics (3-phase process framework) for practices in knowledge management (knowledge creation, application and discovery). Financial, this paper will evaluate the importance of knowledge management and apply the process of data analytics to evaluate the intertwined connection between knowledge management and data analytics. The main purpose of this research is to prove that knowledge management and data analytics should be integrated and aligned to reinforce and inform each other so that business performance is optimized.

The proposed work is organized as follows. Section 2 evaluates the relevant literature sources on data analytics and knowledge management. Section 3 is the methodology section. Section 4 presents a critical analysis of the paper. Section 5is the discussion section. Lastly, Section 6 concludes the paper and provides future research directions.

2. Literature review

G. Bleojua, A. Capatinaa, V. Vairinhosb, R. Nistora and N. Lescac in Ref. [5] evaluate the concept of business intelligence and summarize its processes integrated in collecting valuable and useful data from different datasets, which are available within different enterprise to enhance the process of decision making. Particularly, competitive intelligence can be considered both as a product and process. As a process, the major purpose of business intelligence is to support the decision-making processes and minimize the time spent on making decision regarding the issues to be resolved. For this to take place, it is fundamental to define and implement various basic elements regarded. In addition, from the perspective of a product, business intelligences is based on Information Technology (IT) elements, which are presented to set basic elements and utilized as a major influencer for the Decision Support Systems (DSS) in creating effective analytics for executives and utilized as decision maker.

L. Banica, P. Polychronidou, C. Stefan and A. Hagiu in Ref. [6] evaluate a different perspective arguing that business intelligence is also a major segment of decision making. Based on the Simon's framework, intelligence is the initial phase, which will be utilized in the decision-making process.

In this stage, the decision makers will make or identity the perceptions, which have some issues to be resolved and applying issue structuring strategies. For proper integration, M. Kejriwal in Ref. [7] evaluated in their studies and mentioned that business intelligence tools (business intelligence concepts can be available at the midst of data analytics in enhancing the process of decision-making and another one focusing on the tools and technologies of storing data; and knowledge discover utilized in supporting the opportunities, which have been discovered by the firm for the purpose of making decisions; based on data integration and advance data analytics. In that case, just like problem-solving, the integration of decision opportunities can be integrated to collection of assistances, which business intelligence utilize in enhancing the process of decision making.

J. Graef in Ref. [8] posited that business intelligence considers wide-range processes linked to the extraction of helpful and valuable data from massive data, which is available within the firm in supporting the decision-making process. As such, the systems for business intelligence represent the tools, which establish the interlinked processes of IT remedies and knowledge from professional; so that it can be utilized for business operations, integration, and organization of management practices and provide the required results of intelligence decision-making within the firm.

A. Carneiro in Ref. [9] evaluated the role of knowledge management towards the process of decision-making focusing that many decision makers had depended on knowledge management when making decisions that effectively amount to practical decisions. This statement implies that in a knowledgeable firm, more individuals will be able to contribute in decision-making rather than a single individual; and this means that knowledge is less available. Knowledge can be utilized in the management and maintainability of power, development and renewal of available assets and resources. This shows that firms that have more knowledgeable individuals can come up with effective decisions instead of a single individual making all the decisions.

F. Machlup in Ref. [10] argue that the value of knowledge in the process of decision making is based on the manner in which it has been differentiated from the projected application and how critical it can be utilized and affect the future choices. Knowledge management is allowed a dynamic task of decision making, whereby it is actually based on situations, engagement of individuals from different management levels in accessing the process of making decisions. The requirements of adequate skills and resources and evidence-centered approaches to make decision is apt for effective utilization and operation of economic assessment of knowledge. Due to value utility of knowledge within the firm, the most

Table 1
Data, Information, Knowledge and Intelligence hierarchy perspectives.

Data, Information, Knowledge and Intelligence	Data Process Perspectives	Knowledge Management Perspectives	Comment
Data Processing	Symbol knowledge analysis	Collection of objective, discrete factors concerning an event	Knowledge of nothing - Initial Stage of Knowledge process
Information Analysis	Information, which is processes to be applicable, providing answers regarding when, where, what, and who queries	Information, which makes difference	Purpose of Knowledge
Knowledge Discovery	Information and data application analysis	Derived from brains at work	Process of Knowledge
Bigdata Intelligence	Assessing understanding	High-order concepts lumped in knowledge for practical aims	Result of Knowledge

efficient and effective decisions can be structured, whereas valuable knowledge can only be attained by enhancing and improving resources.

Resultantly, enterprises have to choose the best knowledge and data that have to be utilized so it can be effective for decision-making; and also for firms to become knowledge-based, it is essential to comprehend data value. Knowledge sharing is also a fundamental segment of knowledge discovery practices, which have been applied by workers sharing data for the success of the business. :R. Nelson, V. Meja and N. Stehr in Ref. [11] dispute the utilization and operation of different knowledge; and argue that the usage of data is based on the willingness of individuals and decision makers to utilize it. Also, business executives and managers have to motivate their workers to share skills and come up with novel ideas to help enterprises to attain determined benefits.

Y. Voronova in Ref. [12] argue that members of the firm should have shared skills, languages, technical skills constructed through effective business management practices. Resultantly, if firms do not have effective practices of formal knowledge sharing, the chances of lagging behind or failing to leverage the workers' intellectual funds for organizational growth and knowledge sharing practices allowing the transfer of experience, transfer of knowledge among clients and workers to establish competitive advantage since it will impact the process of making decisions, which will therefore enhance the Quality of Service (QoS) by the firm.

In this paper, Data, Information, Knowledge and Intelligence hierarchy will be evaluated. The hierarchy is a typically utilized construct signifying the ascending status of human knowledge. It has various synonyms, e.g. data hierarchy, intelligence hierarchy and knowledge hierarchy. The various definitions of the Data, Information, Knowledge and Intelligence hierarchy have been provided in Section III. To evaluate data for the research, data from the case reviews and research was collected and a critical research presented in Section IV.

3. Methodology

In this paper we analyzed the qualitative theory, a qualitative research strategy, has been utilized because of the interrelated and available data on Data information, Knowledge, and Intelligence hierarchy, which could be utilized to enhance the generation of theoretical findings. Data utilized in this research is a combination of reviews and cases from past literature sources and the current research.

The cases and reviews were chosen through research processes in popular web e.g. Google Scholar, Ebsco Business Source Complete, ScienceDirect and Emerald based on keywords such as Data Analytics, Knowledge Management, Big Data, and Business Intelligence. The research model is based on critical qualitative research, which has some ethnography similarities, and other types of researches derived from theoretical results from data that occur naturally.

Table 2
Data, knowledge & intelligence.

Data/ information	Data or information integrates raw opinions and facts. It is developed based on formal procedures, executed as a major segment of monitoring, assessment, impact evaluation or research practice. However, it is also produced produce informal procedures.
Knowledge	Whenever data is systematically arranged through analysis, processing and storage, it typically turns into knowledge. Knowledge can be utilized to answer queries and draw critical conclusions.
Intelligence	Intelligence presents the procedure, which integrates the interlinking of understanding, experience, insights for actions, common sense and decision making.

4. Critical analysis

4.1. Data, information, Knowledge and Intelligence hierarchy

The Data, Information, Knowledge and Intelligence hierarchy is typically-utilized construct signifying an ascending status of human knowledge. It has various synonyms, e.g. data hierarchy, Intelligence pyramid and knowledge hierarchy. Researchers provided a critical literature assumption of definitions and structure of this construct. Three different definitions of Data, Information, Knowledge and Intelligence hierarchy based on various perspective have an important relevance for discussion in this research according to Table 1.

4.1.1. Knowledge management

Information management is a fundamental tool for most of M&E systems. However, it is not on its own, mostly in larger programmes and projects. Knowledge management goes an extra mile compared to information management, and can be illustrated as "systematic procedures by with the knowledge attain by the firm is used, shared, accessed, stored, refined, captured and created. Knowledge management is based on the perspective that it is not an end itself, but has to be visualized as a means of allowing business goals to be attained.

The main objective of knowledge management is to allow firms to create or capture critical knowledge, and make it visible to those who can utilize it at an effective time and location. In that case, whereas information management typically considers how raw information and data is accessed, stored and collected, knowledge management goes an extra mile in generating applicable knowledge base on datasets.

A critical method of evaluating this is to visualize information or data as raw opinions and facts, knowledge as analyzed and processed data, and Intelligence as the projected product for the end-users (see Table 2). A typical "People-Process-Technology" model is typically used to support the concept of knowledge management. The model is capable of identifying three major components of effective knowledge management:

- Linking people with knowledge to assist others, and establishing their capacity and willingness to request share or listen.
- Structuring processes to simplify the procedure of distilling, validating and sharing knowledge
- Developing dependable and friendly technologies to enhance communication.

In minor projects, much is not required to invest in technology and processes. However, as a developmental intervention progresses from minor to major projects and to organizations and programmes, things tend to be more complicated, and become essential to depend on more technologies and processes for sharing knowledge, and less concerning personal relationships and contact. Nonetheless, it is dangerous that

CSOs have become concentrated in information management, and hence lose vision on its aim. During the early 2000s, major NGOs developed detailed information management systems; however, it was noticed that these just deliver benefits in case there was critical focus on the people. Technologies and processes have to be development and planned to serve individuals who utilize them, and not contrary to that.

4.1.2. Knowledge management elements

The creation of knowledge takes places where novel data is formed; for instance, when data has been recorded in forms and templates, or when staff opinions have been written down. However, it can also occur when individual combine data or the present knowledge in a novel means to create novel knowledge based on shared experiences at workshops or meetings. The capturing of knowledge concerns the recording or identification of knowledge from outside or within the enterprise. However, it can also occur whenever individuals connect data and the present knowledge through novel means to formulate novel knowledge. For instance, CSOs staff can generate novel knowledge based on shared experiences at workshops or meeting.

The capturing of knowledge reflects on the recording or/and identification of knowledge outside or within the firm. This might be explicit knowledge as printed document or data encrypted in databases. However, it might also include implicit knowledge. This represents the knowledge that is help by the staff, or teams that work to mitigate particular issues. Implicit knowledge can be embedded in CSO relationships, processes and knowledge. Knowledge accessibility takes place whenever CSO searches and acquires knowledge from different sources. This might integrate knowledge with respect to individual members of the staff or colleagues. However, it might also integrate academic publications, standards, guidelines, procedures or policies; or the staff's experience from other enterprises.

Knowledge might also be available from societies of events, networks, external experts or practices (e.g. workshops or conferences). The storage of knowledge is connected to the management of data, and normally utilizes similar processes and technologies. However, it might go beyond the storage of raw information and opinions, and might integrate the capturing of learned lessons, or other forms of analyzed and processed data. Knowledge management and sharing concerns the making of knowledge present to others. For knowledge to have deeper organizational application, it has to be shared and transferred. Knowledge transfer can illustrated as purposed and focused communication to identified receivers, whereas sharing typically denotes to knowledge dissemination in a wider perspective.

Knowledge usage integrates the usage of knowledge for a particular purpose. This is typically an ultimate object of knowledge creation, sharing, storage, access and capture. As per M&E, the objectives might integrate accountability, learning, and project management, issuing evidences for advocacy works, developing communication, marketing and fundraising.

G. Jifa in Ref. [13] have defined Data, Information, Knowledge and Intelligence based on the perspective of data, where data, integrating symbols, is typically processes to generate information that is therefore evaluated to produce knowledge and enhance understanding. Data analytics embraces this technology-based data evaluation perspective, as it is considered in the three critical data analytics process frameworks of Knowledge Discovery in Database (KDD), Sample, Explore, Modify, Model, and Assess (SEMMA) and Cross-Industry Process for Data Mining (CRISP-DM). Three frameworks share the same limitations whereby each was structured based on technical perspective and for technical experts: each ends prematurely at the end of data processing: Every on fails to adjust into knowledge formation, a procedure of disciplinary collaboration of both organizational and technical experts, and into application of knowledge, a procedure for engaging stakeholders and decision makers and applying knowledge in the process of solving problems.

The authors have defined Data, Information, Knowledge and Intelligence from the perspective of knowledge management, whereby data integrates facts concerning events. Data has particular meaning and has to 'inform'; and knowledge derives 'brains of work.' They gave elaborated definitions of knowledge. This explanation goes beyond the technical approach of data processing and puts knowledge based on organizational or human perspectives based on definition keywords: organizations, organizational, insights, experience, knowers, minds.

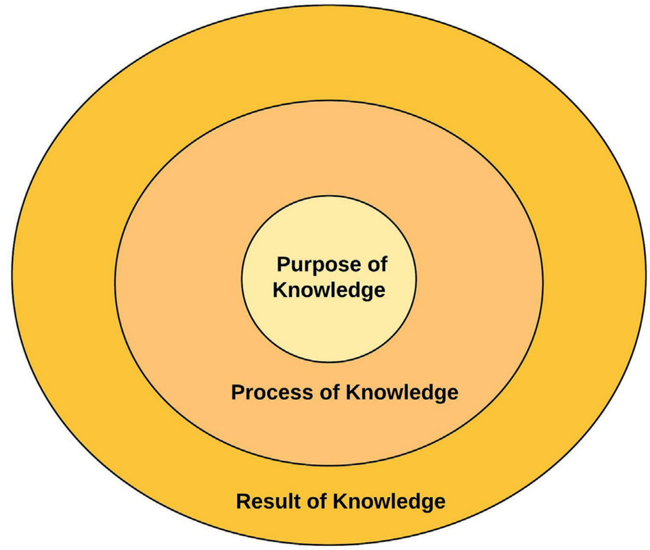

Fig. 1. Begin with purpose of knowledge model.

It is interesting to note that knowledge represents information processed in brains of individuals. It represents personalized data defining Data, Information, Knowledge and Intelligence hierarchy in most profound and succinct manner. Based on this explanation, Data, Information, Knowledge and Intelligence signify four various form of human knowledge and various dimensions of human understanding. Data represents unearthed materials from mines that disclose nothing and therefore limited valuation. Information represents coarsely processed materials mine that depicts 'what', 'where', 'when' and 'who'. Knowledge represents more refined by human brains that depict 'how'. Known-how represents the most useful and practical form of knowledge. Intelligence signifies the known-why; it bases on the pinnacle of human knowledge. Intelligence represents a power and critical form of knowledge, which stimulates human activities as considered in the 'begin-with-why' golden circle framework by where the 'why' signifies how to attain what is shown in Fig. 1.

4.1.3. Tacit knowledge and forms of knowledge

The identification of the significance of personal experience in the search of knowledge can be tracked back to the late 1950s where M. Jarrahi, R. Reynolds and A. Eshraghi in Ref. [14] positivist perspectives of scientific knowledge and concluded that knowledge is personal and necessitates individual commitment. It is believed that our body is an instrument of the wide-range knowledge whether practical or intellectual; stressing on the power of tacit identifying why distinguishing tacit from explicit knowledge; and considering that all knowledge from explicit; with a belief that knowledge is founded from tacit knowledge.

Knowledge is defined as "a skilled set that cannot project." Tacit knowledge integrates most of the human knowledge that has been embodied within the human brains and bodies and may not be explicitly codified or described. Due to this purpose, a discussion on tacit knowledge is considered as "we are in the known that we may tell." Explicit knowledge represents human knowledge, which can be described or codified, based on a language or codified means, and other conceptual methods e.g. gestures, signs, and drawings. The terminologies theoretical/intellectual and practical knowledge are utilized to differentiate explicit and tacit knowledge. Tacit represents practical knowledge

Table 3
Comparison between Explicit and Tacit knowledge.

Tacit	Explicit
• Traditional knowledge (practical) • Simulteneous knowledge (now and here) • Experience knowledge (body) • Subjective	• Digitalized knowledge (theoretical) • Sequential knowledge (then and there) • Rationality knowledge (brain) • Objective

whereas explicit represents theoretical and intellectual knowledge. Two forms of knowledge from varied aspects have been presented in Table 3.

Tacit knowledge is considered to align with the eastern philosophical traditions, which manifest itself as the Zen Buddhism practice whereby explicit knowledge is linked to the western philosophical traditions that manifest in scientific approaches impacted by positivists globally.

4.2. Data analytics

4.2.1. 3-Phase process

Whereas there has been various forms concerning the technical abilities of data analytics because of the technological advances e.g. machine learning, cloud computing and big date, the organizational and people concepts of data analytics are typically neglected and overlooked. The Data, Information, Knowledge and Intelligence hierarchy and the aspect of tacit knowledge presents a systematic model to effectively comprehend intricate end-to-end processes of data analytics.

The process of data analytics is similar to climbing the Data, Information, Knowledge and Intelligence pyramid, and is summarized under three fundamental phases. Every phase corresponds to a 1 or 3 dimension (organization, people and technology), and signifies 1 or 3 philosophical paradigms (pragmatism, constructivism, and positivism) as indicated in Fig. 2.

4.2.1.1. Phase 1: knowledge discovery (data – information). In this phase, raw data from the past sources is combined and processed using computational algorithms and statistical models to derive fundamental information or data analytics that signifies novel explicit knowledge that has been discovered through technological application. Whereas these phases integrate significant human activities e.g. initial project scheduling, the comprehension of organizational needs, and data quality validation, it is mostly technological-based and integrates heavy application of software engineering, machine learning and statistics. This phase signifies the application of the positivists' global perspective where objective knowledge reality is classified using scientific approaches possessing reductionist, deterministic and quantitative characteristics.

4.2.1.2. Phase: knowledge creation (information – knowledge). In this phase, the resultant data analytics are normally consumed and more processed by human brains that interpret data analytics based on peoples' experience, data insights, and the present knowledge body. Information is changed to knowledge whenever it has been processed in the minds of people. This stage also integrates collaboration with professionals from wide-range disciplines to assess explicit knowledge obtained from the previous stage. Novel knowledge, majorly tacit, is formed in this phase. This stage is mostly individual-based and signifies the application of social constructivist and constructivist global view whereby truth knowledge is constructed or created through social interactions, experience sharing, and human collaboration. The constructive inquiry approach is inductive and qualitative in nature.

4.2.1.3. Phase 3: knowledge application (knowledge – intelligence). In this phase, stakeholders and decision makers are engaged, and novel tacit knowledge formed from the past phase is evaluated against business strategies and organizational values. Knowledge application leads to informed choices and action plan purposed at enhancing at enhancing situations and mitigating issues. The resultant actions and decisions can be visualized as explicit knowledge that stems from collective Intelligence of professionals, stakeholders, decision-makers and people involved. During this stage, many firm-based, business strategies and organizational values are the major considerations. This stage signifies the application of pragmatist global view, which focuses on practical

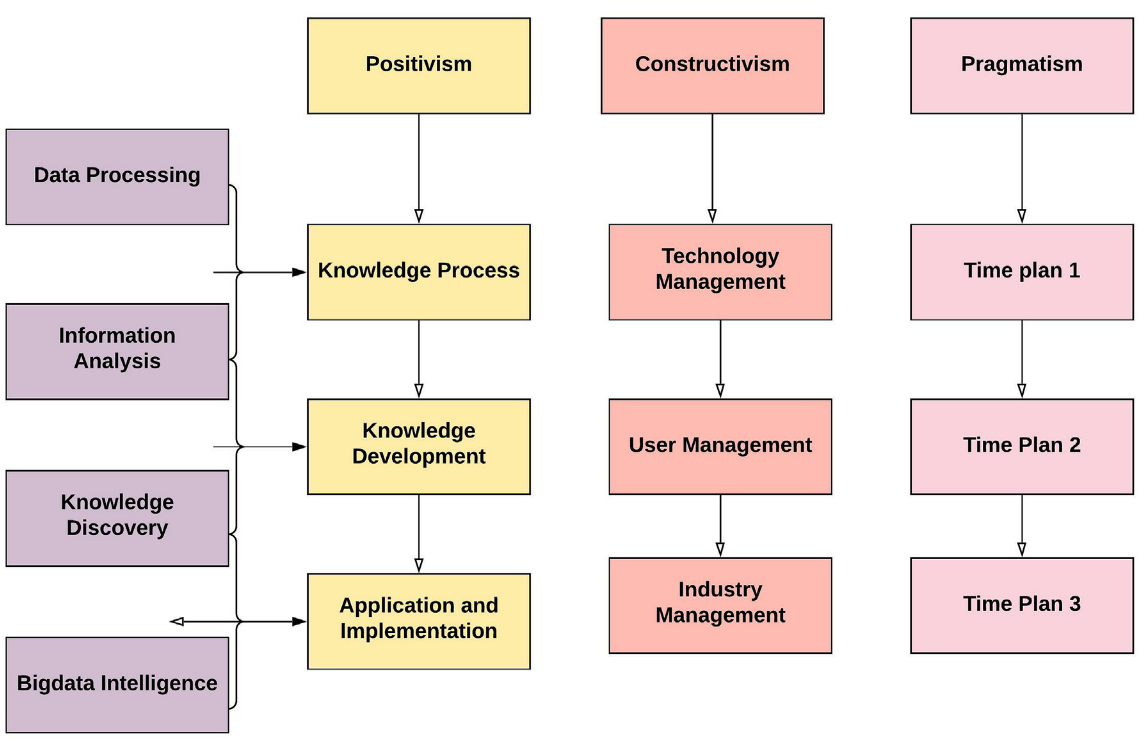

Fig. 2. Process of data analytics alignment with the Data processing, Information analysis, Knowledge discovery and Bigdata Intelligence hierarchy.

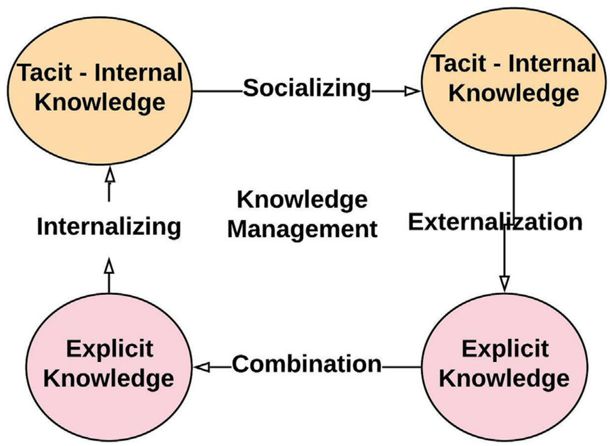

Fig. 3. Conversion mode of knowledge.

Table 4
SECI framework summary.

Mode of conversion	From & To	Definitions
Internalization	Explicit – Tacit	Represents a procedure of embodying explicit skillset into tacit
Combination	Explicit – Tacit	Represents the interlinking of procedures of changing explicit knowledge into systematic and complex set of explicit skillset
Externalization	Tacit – Explicit	Externalization represents a procedure for articulating tacit knowledge to explicit
Socialization	Tacit – Tacit	Refers to the conversion of novel tacit skillset based on shared experiences

knowledge application. The phase considers explicit knowledge that is discovered through the positivist method, and tacit formed through constructivist method, and utilizes them in practical issue-solving. The 3-phases of analytics procedural align effectively with the three timeplans of knowledge management: Timeplan 1- To leverage explicit knowledge; Timeplan 2 – To leverage experimental knowledge; and Timeplan 3 – To leverage collective knowledge.

4.3. Modes of knowledge conversions

The concept of tacit knowledge from both the modern and traditional philosophies has been applied in the process of knowledge management. This is somewhat contrary to the Cartesian Dualism of the object, body or subject and mind that has been the major focus for scientific approaches. The eastern philosophy focuses on the unity of nature and humanity, unity of mind and body and unity of self and others. This form of unit provides a foundation for research's theories regarding the creation of knowledge, which is known as Socialization, Externalization, Combination and Internalization (SECI). This framework illustrates the continuous and dynamic conversion procedure between explicit and tacit knowledge amounting from direct human collaborations and interactions.

Knowledge conversion can be defined as the procedure in which human knowledge is formed and developed based on social interactions between explicit knowledge and tacit knowledge. The SECI framework presents four knowledge conversion modes in a spiral form as indicated in Fig. 3.

Table 4 represent a summary of the four major knowledge conversion modes using succinct and clear definition.

4.3.1. Application of knowledge conversion

If we evaluate data analytics in a holistic manner, we can visualize that the knowledge creation framework is applicable to shed light on intricate processes. In this case, we utilize the Data, Information, Knowledge and Intelligence hierarchy as an effective construct to indicate the three different phases of the processes in data analytics, and map them to four different models of the knowledge conversion framework shown in Fig. 4. The Data, Information, Knowledge and Intelligence hierarchy presents the best mode of conceptualizing knowledge that integrates Data, Information, Knowledge and Intelligence. We evaluate data as explicit knowledge because they signify event of interests, explicit aspects of entities, or codified entities. This may be applicable to any form of data integrating tabular (structured), unstructured (video, audio or textual) and semi-structured. Analytics amounting from the application of computational algorithms and statistical frameworks are considered data that is based on explicit knowledge.

4.3.1.1. Knowledge discovery based on combination. The application of statistical frameworks and computational algorithm to uncover patterns and trends of data from different sources signifies technological dimensions of data analytics procedures. It signifies process of combining knowledge by systemizing information i.e. explicit from diversified sources to create a wide-range basis of explicit knowledge of issues at hand. This represents the procedure of knowledge combination.

4.3.1.2. Knowledge creation based on internalization. After the technical phase has been done, the procedure shifts to individual dimensions, where both business experts and technical professional take combined explicit knowledge and interpret it with respect to professional intuition and experience to internalize it to tacit knowledge. This procedure is knowledge as internalization.

4.3.1.3. Knowledge creation based on socialization. The procedure proceeds with group collaborations whereby people collaborate and communicate to share tacit knowledge, which they attain from internalizing explicit knowledge that has been discovered from information. This interaction produces novel and developed tacit knowledge to all individuals engaged. This procedure is knowledge as socialization.

4.3.1.4. Knowledge application based on externalization. This is the last procedure and is for teams to come up with shared comprehension regarding the issue at hand and design potential solutions. This procedure also integrates the engagement of key stakeholders and decision-makers and integration of different perspectives. The inclusive Intelligence in the mode of tacit skillset from various participants leads to potential actions and decisions that are viewed as explicit knowledge. This signifies the externalization process.

Data analytics represents a procedure of developing a realistic understanding, beginning from phenomenal observations of phenomenon to attain the Intelligence pinnacle, which strengthens the process of making decisions and applying practical action to change or influence a particular phenomenon. Nonetheless, the actual world is constantly transforming, being dynamic and complex. Data analytics with the mandate of supporting issue-solving the enhancing decision-making is not a one-time ambition. Data analytics procedure is iterative and incremental in nature. The complete procedure of knowledge discovery, formation and application is being spiral and creates a foundation for progressive process enhancement e.g. the Plan Do Check Act (PDCA) cycle.

4.4. Knowledge management benefits

The field of knowledge management has witnessed an increased popularity over the past few decades. A. N M Bazlur Rashid and T. Choudhury in Ref. [15] have evaluated the perspectives of knowledge management being considered as fad. The results show firmly that knowledge management is not a fad and it continuous since our economy is centered on intellectual capital i.e. knowledge. Knowledge

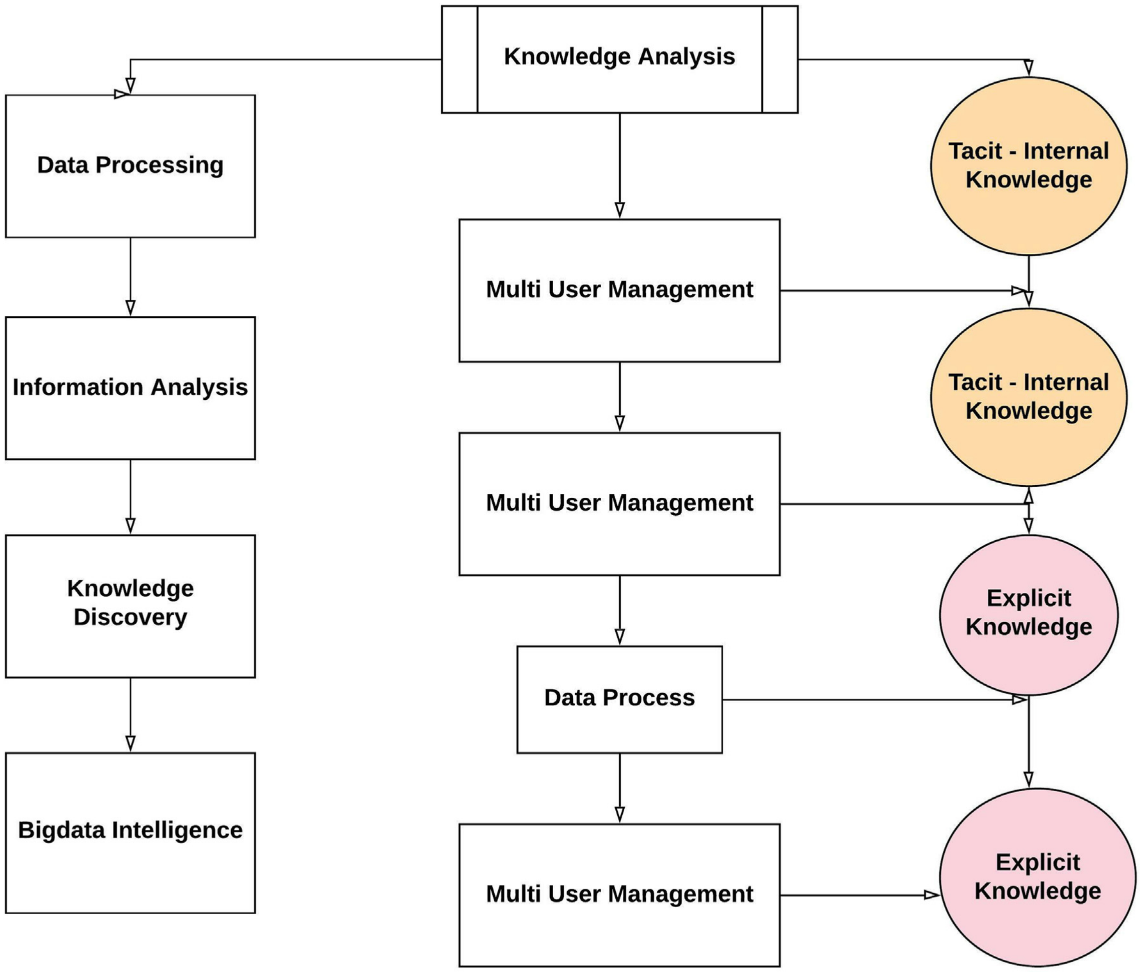

Fig. 4. Application of the knowledge conversion framework in data analysis.

management is proposed for all firms since it aids in the leveraging, sharing, capturing and creation of knowledge for decision-makers. There are wide-range advantages of knowledge management. Enterprises, in the modern competitive edge, are knowledge-intensive, which means that knowledge is considered as their fundamental resource to compete in the market. Nonetheless, firms do not manage knowledge the same way finances are being managed. The authors evaluated fifteen years of experience in the domain of knowledge management and classified arguments under three major classes:

4.4.1. Benefits based on effective processing of knowledge and information

This class evaluated:

- Prompt accessibility to data
- Minimal duplication and redundancy
- More time for experts to concentrate of more significant problems
- Identifying the knowledge sources and identifying who does what
- Enhanced quality of knowledge and data
- Accessibility of the present knowledge understanding

In case the above benefits have been attained, it should project to the second class.

4.4.2. Internalize benefits to the enterprise

This class focuses on:

- Eliminating unwanted practices and sharing the effective ones
- Boost the speed of marketing novel services and products
- Eliminating reinventing wheel that amounts to reduction of costs
- Capturing valuable skillset before professionals retire or move to another department or organization.
- Minimize the timeframe for processing data which amounts to prompt issue-solving and reduction of costs

4.4.3. Consumer and shareholder benefits

This category integrates:

- Enhancing the client retention and consumer satisfaction rate
- Prompt issue-solving
- Consistent with clients irrespective of their location
- Attaining significant insights from clients that enhance the service or product quality
- Effective valuation for costs
- Enhanced market reputation.

4.5. Big data benefits

There are three major Vs of massive date: Velocity, Variety and Volume. For the aim of developing the knowledge management framework, it is fundamental to evaluate if there are more. These features are discussed to evaluate the challenges, advantages and nature of massive data.

4.5.1. Volume

Volume is the most common feature of massive data considering that 90% of the present data is formed in the past two years. In addition, staggering information and datasets are produced every minute. In 2016,

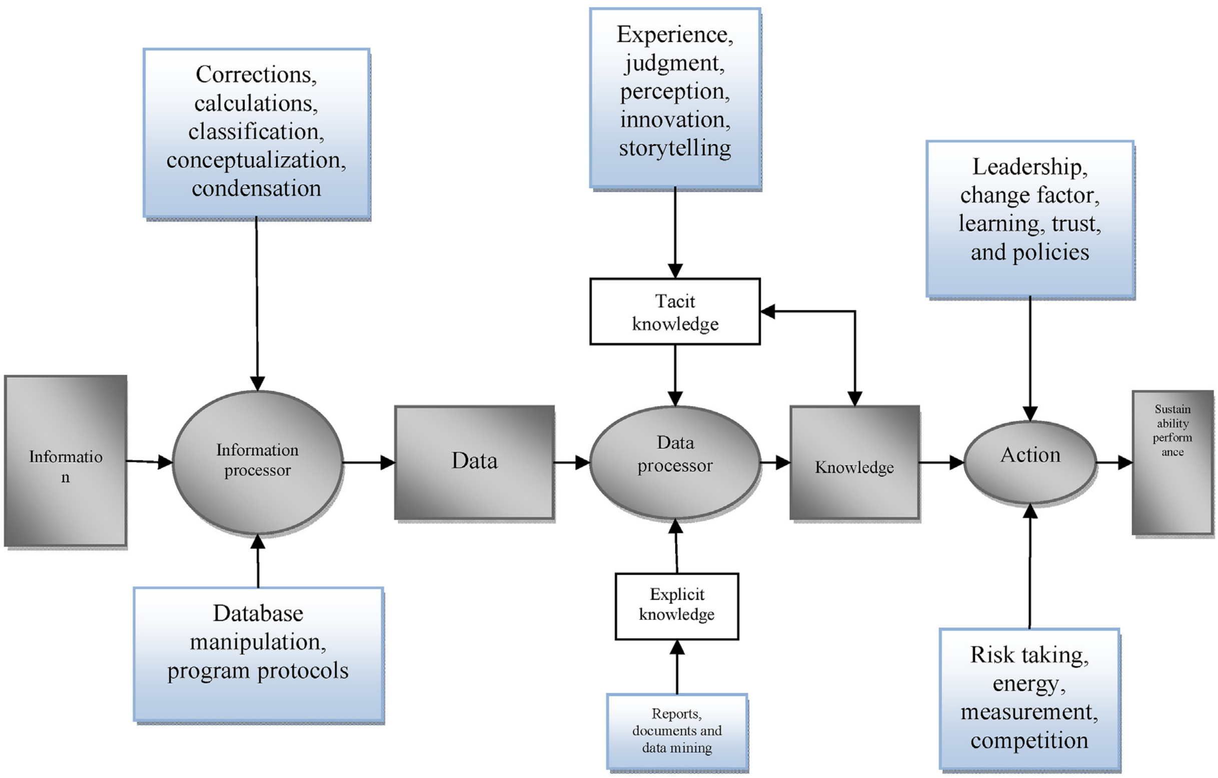

Fig. 5. Initial Model of knowledge management/creation.

about 1 trillion images were captured and this value rose by 9% in 2017. With the increasing number of mobile devices, it is not surprising to visualize big data penetrating through the global mobile traffic integrated to about 6 exabytes in single month. Exabytes are normally the same as 10ˆ18.

4.5.2. Velocity

This element represents the overall speed of streaming, refreshing, producing and generating data. Velocity implies that data is accessible in real-time and minimal time is wasted to retrieve it.

4.5.3. Variety

Variety signifies the condition of data. Most of datasets are unstructured e.g. those in traditional datasets. Data is mostly unstructured or semi-structured. Adding to the multimedia type of data, there are machines, sensors and click, just to mention but a few.

There are 7 other Vs, which have to be considered in this case: value, visualization, volatility, vulnerability, validity, veracity, variability. For the purpose of this research, it is fundamental to explore these features to critically comprehend their implications on recent understanding regarding big data analytics.

4.5.4. Variability

This feature focuses on data sources and types. Variability reflects on the uneven velocity taken to load information to the right database engines.

4.5.5. Veracity

Veracity represents the classical Garbage in, Garbage out (GIGO). This feature is one of the most critical V feature, identifying the dirty dataset, which might eliminate the value of massive data and costs linked with it.

4.5.6. Validity

Validity is the same as veracity. It is estimated that about 60% of data analysts spend time cleansing information and data for analysis. It is fundamental to follow a policy to ensure that consistent and quality data is available to users.

4.5.7. Vulnerability

Privacy is a major concern with big and small data. Hacking done in 2016 results to the stealing of data from 167 LinkedIn accounts, and more than 300 million emails and passwords from the Myspace users lost.

4.5.8. Volatility

This is based on the freshness of information and data and how long it can stay useful and relevant. Resultantly, volume and velocity of data should stimulate management to consider data volatility. Data has to be related to the enterprise functions and needs.

4.5.9. Visualization

Memory limitations, poor data scalability and feedback duration might affect the visualization of data. Tradition graphical presentation would not be operative to massive data; thus, other graphical representation e.g. data clustering, parallel coordinates, sunbursts, cone tree, circular network diagrams, have to be considered in this case.

4.5.10. Value

The value feature is considered by various fundamental features. With organizational value, other Vs can be disregarded. Value denotes to the comprehension of consumers' needs, structuring targets, optimizing procedures or generally enhancing organizational performance. Extracting business value from massive data is not attained without a particular strategic approach.

5. Discussion

In this paper, a framework for knowledge conversion has been evaluated. We have also evaluated the knowledge creation model (see Fig. 5), which has been modified (see Fig. 6) to focus on actions of the final outputs for any knowledge creation task. Without significant action,

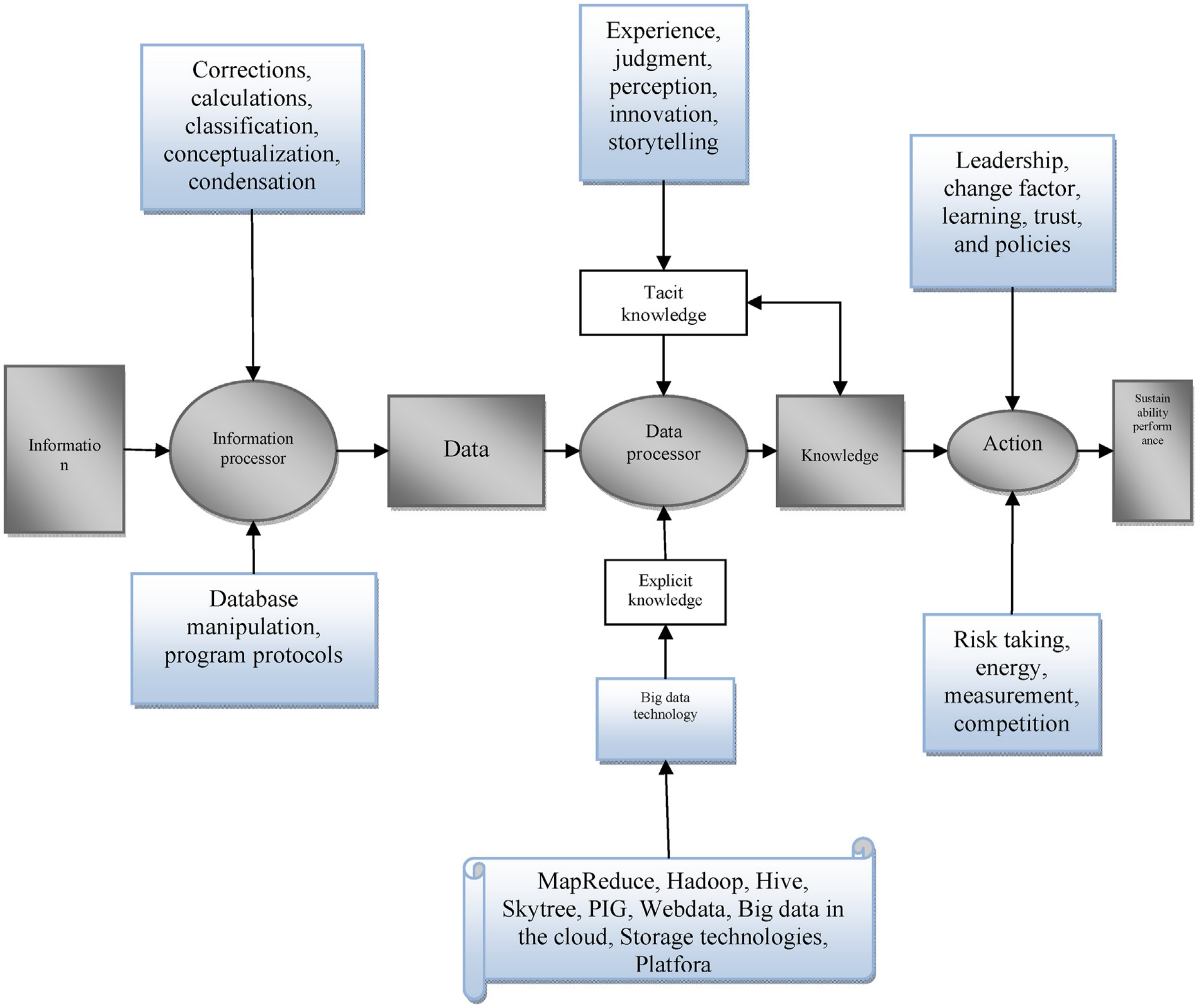

Fig. 6. New Model of knowledge management/creation.

knowledge, irrespective of its cost, will be insignificant. The framework's nature is organic and can be changed to changes in the business world and IT. The connection between big data and knowledge management targets at integrating data from various perspectives to provide the best insights needed to make proper decisions.

This paper puts more emphasis on knowledge management, which is not just learning about the business, but also how to transform it. The research posited that irrespective of the success measures, client stratification, robust security, effective development and profit to develop in the competitive knowledge age is vital. In that case, the people and organizations have to be knowledgeable through various phases of transformation within the environment. There is clear proof that data science is becoming a fundamental segment, which will provide employment opportunities irrespective of the individuals' career stages.

Based on this model (Fig. 5), it was designed to deal with knowledge management/creation for small data fields. Based on the model, it is evident to the observer that the information processors represent the database management system. The application of the process is also applicable for massive data, except that its engine needs updating. Hadoop provides main and timely integration and not typical replacements. Database management systems will progressively be in the market. Most enterprise depends on database management systems and is not projecting to replace them any time soon. Tacit knowledge will therefore not change, it will still base in most individuals' minds. Intuition, perception, innovation, judgment and other fundamental factors will continue being fundamental inputs to be procedure of creating knowledge.

The factor that might potentially transform is technology and the sizes of technological tools, which are in support of explicit knowledge. It has to be noted that for massive data to be effective and successful, it is necessary to integrate other developed and designed technologies. Moreover, the connection between classes, reporting, queries, databases, knowledge, information and data will at least require adapting to most initiatives that pertain to massive data. These integrate Hive, Hadoop and MapReduce.

The novel model comes up due to modification made from the traditional model; and this makes it ready to handle novel elements of massive data. The framework still maintains all the fundamental and productive phases evaluated in knowledge management/creation. The framework also integrates intangible elements such as meta-learning, politics, trust, factors of change and leadership as determinant factors for technological applications to be a success. The end results of this is sustainability performance, which means that success alone is not apt. Success requires evaluation, recharging and willingness to mitigate organizational obstacles, which affects it from being attained.

This study was relevant since the issue of knowledge management is a prevailing concern for many decades. Enterprises have achieved significant understanding of knowledge value as a critical asset of business survival. Massive data has expanded into the scene with calls for change in the processes of capturing, cleansing, processing, updating and sorting through massive sets of data initially. This paper aims at showing the implication of big data as an inescapable factor and to connect it to the wide-range field of knowledge management. Knowledge is the result of both knowledge management programs and big data projects. So, these two concepts can be combined. Towards the end of this research, a modified model of knowledge management/creation has been presented; but integrated more elements that pertain to big data.

6. Conclusion and future directions

Data analytics is a critical tool, which can assist enterprises and individuals to overcome data overload and aid enterprises to enhance their performance, and assist communities to handle social challenges and to improve the conditions of humans. To attain better results, enterprises and analysts should focus beyond technological dimensions, stress on the requirement for collaboration and engagement and focus on business strategies and social values as fundamental forces enhance data analytics. This paper has used the concept of the Data, Information, Knowledge and Intelligence hierarchy, interlinked with tacit knowledge power and the theoretical perspective of knowledge conversion to provide an illuminating theoretical model, which integrates the three major phases: Knowledge application, Knowledge Creation and Knowledge Discovery; and three dimensions: Organizations, People and Technology; and three paradigms: Pragmatism, Constructivism and Positivism of data analytics into a comprehensive dimensions.

The theoretical evaluation and conceptual framework presented in this research contributes to the body of knowledge by enhancing the understanding of big data and processes of data analytics and its connection with the practices and theories of knowledge management. Data analysts and practitioners can utilize insights provided in this research to guide efforts in analytics to enhance engagements and results. Scholars can utilize insights in this paper to enhance data analytical programs and coursework designs to enhance pedagogical and instructional quality. Future research is required to provide an in-depth evaluation of the new model of knowledge management/creation presented in this paper. In addition, validation and improvement on the proposed models and theory is needed in future research.

Declaration of competing interest

We don't have any conflict of interest with any authorities.

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