Big data, knowledge co-creation and decision making in fashion industry

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ABSTRACT

Big data has become a buzzword and has been one of the most sought after topics for research. The applications of big data have been studied in various important contexts. However, very little has been explored in the realm of integrating knowledge co-creation with the usage of big data when it comes to evidence-based decision-making. The current study empirically investigates data from four fashion retailing organizations. Evidence from our findings suggests that knowledge-based interactions between the customers and the salesforce in those organizations form the core of knowledge co-creation. The findings have revealed that big data indeed can assist in knowledge co-creation, which can in turn adequately lead to evidence-based, effective and efficient decision making for better business returns.

1. Introduction

The term "big data" is being labelled as the next big thing as far as innovation is concerned (Gobble, 2013). Big data is capable of bringing in significant transformations for improving various business ecosystems (Brown, Chul, & Manyika, 2011). The implications of big data for business solutions are far reaching, extending to all domains including organized retail (McAfee & Brynjolfsson, 2012). Organizations in this sector are increasingly collecting, storing, and analyzing substantial granular data and information – acquired through systematic processes and systems – which are essentially about products or services meant for sale (along with all tagged information), such as people (both customers and employees), and transactions (primarily the interactions and sale closings between employee-customer pairs). This data-linked practice to boost consumer purchases has seen more engagement than ever before. The standard collaboration tools include cloud services, email storage, POS data tracker, mobile devices and other similar gadgets required to conduct business and interact with suppliers, customers and other stakeholders (Aswani, Kar, Ilavarasan, & Dwivedi, 2018; Dwivedi, Kapoor, & Chen, 2015; Shirdastian, Laroche, & Richard, 2017).

Such applications create, receive and collect machine and/or sensor-generated data messages at very high volumes, which then drive business processes. As such, detailed insights and patterns of data can be identified, which tend to reveal, for example, a customer's tastes,

purchase preferences, levels of spending; and also more importantly, calculated enticement becomes possible. For instance, if User 1 buys Item 1 and wishes for Item 2, whilst User 2 simply purchases Item 1, then it is highly likely that when strategically focused and pushed, User 2 will also end up wishing for Item 2, and all of this can be managed in real-time. To date, the extant literature and academic discussions have mostly dealt with the aspect of generating more revenues through the sale of, or adding value to, or modifying an already created Item 2.

However, it is plausible that a newer Item 2 can be created from scratch, starting with ideation at the POS itself when a derivative is obtained from interacting knowledge fragments of the salesforce and the customers. That said, there is a pressing need for education, training and awareness for this, which can also be achieved during these processes. The organizations' expected objective will be in creating newer cost-effective products that not only induce a spike in customers' interest (as well as revenues) but also allow greater diversification in the portfolio of products for competitive advantage. Decision-making related to creating these cost-effective products will be supplemented by evidence from big data-based.

Big data helps organizations become resourceful enough to tackle diverse business challenges (Gehrke, 2012; Yaqoob et al., 2016) and build organizational capability (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Davenport, Barth, & Bean, 2012; El-Kassar & Singh, 2018). Essentially, big data refers to large volumes of data sets that are required to identify observable and meaningful underlying patterns of/

from data-oriented/data-supported/data-generating activities in order to make efficient and effective decisions in the organization (Boyd & Crawford, 2012). It is implied that relevant organizational knowledge can be extracted from prodigious volumes of big data available to retail organizations. Along with that, the professionals'/personnel's personal knowledge will also be at those organizations' disposal. Such knowledge may combine and recombine to give rise to an organizational process of knowledge co-creation, involving other stakeholders (customers) through the use of information communication tools (ICT) for their positive impact on SECI (socialization, externalization, combination and internalization) (Lopez-Nicolas & Soto-Acosta, 2010). Furthermore, the knowledge co-creation process will be catalyzed by the inducing factors such as intention, autonomy and fluctuation. In the end, the entire process will lead to possible assistance in evidence-based decision-making. The aforementioned form of decision-making in essence allows efficient and effective decisions to be made. These decisions are likely to generate value for the business (Rehman, Chang, Batool, & Wah, 2016).

At the same time, during the entire organizational process of knowledge co-creation, the elements of relevant organizational knowledge will be defined by individual knowledge and group knowledge, while personal knowledge will be defined by explicit knowledge and tacit knowledge. In this context, knowledge will refer to knowledge of customers [owing to the nature of the selected sample]. It has been posited that no organization can exist in isolation and they will regularly interact with their environment (which itself changes dynamically), thereby dispersing data, information and knowledge by various means, building the organizations in that manner as well as helping the organizational members understand their organizations and their requirements (Nonaka, 1994). Thus, a retail organization can rely on efficient and effective evidence-based decision-making for generating business value through knowledge co-created in the organization – which carries the potential of relevant organizational knowledge (at individual and group level) as extracted from big data and personal knowledge of employees (both explicit and tacit). Evidence-based decision-making can prove to be a core competency for the organization. In order to reap the benefits, the organization will be making different attempts for advancing in the forward-looking direction.

In this paper, we are interested in uncovering the facets of such activities that outline an organization's survival based on big data and whether there are significant disparities existing across small and big fashion retail organizations. Therefore, the principle objective of this paper is to investigate whether the notion of knowledge co-creation is relevant and understandable when it comes to the bigger picture concerning the topic of big data. This becomes imperative as it is worthwhile to make judicious estimates while making provisions for resources that aid in capturing big data, robust systems for both acquisition and storage, and a filtering mechanism to retain only relevant data, etc. In order to gauge the relevance of big data vis-à-vis knowledge-based interactions, this process is envisaged to ensure that costs are kept in check and in the process financial resources are freed up that may then be diverted towards the creation of newer, in-demand, products with friendly price-tags. This will then also be the output of knowledge co-creation, and not merely value addition or creation (Malik, Pereira, & Budhwar, 2017). Eventually, organizations stand to benefit from sets of cost-effective, fresh ranges of in-demand products on a regular basis and this in turn will benefit the customers (people) at large. In practical terms, retailing as an industry will be able to construct updated models of business processes that rely on evidence-based decision-making as an output of co-created knowledge. Eventually, decisions which are commensurate with evidence from big data fragments will provide a great deal of support to various business functions throughout an organization.

We conceptualized a qualitative study to discover the underlying patterns followed by the fashion retailing organizations and the ingrained principles which overall provide backing to their customer-

driven operations. This study will focus on the holistic process of big data-oriented requirements for knowledge co-creation and not on the specific procedures to carry out such work (which implies building algorithms or stating parameters for capturing big data, followed by their use). Since a deeper exploration has to be undertaken, given the dearth in studies on the relationship under investigation, it is appropriate to embark on a qualitative study (Creswell, 2013; Patton, 1990). Starting with the literature review, then traversing through the methodology and findings, the paper concludes with a discussion and future research directions.

2. Literature review

2.1. Big data: its background and relative importance

Currently, organizations have started to believe that they are faced with 'profound changes in the way they manage their business, their customers and their business models' – this has happened because they are being 'overrun by a data-driven revolution in management', which has been caused 'due to the widespread availability of big data and the fast evolution of big data technologies' (Raguseo, 2018). Of late, the concept of 'big data' in the form of popular terminology has generated what can be referred to as significant attention across countries and industry sectors. 'Big data' has enough potential to be extensively used in a range of fields of business management like marketing and retail (Fosso Wamba, Angappa, Papadopoulos, & Ngai, 2018). 'Big data' analytics is said to deal with transaction data that belongs to 'streaming data and high-dimensional data' from 'distributed computing networks' (Chen, 2018). In this regard, it will be valuable to mention the relational matrix as put forward by Jabbour, de Sousa Jabbour, Sarkis, and Godinho Filho (2017), illustrating the complexity of 'big data' and concurrent stakeholders' management. It is also argued that productive synergy between an industrial wave generated by 'big data' and automation, along with environmentally-sustainable business practices, is dependent on adequately comprehending the role played by a logically arranged and carefully considered set of critical success factors (de Sousa Jabbour, Jabbour, Foropon, & Godinho Filho, 2018). Scholars are of the opinion that searches performed online via search engines connected over the internet attract a huge number of 'hits' and this number continues to grow exponentially and concurrently generates 'big data' (Frizzo-Barker, Chow-White, Mozafari, & Ha, 2016). This is both impressive and noteworthy because 'big data' is at play and is being demonstrated in action rather than adopting a form of notional academic discussion. It is not wrong to believe that this phenomenon and its current scale owes a great deal to the synchronous assistance received mainly from the widespread acceptance of mobile devices, social media platforms (Kamboj, Sarmah, Gupta, & Dwivedi, 2018), including YouTube, Facebook and Twitter, and 'Internet of Things' related concepts (e.g., RFID technology) by the general populace at large (Hussain & Dwivedi, 2014; Shareef, Mukerji, Alryalat, Wright, & Dwivedi, 2018). Additionally, it is known that the greater the customer (public) participation and number of interactions, the better the appraisal of retail (service) quality based on available large volumes of data, and even vice versa (Song & Guan, 2015). The number of identifiable mobile-phone users are growing by the day; a significant proportion of those users owning smartphones have the capability for 'turning themselves into data-streams' (Shah, Horne, & Capellá, 2012). Similarly, the video platform for free public use, YouTube, continuously receives very large volumes of data – as much as 24 h of content every 60 s – meaning a whole day of uninterrupted, contiguous video being uploaded every minute (The Economist, 2011). At the same time, in the retail space, the systematic and serialized identification of manufactured and/or transferred goods, efficient real-time tracking of the same (for instance, RFID-enabled tags attached to individual items) and related activities have already generated a great deal of operational and strategic data across the value chain of all industries (Ngai, Poon, Suk, & Ng, 2009)

along with a large volume of RFID data. The aspects of contextual conditions like culture or size of an organization have been explored to identify different organizational capabilities and their performance effects as conveyed by 'big data' (Dubey et al., 2017).

Moreover, scholars and practitioners have even considered 'Big Data' as data which may be adequately and consistently sourced from various channels including sensors, satellites, social media feeds, photos, video and cell phone and GPS signals (Rich, 2012). Thus, it can be said that professionals engaged in retailing can access data that is continuously generated by 'traditional devices', such as POS, RFID and also GPS, as well as a vast amount of data obtained from 'unstructured data sources', such as digital clickstreams, camera and surveillance footage, imagery, social media postings, blog/wiki entries and forum discussions. Thus, big data analytics capability demands a good deal of organizational flexibility for proper functioning of agile work systems (Dubey, Gunasekaran, & Childe, 2018). However, the emerging nature of 'Big Data', which is still conceptually at a very nascent stage, cannot be ignored. As such, several definitions of the concept itself exist currently. For convenience and by focusing on the requirements of this paper, we shall adopt the unified concept of 'big data' presented in the work of Fosso Wamba, Akter, Edwards, Chopin, and Gnanzou (2015, pgs. 235–236). This unified concept is founded upon the notion of 'V', in order to define 'big data' (Gartner, 2012; Kwon & Sim, 2012; McAfee & Brynjolfsson, 2012), where it can be looked upon as a combination of 3 Vs –'Volume' or the large amount of data that either consume huge storage or entail large numbers of records of data; 'Velocity', which is the frequency or the speed of data generation and/or frequency of data delivery; and 'Variety', to highlight the fact that data are generated from a large variety of sources and formats, and contain multi-dimensional data fields including structured and unstructured data. Several recent studies suggest that big data and predictive analytics positively and significantly influence organizational performance (Dubey et al., 2017).

Adding to the definition above, scholars and practitioners have included another 'V' – 'Value' (now 4 Vs) in order to stress 'the importance of extracting economic benefits from the available big data'. Adding another 'V', White (2012) suggests a fifth dimension - 'Veracity' – which, he argues, is crucial and needs to be embedded within the definitions of 'big data', so that the 'importance of quality data and the level of trust in various data sources' can be highlighted. A number of analysts have noted on different occasions that 1 in every 3 business leaders 'don't trust the information they use to make decisions' (LaValle, 2009). Therefore, it is possible to infer that when integrated or recombined with other data and information, data obtained that is not worthy or of satisfactory quality will result in erroneous interpretation and/or false correlation – meaning the responsible organizational head or member might end up making a loose or incorrect analysis of a business opportunity or environmental challenge (White, 2012). Seles et al. (2018) explain that 'big data has gained increasing prominence due to its potential to transform ways of doing business' and that it is quite 'important to understand the implications which big data will have for managing corporate responses to the opportunities and challenges' presented by different agents.

We therefore argue that 'big data' should not only be considered in terms of its orientation towards business analytics and business intelligence, but also – rather more – in terms of its application in developing high-level skills or core competencies that allow organizations to exploit/utilize modern age/state-of-the-art IT tools and architectures. All of this favours the avowed purpose of collecting relevant data from multiple sources, sharing those with key members, retaining within organized storage structures, extracting patterns, and analyzing to produce valuable insights, ultimately raising stakeholder awareness of those insights. Therefore, we understand 'big data' as that holistic approach which allows organizations to 'manage, process and analyze 5 Vs (i.e., volume, variety, velocity, veracity and value)' in order to create special knowledge by assimilating and absorbing meaningful insights – for ensuring sustained business practices, business value delivery, measuring returns performance and establishing the organization's superiority over competitors (Akter et al., 2016; Fosso Wamba et al., 2017).

2.2. Knowledge co-creation: an organizational virtue

Knowledge is not the 'prerogative of scientists' alone, as knowledge is 'socially constructed' – indicating the constructivist principle underlying knowledge and its creation. We argue that this refers to a contiguous process whereby 'context' and 'content' are disconnected from each other, and that continues until the 'context' starts to withdraw over time and is dissolved in history to eventually become invisible (Latour, 1987). Taking up the particular case of 'controversies', wherein it will be fair to assume that the 'black-box' is yet to be shut, makes it quite clear that knowledge – especially scientific – is definitely equivocal, and that there are many different perspectives, each of which shall essentially be owned by individuals and supported by multiple facts, opinions and values. Therefore, by not according any special status to specialists as opposed to laymen during dialogues within or beyond local set-ups meant for familiarization with knowledge, all citizens (including information providers) acknowledge reception of proper knowledge meant for them (Burgess et al., 2004). Earlier, it was assumed that knowledge was held only by specialists who were exposed to it or created such knowledge; however, knowledge was passed on to general collaborators of specific activities (like the salesmen knowing about a customer's preferences for making purchases and not just the marketing head for the region) in depersonalized forms (examples: information packs, SoPs, videos, presentations, etc.) as people at large (specifically, organizational members) began to believe that dissemination of knowledge is pertinent and that decision-making processes are linked to people and their choices.

We contend that knowledge is created in all forms of dyads, such as scientific knowledge versus intuitive/informal knowledge, expert/specialist knowledge versus knowledge held by laymen (generic knowledge), transdisciplinary knowledge, which has its origins in multiple spheres and sub-spheres, versus core knowledge available in a single domain. George, Haas, and Pentland say that there lies 'a significant opportunity to leverage in the analysis of highly unstructured and large volumes of data' that are available to an organization for knowledge building. Big data plays a crucial role in IT-supported knowledge co-creation, allowing 'effective decision-making and improving many business functions'. Unravelling this potential is supposed to epitomize the 'next Big Data challenge for businesses, concerning how to use big data to extract useful information to make more informed decisions and develop a competitive advantage'.

However, the biggest challenge remains as to how a predominant vision can bring together knowledge (inclusive of all kinds of knowledge-owners/knowledgeable people) and achieve an integrated whole (Regeer & Bunders, 2003). This is of great significance when it comes to organizations, especially the ones that are trying to maximize their business returns based on big data applications (Gandomi & Hiader, 2015; Raguseo, 2018). International ccompanies that retail fashion products, such as Amazon, eBay and Walmart, are increasingly 'using big data analytics to effectively manage vast amount of knowledge available, communicate regularly with their customers and even enhance their operations' (Davenport, 2012).

Thus, the perspective on knowledge integration – where the principal assumption is that knowledge is acquired and meaning is assigned to it through increased 'social participation' of organizational members – holds and endorses the synonym for the entire process as knowledge co-creation. It can be observed that knowledge in essence is 'socially co-created' inside the organization – primarily by its members (for example, retail managers and trainee staff) and other stakeholders (for example, customers).

Therefore, we assert that knowledge, communication and an

individual's behaviour are 'inseparably linked', as they create one another (Singh, 2008) in their quest for knowledge creation and that, in turn, act as enablers of organizational innovation (Esterhuizen, Schutte, & du Toit, 2012). Khan and Vorley (2017) have emphasized the fact that 'there is an opportunity in big data to discover hidden knowledge, generate new knowledge which is vital to empower and enhance knowledge management using big data analytics'. Wang and Wang have opined that big data analytics can assist not only in the 'sharing/ exchange of common and specialized knowledge' for business intelligence, but also 'helps in extending human knowledge'. Recent advances in information technology (IT) paved the way for the advent of business intelligence (BI) systems, which have 'increased the ability of organizations to collect and analyze data to support decisions'; however, there is 'little focus on how big data might play a role in organizational knowledge creation' (Shollo & Galliers, 2016). Subsequently, a 'big data analytics-supported transformation model' was developed by Wang, Kung, Wang, and Cegielski (2018), which reveals that causal relationships exist among big data analytics applications, IT-enabled transformation practices, benefit dimensions, knowledge capabilities and business values.

The discussion above directs us to the broad research question/idea for academic enquiry – can big data trigger knowledge co-creation that will subsequently aid organizations in evidence-based decision-making? This question is explored further in the next section.

2.3. Research framework

We draw on Nonaka's (1994) theoretical contributions on the SECI model of knowledge dimensions, which explains the overall process of knowledge creation in a concise manner. After the four modes – socialization (S), externalization (E), combination (C), and internalization (I) – are complete, the process transcends to a newer level that is referred to as the 'spiral' related to knowledge co-creation (Acharya & Mishra, 2017). The theoretical model above provides a relevant framework for managing the inter-linked, knowledge-based processes. Forms of knowledge, techniques to manage that knowledge and related theories have evolved over time and every specific context has its local requirements for the same. As concerns the current study, Nonaka (1994) proposes that in the fundamental cycle of knowledge management, where the cycle once again returns to the mean position to 'create' (suggesting knowledge co-creation as a result), the SECI model becomes all the more relevant and important.

Additionally, it is known that convenient 'quantitative tools, metrics and indices' have been developed through extensive research and improved over time in order to 'support the decision-making process' (Provost & Fawcett, 2013) – although such approaches can be easily applied to individual organizations or a single organizational system, where decisions are made independently by a knowledgeable or knowledge-based corporate entity or a group of such entities that are highly cooperative (Tseng, Tan, Chiu, Chien, & Kuo, 2018) and tend towards co-creation for superior delivery of output/service (Payne, Storbacka, & Frow, 2008). Here, service itself can be looked upon as the 'underlying basis of economic exchange', which is a result of an application of competences like knowledge and skills by one party for the benefit of another. On the other hand, service system refers to configuration of resources (including people, information, and technology) connected to other operational systems through value propositions (Vargo, Maglio, & Akaka, 2008). Bringing people (knowledgeable employees and consumers) and IT together has inadvertently become compelling for business practices to thrive and for research to take note of. Moving from a traditional product or organization/firm-centric view of value addition, personalized experiences for consumers – through co-creation – have taken centre stage, as consumers have become more 'informed, networked, empowered, and active (Prahalad & Ramaswamy, 2004). This shift was somewhat conspicuous in the space of design and fashion retailing. Designers managed to get increasingly

closer to their prospective consumers and whatever they designed and retailed used were co-created, where the roles of designers and consumers are ever-evolving (Sanders & Stappers, 2008). Therefore, deviation from a direct consumer-centric approach to co-creation that enabled collective creativity and innovation became a reality. Yuanzhu, Kim Hua, Guojun, Leanne and Minglang suggested that 'big data facilitates product innovation processes, by shortening the time to market, improving consumers/customers' knowledge for product adoption and reducing costs'.

As mentioned earlier, we see that knowledge co-creation forms the crux that balances sourcing of knowledge from big data and decision-making. Decision-making carries both tangibles and intangibles, which are to be measured alongside each other; also, the trade-off (derived from comparisons, observations, etc. and dependent on judgements of experts for developing a priority order) between the two categories needs to be evaluated to find out how well the organizational objectives are met (Saaty, 2008). Mathematically, the primary concern surrounds the 'problem of aggregating multicriteria to form an overall decision function' (Yager, 1988). However, behavioural decision-making provides important insights into managerial judgements and has been considerably evolving since inception (Bazerman & Moore, 2008). This is particularly true for the global fashion industry (Bakewell & Mitchell, 2003). Non-conformity of behaviour to theoretical standards has given rise to decision-making and analysis as an art, while a 'sizeable array of decision aids' for smoothening decision-making processes gets 'capitalized on a big data analytic approach' (Beach & Lipshitz, 2017; Zhao, Liu, Zhang, & Huang, 2017).

In the given context of research, it is presumed that knowledge units will evolve from judicious collation of fragments of big data, and these knowledge units will consequently give rise to unified, recombined knowledge (through the process of co-creation) that can put forth strong, concrete evidence (decision aid) for making better decisions that favour the organization. The Fig. 1 explains it succinctly.

The research framework (Fig. 1) of our study suggests the following:

- ROK defined by: individual K (IK) and group K (GK) [along with its dimensions], where ROK = relevant organizational K
- PK defined by: explicit K (EK) and tacit K (TK) [along with its dimensions], where PK = personal K
- In the organizational set-up, interaction between PK and ROK combined with fragments of big data leads to knowledge co-creation (KC) for value delivery

We posit that KC will help the organization to accumulate enough 'evidence' that can lend support in improved organizational decision-making. This in turn will propel the organization forward and record enhanced performance (AlShaima, Singh, Farouk, & Sohal, 2016; Bozionelos & Singh, 2017). Such evidence-based decision-making becomes a core competency (CC) of an organization. Additionally, inducing factors for KC [catalyzers] = intention [individual level], autonomy [group & organizational level], fluctuation [overall, extra-organizational level] have been incorporated in the model. The employees' commitment underlies psychological ownership of knowledge creation activities, and certain important factors/components are supposed to induce commitment within individuals for promoting formation of new knowledge together, i.e. knowledge co-creation (Nonaka,
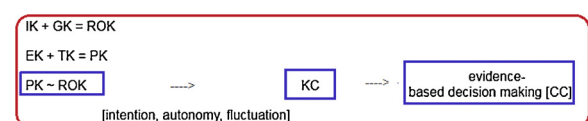
Here, K represents knowledge

Fig. 1. Schematic model for research study.
(Authors' interpretation and representation).

1994). These factors are indicated in the model as intention, autonomy and fluctuation.

2.3.1. Intention

This principle is majorly concerned with an individual's worldview and his/her approach towards deciphering the immediate environment. Acquiring relevant information from the environment for adapting to the prevailing conditions in the best possible manner increases the degrees of meaningfulness and purpose in the organization (Eigen, 1971). Based on a frame of judgement, the individual will capture information from the environment, in the given context, and become knowledgeable in order to prosper or survive (Shimizu, 1978).

2.3.2. Autonomy

This principle is applicable at the individual, the group, and the organizational level. Personality of individuals will definitely vary and they will have different intentions; it becomes possible for the organization to bring in or unravel newer, unseen opportunities by allowing a set of individuals to act autonomously, either separately (at the individual level) or together at once (at the group level) (Nonaka, 1994). When minimum autonomy is ensured overall (at the organizational level), the basis for self-organizing for creating knowledge is established through knowledge-user sense of psychological ownership of knowledge (Liu, 2012), as greater flexibility is attained relating to gathering, conveying and interpreting information (Morgan, 1986).

2.3.3. Fluctuation

As mentioned above, continued interaction with the external world is particularly important in the case of knowledge co-creation (Nonaka, 1994). Ever-changing patterns of interactions among engaged individuals in their given immediate environment allow them to recreate their personal/indigenous systems of knowledge and take into account any forms of chaos, discontinuity, ambiguity, randomness or redundancy generated from within the organization or in the environment (Acharya & Jena, 2016; Al Mehrzi & Singh, 2016; Nonaka, 1994). This may result in periodic 'breakdowns' in human perception and increase the number of instances leading to behavioural contradictions (Piaget, 1974). As such, instead of wide-ranging disorder, a recurring pattern of interaction emerges, which cannot be readily predicted (Gleick, 1987).

Therefore, we understand that in the fashion retail sector, the respective knowledge base of both customers and salesforce interact dynamically and along with the economic transactions facilitated by them, it is envisaged that this process will generate large volumes of data. This so-called big data will contain usable references, insights and patterns, which, when explored further, will reveal the evidence required for taking efficient and effective decisions. Such decision-making can happen after knowledge co-creation across the organizational hierarchy.

3. Methodology

3.1. Research design and context

In order to explore the bigger picture involving big data applications and knowledge co-creation, a conventional form of narrative approach was used to conduct this study. We argue that in the current context, this would be the most relevant for this research; however, the chosen approach does not undermine the importance of other forms – lists, tables, taxonomies, etc. The narrative approach adopted is available within an overarching qualitative research design, which was appropriate given the nature of academic enquiry undertaken. Ideally, qualitative research is recommended for academic researchers and writers when a complex phenomenon has either not been explored or has remained underexplored in the past. It is imperative that a qualitative researcher conducts an in-depth, rigorous qualitative enquiry within

the approved boundaries of qualitative practices. Such situations/settings need to be exploration and the focus should be on appreciating the meaning that participants (interviewees) assign to the phenomenon in question (Creswell, 2013). Understanding the meaning in a broad sense (including cognition, affect, intentions or anything else that can be encompassed in the participants' perspectives) leads to the part of reality under examination (Maxwell, 2012; Menzel, 1978). This kind of concentration on meaning is central to the 'interpretive approach' – which can be regarded as a 'fundamental aspect of most qualitative research and a key difference between qualitative and quantitative research' (Bhattacharya, 2008; Maxwell, 2012). Since the typical coverage accommodates a comparatively small pool of people who can provide rich insights pertaining to the research problem, qualitative researchers adopt the technique because individuality of both participants and situations are preserved (as opposed to collecting data/information from larger samples and aggregating those to arrive at directed generalizations) and influence of particular contexts on the participants' actions is shown (so that it is revealed 'how events, actions and meanings are shaped by the unique circumstances in which these occur') (Maxwell, 2004).

Moreover, narrative inquiry has for long been suggested for research in organizations primarily because it captures a 'sequence of events' like the arrival of big data, taken through the core process of knowledge co-creation, ending in evidence-based decision-making – all from the participants' point of view in that sequence (Endres & Woods, 2007; Warren, 2004). It is known that narratives are capable of producing rich, thick data (Willis, 2006), which is an indispensable aspect of any qualitative research study. These narratives are practically instruments of interpretation (Lawler, 2002) with the help of which people could make sense of their personal experiences, and at the same time offer genuine reasons and opinions pertaining to their intent/actions related to those experiences (Shkedi, 2005). We posit that the narrative captures and demonstrates how a sequence of events actually unfolded over time, and had an impact on the individuals involved (Polkinghorne, 2003).

In a qualitative study, the interest lies in 'process rather than outcomes' (Merriam, 1988). It means that the processes which remain unidentified by experimental or survey research get noticed by qualitative research, not that the outcomes are grossly ignored (Maxwell, 2012). Here, we have used narratives to reveal how big data is acquired through various applications and technology networks, knowledge elements of employees recombining and interacting with available organizational stimuli/catalysts. Furthermore, this study was also designed to establish how co-created knowledge helps influence decision-making to improve performance. This is in tune with Weiss' (1994) illustration, where he affirms that in qualitative interview-based studies, proper demonstration of a relationship rests heavily on descriptions of phenomena comprised of a flow (visualizable sequences) of events – conveying that the process is of prime importance, over and above the outcome.

We collected and analysed narratives of organizational heads and organizational members (top/middle-level managers, employees and line-staff – whichever was applicable in a given situation) linked to big data, as a starting point, and knowledge co-creation, that together assist an organization in evidence-based decision-making for healthier overall performance. The study was purposefully conducted in firms operating from Kolkata – a metropolitan city in eastern India, where the most affluent (expensive monetarily and inhabited largely by HIGs – high-income groups and partially by MIGs – middle-income groups) area became the research context. These firms cater to customers / buyers from the HIGs and the MIGs.

3.2. Sampling and data collection

We used purposive sampling to identify dependable participants to investigate big data and knowledge creation as presented in the Fig. 1.

They were initially contacted over the phone (not amounting to cold-calls) and email communications were sent out (if and wherever necessary). Patton (1990) explains that purposive sampling is generally utilised to identify those participants who would 'most likely yield rich information about their experiences', relating to the earlier mentioned broad research question that engulfs the overarching idea concerning the bigger picture of big data in concurrence with knowledge co-creation. Qualitative research of this sort is challenging for the researcher in terms of both the accessibility and willingness of participants to share relevant details of their experiences (Cope, 2011). We managed to establish rapport with the soon-to-be participants through informal discussions. A few interactive sessions were held (both online and offline) to explain the utility of this research in a very lucid manner to the participants and make them comfortable around us as well. Similar to Cope's (2011) work, a snowball technique was implemented, wherein the initial stage comprises identifying participants of interest in four relatively distinct organizations. Two organizations were large-format fashion retail stores and the remaining two were high-end fashion boutiques engaged in the retailing of branded and designer fashion apparel and accessories, and they in turn knew other participants who were likely to provide information-rich narratives required for this study (Maxwell, 2012; Patton, 1990). Additionally, we declare that one of the authors has been associated with this industry in various capacities for the last 7 years and thus has cultivated a significant amount of expertise to observe, interact with, understand and extract germane views from the participants. That said, we were aware of the issue of objective detachment and bias, which we minimised, as the other authors of this research, not affiliated to fashion industry, were equally involved in the analysis of the findings.

The organizations under study had well designed architecture to communicate with their customers via social media platforms. These organizations leveraged ICT tools to reach out to customers, to collect and store information, and to extract patterns for gaining insights into how to bring their customers back to the store for repeat purchases. In this study, 59 participants volunteered to participate, but 48 participants were identified as having narratives with rich information with adequate detailing of their experience related to the topic/theme of research. All participants were requested to choose pseudonyms for themselves in order to maintain anonymity. We collected adequate data – by devoting roughly 3 months (until saturation was reached) – through semi-structured, semi-formal interviews to ensure the gathering of in-depth information about the participants' lived experiences of big data and knowledge co-creation that resulted in enhanced decision-making processes in the organization. It may be interesting to note that such forms of interviews constitute the major method of data collection in qualitative studies, especially in narrative research (Creswell, 2013; Elliot, 2005). Flick (2006) suggests that to remain consistent while undertaking a narrative approach, the researchers must use a broad, instantaneous opening or guiding question so that the participants feel encouraged enough to tell their story related to the topic/theme and thus share their experiences in detail with the researchers, preferably in an uninterrupted manner. Incorporating such an enabling question (which is usually not pre-prepared) is a common tactic in qualitative research and empowers the interviewee to describe his or her actual experience from their personal and perceptive viewpoint (Creswell, 2013).

All of the participants in the study brought up the notions of big data and knowledge co-creation within the all-encompassing framework of telling their story linked to evidence-based decision-making for business value creation. We contacted three participants for the follow-up, probing questions (for purposes of validation as well) to facilitate eliciting extra details regarding the connection between big data fragments and co-creation of unified knowledge that supports improved decision-making in the organization, and to ascertain regularity in their versions. Use of big data surfaced in all of the participants' descriptions of knowledge co-creation for business results. However, some of the

Table 1
Distribution of participants across the organizational hierarchy.

	Indicative level in the organizational hierarchy	No. of interviewees
1	Top Management/CEO/Owner	1
2	Manager/Store In-charge	3
3	Retail Operations Supervisor	18
4	Retail Attendant	26

participants were followed up with probing questions to understand how big data featured in their experience of knowledge co-creation. These follow-up questions were selectively asked after the participants had finished narrating their experiences. Such functional probes help elicit additional information and that was carefully implemented so that the flow of participants' stories was not interrupted (Morse & Richards, 2002). The interviews lasted approximately 1.5 h and were conducted with sufficient attention. We also collected data from relevant media articles, notes, memos and communication material/non-transcribed phone conversations with the participants, which served as secondary background data to help verify the sequence of events as revealed through the participant interviews (Creswell, 2013). The sample in this study were working across different hierarchical levels in their organizations and their demographic characteristics for knowledge-interactions are presented in the Tables 1–3.

4. Data analysis and findings

During the phase of analysing the data, the authors initially developed chronologies of events for the participants. This is because individuals inadvertently fail to relate their stories in a continuous, coherent manner that delineates the sequence of events with enough clarity (Creswell, 2013). These chronologies contained representations of reporting that concerned involvement of the participants, pertaining to acquisition of big data fragments, relating those to other available information which is meaningful, adapting to the organizational context of usage of big data and meaningful information, entering the process of knowledge co-creation through recombination of available elements for the same, and progressing towards evidence-based decision-making for better organizational performance.

We coded the initial interviews of the selected participants with a limited set of open codes that had emerged from scanning the raw interview transcripts and from knowledge of existing literature regarding the idea under examination (Creswell, 2013). Examples of initial codes used in the research study included "gathering big data", "experience with knowledge co-creation", 'impactful decision-making", etc. Following suggestions by other scholars in the field, efforts were made to expand the initial set of codes into a detailed set abstracted from the data available (Lieblich, Tuval-Mashiach, & Zilber, 1998; Richards, 2009). On a few occasions, margin notes made during re-readings of interviews became useful; also, analytic memoing – which refers to critical conjectures about the happenings in the set of open codes – assisted in expanding the initial set into the detailed set of codes. Some examples were "deterministic links between big data and knowledge co-creation", "decisions and behaviour around big data applications for process improvement" and "appearance of patterns while integrating the big data fragments". Table 4 shows stage-wise chronological

Table 2
Distribution of participants across the bands of experience.

	Band of experience in the organization	No. of interviewees
1	< 2 years	21
2	2–5 years	17
3	6–8 years	6
4	8 years or more	4

Table 3
Distribution of participants according to their educational profiles.

	Educational qualification	No. of interviewees
1	< Graduation	10
2	Graduate	24
3	Postgraduate	13
4	Postgraduate +	1

arrangement, which describes the feasible objectivity of this study:

To ascertain commonalities across the participants' versions of perception, we analysed in-depth stories/narratives of the participants (Morse & Richards, 2002) to interpret the relationship between big data and knowledge co-creation that leads to evidence-based decision-making meant for improved organizational performance. We looked for such patterns in the conventional temporal ordering of events for the participants (Miles & Huberman, 1994) and themes embedded in specific periods (Elliot, 2005). We were specifically interested to note the deviations, going beyond the underlying pattern of commonalities, for enriching their obtained insights.

Investigating further, potential themes emerging out of the narratives were loosely considered as 'hypotheses' which can be 'tested' (drawing a parallel with quantitative studies) by revisiting the data, field or even literature – as propounded by the method of retroduction – and the extent to which evidence might support these was also unearthed systematically. It is imperative that the interpretation of all gathered data was consistent, for which the authors engaged in dialogues among themselves as well as a small number of the participants from the existing pool – which concurrently addressed the issue of validation and reliability through triangulation. Such dialogues helped the authors to establish unanimous agreement on putting labels on codes, assigning quotes to the codes, exclusion of irrelevant statements, thus eliminating any discrepancies surrounding coverage of relevant data only by the codes (which ultimately become the themes) (Burla et al., 2008; Graneheim & Lundman, 2004). The rigour of qualitative research helped us to provide a concise account of their findings.

Therefore, how does big data relate to the process of knowledge co-creation? Research will go on to show that it is indeed a difficult journey to source big data and end up with crafting business value by co-creating knowledge in between. However, it will not always be a series of turbulent events that are capable of disentangling the organizational fabric of sustained delivery and performance. Participants described the possibilities of the process in their versions. In principle, the participants agreed to the fact that organizations (typically from this industry) will need to focus on building capabilities for using and analysing big and complex data sets, as that would imply a starting point has been accommodated to exploit business opportunities and eventually craft business value.

Big data inadvertently becomes a source of competitive advantage in the form of aiding in consolidation of core competencies – one such core competency being evidence-based decision-making, which arises out of exposure to co-created relevant knowledge. In the domain of fashion retailing, it was accepted by the participants that big data has the potential to provide unmatched customer experience. However, this is not possible simply by holding big data in isolation – it is imperative that relevant knowledge is co-created by incorporating big data into the fold, for facilitating the application of minds in order to arrive at a juncture from where the way forward guides the organization to construct business value through evidence-based decision-making. The participants opined that co-created knowledge will help in understanding the modifications in a business cycle and those pieces of evidence can make effective and efficient decision-making more plausible.

It was otherwise evident that the volumes of big data handled by the two organizations – a large format fashion retail outlet and a comparatively smaller boutique – are not the same, whereas the nature (for

Table 4
The chronology of relationship between big data and knowledge co-creation.

	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
Chronological advancements	Involvement of employees in acquiring big data fragments available in the systems from various customer (source) transactions (events) – a difference being that large format fashion retailing has more sophisticated and/or robust systems.	Both individual knowledge (IK) and group knowledge (GK) are available in the organization – from past events involving multiple sources. Relevant organizational knowledge (ROK) is thus brought forth.	Experiential learning and logically drawn inferences give rise to personal knowledge (PK). Some of it is residing within the employee as tacit knowledge (TK) and the rest of it is ideally explicit (clearer to others) and thus more accessible (EK)	Elements from stages 2 & 3 combine and/or recombine for knowledge co-creation (KC) that is essential for collation of insight-based evidences available from various sources	Decision-making is greatly influenced by such evidences, leading to: (i) core competency or capability, (ii) improved organizational performance, (iii) business value creation, etc.

Table 5
Key findings with higher degree of agreement with past researches.

1.	"it is possible to enhance transparency in knowledge interactions when big data is systematically incorporated"	Schadt, Linderman, Sorenson, Lee, and Nolan (2010), Brown et al. (2011), Bughin, Livingston, and Marwaha (2011), LaValle, Lesser, Shockley, Hopkins, and Kruschwitz (2011), Ann Keller, Koonin, and Shipp (2012), Beath, Becerra-Fernandez, Ross, and Short (2012), Boyd and Crawford (2012), Wang et al. (2018)
2.	"big data is instrumental in enabling experimentation by organizations in order to discover new needs and aspirations of customers, exposing unseen variability in their tastes and preferences and improving overall performance by making evidence-based decisions to increase sales"	Bughin, Chui, and Manyika (2010), Schadt et al. (2010), Brown et al. (2011), LaValle et al. (2011), Sobek et al. (2011), Anderson and Blanke (2012), Ann Keller et al. (2012), Beath et al. (2012), Boja, Pocovnicu, and Batagan (2012), Boyd and Crawford (2012), Hsinchun, Chiang, and Storey (2012), Davenport et al. (2012), Acharya and Jena (2016)
3.	"big data can help in co-creating knowledge in the organization for developing manageable target segments of the customer-population and subsequently initiate customized actions for objective-driven business results"	Hsinchun et al. (2012), Smith, Szongott, Henne, and von Voigt (2012), Soares (2012), Tankard (2012), Shirdastian et al. (2017)
4.	"by application of big data, decision making will find support from system automation and algorithms designed to fulfil specific purposes"	Gehrke (2012), Huwe (2012), Ohata and Kumar (2012), Alharthi et al. (2017), Santos et al. (2017).

example, elements of customer profiles) as well as sources (for example, social media platforms, POS, CRM systems, etc.) of big data remained broadly similar. At the same time, the techniques of gathering insights from captured big data in both the organizations were partly dissimilar, as the larger organization had access to extra financial resources that allowed them to deploy more sophisticated systems to handle big data related activities. However, as mentioned earlier, the application of the essence from big data has to be coupled with knowledge (ideally co-created in the organization) and this increases the parity between the two organizations. It is apparent from previous research in the field that big data is rendered useful in terms of crafting business value (Alharthi, Krotov, & Bowman, 2017), though the focus on the core intermediary process of knowledge co-creation has not not receive attention. Certain aspects of the relationship between big data and knowledge co-creation could be verified from data (narratives) as well as by referring to the extant literature (Table 5):

A few aspects of the aforementioned relationship were verifiable and ingrained in the data, even though those received partial support from the literature (Table 6):

These consolidated findings helped us to consider the notion being explored in this research study: it is conceivable that acquiring and assimilating big data fragments play the role of an inducer in knowledge co-creation, coupled with which evidence-based decision-making for an organization's betterment is assured in the end. A flow-chart was prepared to capture the very crux of the findings as shown below (Fig. 2):

5. Discussion

The primary purpose of this paper was to make a qualitative discovery about the relationship between big data and its influence on knowledge co-creation in the organization, which was expected to consequently lead to evidence-based decision-making for constructing business value. Prior research offered support to certain findings, while the remaining findings were partially verified from the available literature. In this study, we found that big data indeed played a dominant role in effecting knowledge co-creation within the organization. When insights from big data and such co-created knowledge are recombined, evidence is extracted from the interactions that help in making efficient and effective decisions. It could be inferred that over time, when this decision-making capability becomes a core competency of the organization, business returns increase as much as business value is crafted as a favorable result. This was particularly true when one looks beyond the traditional concept of a market, where consumers are treated as 'outsiders' and kept outside the boundaries of the organization and thus separate from the process of value creation. According to Porter, even the traditional 'value chain' still epitomizes what can be looked upon as the 'unilateral role' of any organization in creating value. Therefore, the traditional market was viewed either as the locus of exchange (where economic transactions mainly took place) or as an 'aggregation of customers' who were detached from the core value creation process. This aforementioned notion gradually came to be dissolved and was rejected by conscious organizations – from an organization-centric

Table 6
Key findings with moderate degree of agreement with past researches.

|		
1.	"innovation in terms of refined business models to push sales of products, especially in the case of fashion retailing, was definitely possible because of big data getting coupled with knowledge co-creation"	Soares (2012), Strawn (2012), Tankard (2012), Dubey, Gunasekaran, Childe, Fosso Wamba, and Papadopoulos (2016)
2.	"utilization of big data can bring about organizational change that extends the cause of knowledge co-creation via the talented and/or knowledgeable workforce"	Frederiksen (2012), Gorton, Greenfield, Szalay, and Williams (2008), Bughin et al. (2010), Hsinchun et al. (2012)
3.	"ease of access to big data aids in gaining further insights that assure reforms in the overall knowledge co-creation process and increases organizational performance along with business value"	Ishii and Fernandes de Mello (2012), Meijer (2012), Ohata and Kumar (2012), Smith et al. (2012), Tattersall (2012)
4.	"it is possible to overcome challenges of organizational dynamics and/or restructuring through evidences from big data, as knowledge workers can co-create knowledge to inspect which newer business process (sourcing, crafting, sale) will entail better propositions (ROI)"	Ohata and Kumar (2012)
5.	"big data applications and extraction of insights that are worthy and meaningful to decide on further course of action (e.g. in terms of better overall performance or strategy) help in knowledge co-creation and that knowledge allows us to assess effectiveness, efficiency and fairness of organizational policies (decision-making)"	Boyd and Crawford (2012)
6.	"senior personnel explain the best ways to handle big data while fresher's devise newer methods of spotting and using big data – this mode of operating definitely aids in knowledge co-creation, which eventually becomes the strength (core competency) of the organization"	
7.	"an integration of sales, consumer-preferences, inventory, location, time gives rise to large volumes of big data – and this can lead to proper knowledge co-creation, which in turn will filter out sorts of irrelevance and aid in adequate tweaking of business requirements (retail planning, visual merchandising, trend forecasting, store density optimization, etc.) for improved business results"	Ohata and Kumar (2012)
8.	"acquiring big data will not remain expensive in the coming years, although interpreting from it to make the business remain and advance will ask for co-created knowledge, supposed to be retained for future needs"	Acharya and Mishra (2017).
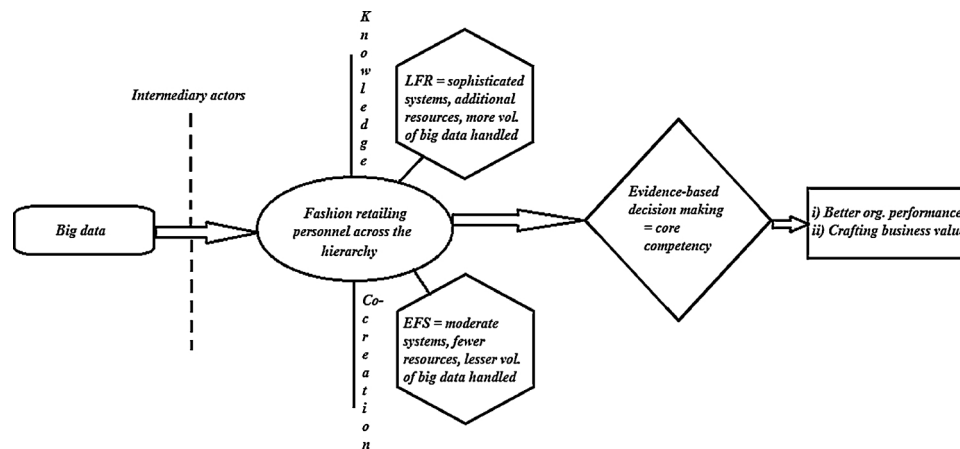
Fig. 2. A snapshot of the research outcomes.
Here LFR = large format retail, EFS = exclusive fashion store (boutique).

perspective; they tended to move towards a customer-centric perspective.

Earlier, customers became 'targets' of whatever (good or service) an organization offered to them. Now, there has been a perceptual shift with customers becoming more aware and knowledgeable in this age of information overload (Shiau, Dwivedi, & Yang, 2018), as they actively search for information to compare between two or more offerings, consult over their personal networks regarding an offering (good or service), and supposedly make wiser choices than ever before. Furthermore, social media big data helps ensure effective response in decision-making (Pogrebnyakov & Maldonado, 2018; Ragini, Anand, & Bhashkar, 2018; Stieglitz, Mirbabaie, Ross, & Neuberger, 2018), provide platform for marketing and advertising of products & services (Alalwan, 2018; Alalwan, Rana, Dwivedi, & Algharabat, 2018). The social media can be used by organizations in facilitating relationship amongst users from diverse backgrounds (Kapoor et al., 2018) and big open linked data (BOLD) for better business decision-making, competitiveness and firm performance (Dwivedi et al., 2017).

Access to relevant big data (which uncovers purchase and preference patterns of customers) is at the disposal of employees of an organization – arguably the 'internal customers' of the organization and the organization can leverage such big data for assessing the creditworthiness of buyers, suppliers and even the wholesale & retail sale dealers (Kshetri, 2016). Studies in the past did not emphasize this fact that the presence of employees, who were progressively becoming empowered with appropriate knowledge, is vital as far as the business proposition, vis-à-vis customer learning, is concerned; and thus, it cannot be completely ignored. Prahalad and Ramaswamy (2004) explain that new-age customers are practically armed with the newest tools of categorical dissection, can establish if an acceptable differentiation amongst the choices is available and are keen to 'interact' with organizations to co-create 'value' (as in the case of online selling of airline or movie tickets). However, even before value may be co-created, somewhere midway between obtaining big data and establishing business value lies the steady and responsible flock of human resource that plays a pivotal role surrounding co-created knowledge.

It is a common belief that customers will simply try to negotiate, opt for commoditized, smart and cheap products (goods or services) and continuously search for the same. This is not fundamentally true in most of the cases of transactions (or sales) – customers are willing to pay in accordance with the utility derived from a product and that might supersede the cost of production involved (which is absolutely observable in fashion retailing, while catering to a distinct set of customers). These customers wish to engage themselves in a dialogue with the organization and co-create 'value' experience (Prahalad & Ramaswamy, 2004). Although this has been happening as a reactive

measure to boost sales, when managers struggle to make differentiated offerings in the face of globalization, technology transfer and calculated outsourcing, it can be effective to employ tactics and/or strategies of being proactive. Utterly relying on customers' knowledge to satisfy them or inadvertently being product-centric and offering only what the organization believes is right for the target market are two extremes, embedding a range of variants in between. Customers are likely to find a few of those beneficial, based on their own mindset and perspective.

However, in order to make efficient and effective decisions regarding a product to be offered, a balance has to be struck. Big data fragments will carry certain (numerical) evidence and managers will need to extract and then combine this with the insights gathered by other personnel, who are in closer contact with customers. Knowledge is co-created in the middle when professional (formal or informal) interactions happen and this blend allows managers to creatively and innovatively manage dependable selling of fashion products (as reduction in prices to clear the inventory cannot be an economical or sustainable solution for this kind of product). Therefore, we argue that focusing on knowledge co-creation is advisable since it absorbs elements from big data and assists in evidence-based decision-making for constructing business value, which perhaps otherwise would not be co-created by receiving input from customers.

Moving forward, our fellow researchers may explore further developments in new product development practices that utilize evidences from big-data, by understanding the consumer-organization interaction effects as opposed to traditional methods of building newer products (which conservatively rely on unidirectional communication). Additionally, knowledge co-creation can have a significant impact on re-organizing the knowledge management and usage cycle that will in turn help in the progress of knowledge-driven organizations (which have been depending on big-ticket investments of late, like in the arena of infrastructure consulting). It would be highly advisable to nurture the existing pool of specialist knowledge workers, who have the responsibility of expanding the pool itself for a developing knowledge economy. In that case, research in future will aid in extracting deeper underlying insights for the same.

6. Conclusions

Based on the findings of the study, we conclude that leveraging big data helps organizations to co-create knowledge and that in turn to influence evidenced-based decision-making. The findings of the study suggest that organizations to institutionalize a system in place wherein employees and customers together co-create knowledge to take evidenced-based business decisions. Knowledge co-creation takes place in the middle when professional (formal or informal) interactions between

organizational members and customers happen that allows managers how to manage dependable selling of fashion products than reduction in prices to clear the inventory. Our study suggests that organizations need to focus on knowledge co-creation as it absorbs elements from big data and together assists in evidence-based decision-making for constructing business value.

7. Limitations and suggestions for future research

Our study like any other studies in the business domain is not without limitations. First, we used qualitative methods to find answers to key research questions. Therefore, we suggest that future research should extend our framework and use both qualitative and quantitative methods to find answers to key issues of linkages amongst big data, knowledge co-creation, and evidence based decision-making in the organization. Another limitation of the study is that we chose fashion industry to conduct our study. Hence, we suggest that future researches should make a comparative study across different industry to advance the theories.

Appendix 1. Guiding questions used in interview schedule

Some of the broad guiding questions from the interview schedule are given below:

- Are you aware of the term/concept called 'big data'? If so, what do you know about it and/or what does it mean according to you?
- Is knowledge treated as an asset or a resource by your organization? If yes, then to what extent is exchange of knowledge allowed?
- How do you feel is the power of 'big data' when it comes to knowledge-driven activities in your organization? Is it useful? If so, in what manner?
- What has been the overall effect of 'big data' on decision-making with regards to fashion-conscious customers (end-users/consumers)?
- Can you decipher the nature of knowledge co-creation in your organization? How do you view its significance, if any, in fashion industry?
- Do you believe that an intermediate process of catalyzing – like knowledge co-creation – is necessary to achieve business results?

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