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https://www.emerald.com/insight/2040-8269.htm

Received 11 March 2019
Revised 26 June 2019
Accepted 26 July 2019

Storytelling, business analytics and big data interpretation

Literature review and theoretical propositions

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Abstract

Purpose – The purpose of this paper is to explore the role of storytelling in data interpretation, decision-making and individual-level adoption of business analytics (BA).

Design/methodology/approach – Existing theory is extended by introducing the concept of BA data-driven storytelling and by synthesizing insights from BA, storytelling, behavioral research, linguistics, psychology and neuroscience. Using theory-building methodology, a model with propositions is introduced to demonstrate the relationship between storytelling, data interpretation quality, decision-making quality, intention to use BA and actual BA use.

Findings – BA data-driven storytelling is a narrative sensemaking heuristic positively influencing human behavior towards BA use. Organizations deliberately disseminating BA data-driven stories can improve the quality of individual data interpretation and decision-making, resulting in increased individual utilization of BA on a daily basis.

Research limitations/implications – To acquire a deeper understanding of BA data-driven storytelling in behavioral operational research (BOR), future studies should test the theoretical model of this study and focus on exploring the complexity and diversity in individual attitudes toward BA.

Practical implications – This study provides practical guidance for business practitioners who struggle with interpreting vast amounts of complex data, making data-driven decisions and incorporating BA into daily operations.

Originality/value – This cross-disciplinary study develops existing BOR, storytelling and BA literature by showing how a novel BA data-driven storytelling approach can facilitate BA adoption in organizations.

Keywords Storytelling, Decision-making, Big data, Business analytics, Data interpretation, Behavioural operational research

Paper type Conceptual paper

1. Introduction

The increasing number of organizations adopting big data practices has led scholars to become interested in the drivers and challenges of business analytics (BA) (Sivarajah *et al.*, 2017). BA is an emerging trend and has been defined as "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" (Davenport and Harris, 2007). Prior research has explored how companies can benefit from data and analytics through the positive relationship between BA and business performance (Aydiner *et al.*, 2019), the impact of BA on value creation (Seddon *et al.*, 2017) and on strategic planning (Kunc and O'Brien, 2019). Despite the value that BA offers, however, organizations face behavioral challenges when adopting BA

Management Research Review
Vol. 43 No. 2, 2020
pp. 204-222

2040-8269
DOI 10.1108/MRR-03-2019-0106

into daily operations (Agarwal and Dhar, 2014; Vidgen *et al.*, 2017). Extant research has primarily focused on the *organizational* adoption of analytics (Caesarius and Hohenthal, 2018; Gunasekaran *et al.*, 2017; Kwon *et al.*, 2014; Lai *et al.*, 2018; Moktadir *et al.*, 2019) while overlooking behavioral factors that underlie *individual*-level BA adoption (Shahbaz *et al.*, 2019; Verma *et al.*, 2018). Without a deeper understanding of the behavioral and psychological factors motivating human behavior, it remains unclear how wide usage of BA in organizations can be achieved.

Given the complexity of big data processed with BA technology, there is a need to address managerial challenges of interpreting data for decision-making (Bumblauskas *et al.*, 2017). Although prior research has demonstrated the importance of using BA data for decision-making (Al-Kassab *et al.*, 2014; Li *et al.*, 2016), there is little research on how data interpretation quality influences data-driven decision-making. Despite an increasing number of studies highlighting such new jobs as data scientists (Costa and Santos, 2017; Davenport and Patil, 2012; Harris and Mehrotra, 2014) and data translators (Brady *et al.*, 2017), extant research neglects how organizations can improve *existing* employees' skills in data interpretation to enable better decision-making. The lack of this knowledge is an obstacle that prevents organizations from successfully integrating and using BA on a daily basis.

With the emerging role of storytelling in the information systems literature (Davison, 2016) and operational research (OR) (Klein, 2009; Klein *et al.*, 2007; White and Taket, 2000), this study utilizes a storytelling lens to explore its role in BA data interpretation and decision-making. While prior literature has examined storytelling in creative problem solving (Klein, 2009), in technology adoption (Boldosova, 2019) and in change management (Klein *et al.*, 2007), it remains unclear what implications storytelling has for BA-driven decision making in organizations. In contrast to extant research that concentrates on storytelling as a visualization tool (Gershon and Page, 2001; Kosara and Mackinlay, 2013), we conducted a comprehensive interdisciplinary literature review to explore storytelling as a verbal narrative technique generating memorable knowledge from big data.

Focusing on the abovementioned research gaps, this conceptual study is motivated by two research questions. First, how can BA data-driven storytelling improve individual data interpretation and decision-making quality? Second, building on the first question, how can organizations using BA data-driven storytelling improve an individual's *intention* to use BA and, subsequently, an individual's *actual* BA use? Guided by theory-building methodology (Corley and Gioia, 2011; Whetten, 1989), we focus on mapping the conceptual landscape of the studied phenomena, identifying gaps in the literature and proposing new connections among established concepts to advance theory on this emerging topic. Drawing on multiple styles of theorizing (Cornelissen, 2017), this study adopts the propositional style of introducing theoretical ideas and arguments. One of the main contributions of this study is a unique synthesis of insights from OR, BA, storytelling, linguistics, psychology and neuroscience to theorize the way in which storytelling affects BA use in organizations.

As a result of extensive literature review, the present study introduces the concept of *BA data-driven storytelling* as a novel strategic narrative technique that supports employees in interpreting BA data and in making better and faster decisions. This review indicates that storytelling positively influences human behavior toward BA use in organizations. We encourage organizations that wish to facilitate effective BA use in daily decision-making to concentrate on dissemination of stories among employees to fully maximize the value of BA.

2. Methodology

We searched several databases (e.g. Scopus, Emerald, EBSCO, Wiley) for journals in management, information systems, operations, psychology, neuroscience and linguistics to retrieve the relevant research for this cross-disciplinary literature review. This process involved the identification of the keywords, extraction of articles, assessment of the article quality, content analysis, theory synthesis and, finally, new theory building. After mapping out the conceptual landscape of the studied phenomena, we identified research gaps in the literature which we subsequently addressed by introducing a novel conceptual framework and propositions (Figure 2).

The key scientific fields and concepts that were analyzed to develop the model and propositions are illustrated in Figure 1. A detailed discussion of these constructs and corresponding research gaps is provided in the subsequent sections of this study.

3. Literature review

3.1 Adoption of analytics in organizations

An increased focus on analytics has led to a growing interest among researchers in the adoption of big data analytics (BDA)[1] from organizational and individual perspectives. Researchers have highlighted the importance of big data and predictive analytics acceptance, routinization and assimilation in improving supply chain and organizational performance (Gunasekaran *et al.*, 2017). Prior research has also explored how data quality and data usage experience influence the acquisition intention of BDA in organizations (Kwon *et al.*, 2014). Moktadir *et al.* (2019) identified the key technology-, expertise-, investment-, data-related and organizational barriers preventing BDA adoption in manufacturing supply chains. Resistance to BDA adoption has been studied to improve the adoption of analytics at the organizational level (Caesarius and Hohenthal, 2018). Finally, existing research highlights the usefulness of analytics and top management support as the key factors in organizational intention to adopt BDA (Lai *et al.*, 2018). However, despite a number of studies on organizational BDA adoption, there is limited research on individual-level adoption of analytics. For example, Verma *et al.* (2018) contribute to knowledge on individual-level BDA adoption by focusing only on system and information quality of BDA, while neglecting other underlying factors. Although Shahbaz *et al.* (2019) suggest that resistance to change prevents employees from adopting BDA in health care, there is limited discussion on how to avoid and overcome resistance to change at the individual level in organizations. The lack of research on the factors facilitating individual-level analytics adoption remains an obstacle and obstructs successful use of BA on a daily basis in organizations.

Although several scholars have focused on the drivers, challenges, opportunities and implications of BA in OR practice (Hindle and Vidgen, 2017; Liberatore and Luo, 2010; Ranyard *et al.*, 2015; Vidgen *et al.*, 2017; White *et al.*, 2016), there is a lack of behavioral studies exploring BA use with individuals as the unit of analysis. While analytics is positioned in the intersection of such research disciplines as information systems, OR and artificial intelligence, there is limited interaction among BA, psychology and behavioral science (Mortenson *et al.*, 2015). Correspondingly, these gaps in the literature suggest the need to further address the concept of BA in behavioral operational research (BOR) (Hämäläinen *et al.*, 2013; White *et al.*, 2016) and to deepen the understanding of behavioral and psychological factors underlying individual BA adoption in organizations.

3.2 Business analytics in behavioral operational research

A growing community of researchers has been engaged in shifting the research focus from traditional OR towards a new, emerging subdiscipline of BOR (Franco and Hämäläinen, 2016). An increased interest in the behavioral aspects of OR has been driven by the highlighted relevance of modeling human behavior, problem solving and decision support

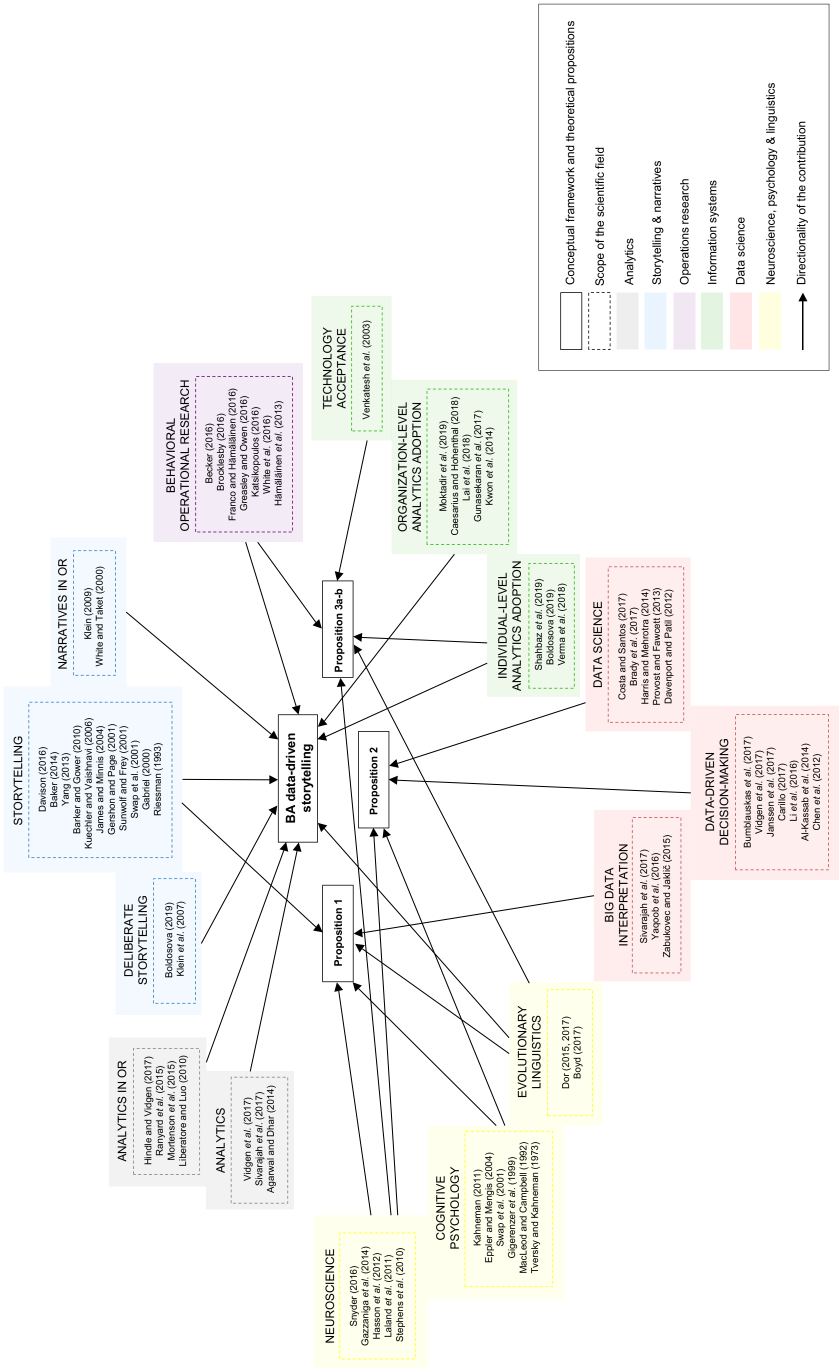


Figure 1.
An overview of theoretical constructs with central references given for each field

(Hämäläinen *et al.*, 2013). Acknowledging the importance of BOR in explaining human behavior with *models* (Greasley and Owen, 2016; Katsikopoulos, 2016), we use a theoretical modeling approach in this study to describe the behavior(s) of individuals interacting with BA.

The emergence of BA has led to a growing interest among researchers and practitioners in exploring the behavioral challenges that organizations face when trying to adopt BA into daily operations (Agarwal and Dhar, 2014; Sivarajah *et al.*, 2017). Organizations struggle with a lack of knowledge, experience and confidence in their efforts to reap the benefits of analytics in daily operations (Caesarius and Hohenthal, 2018; Kwon *et al.*, 2014). Individuals hesitate to accept unfamiliar technology and resist changing their analytical problem-solving skills (Vidgen *et al.*, 2017). The use of big data for decision-making poses a number of behavioral challenges as it requires a shift from traditional decision-making processes (White *et al.*, 2016). Decision-makers encounter information ambiguity, complexity and overload, which result in difficulties with identifying relevant information, recognizing patterns and making accurate decisions. These behavioral impediments fundamentally constrain individual-level BA adoption and usage, thereby limiting organizations in unlocking the full potential of BA (Bose, 2009; Davenport *et al.*, 2012; Sivarajah *et al.*, 2017).

Following recommendations from BOR to expand interdisciplinary research (Brocklesby, 2016; Franco and Hämäläinen, 2016; Ranyard *et al.*, 2015; Royston, 2013), this article focuses on strengthening bridges between academics and practitioners by extending BOR to practical BA challenges. Drawing upon an extensive review of literature related to BA, and given the lack of BOR studies on BA (White *et al.*, 2016), this article contributes to incorporating BA into BOR while deepening our understanding of the behavioral factors that facilitate BA-driven decision-making.

3.3 Big data interpretation and decision-making

Prior research demonstrates the challenge for practitioners in managing the complexity of big data and BA technology to interpret findings and use them for strategic decision-making (Bumblauskas *et al.*, 2017; Calvard, 2016). In striving for simplicity, companies face the emerging paradox of *simplexity* (Cunha and Rego, 2010): the need to balance managing vast amounts of complex data and applying data interpretation techniques to simplify findings for decision-making.

Researchers from multiple disciplines have observed how BA has become a trending practice for organizations seeking to use big data for informed decision-making (Bumblauskas *et al.*, 2017; Janssen *et al.*, 2017; Wamba *et al.*, 2015). To ensure high-quality decision-making, it is crucial for BA users to understand both business and technical data if they seek to turn raw data into actionable knowledge (Li *et al.*, 2016). Despite the variety of existing big data analytical methods and visualization tools (Yaqoob *et al.*, 2016), individuals must give data meaning by putting it into context, thus maximizing the value of data (Carillo, 2017).

Numerous researchers have highlighted the need to understand how to translate big data into valuable insights, which in turn, can lead to improved decision-making and problem solving (Brady *et al.*, 2017; Bumblauskas *et al.*, 2017). The emergence of data science as a discipline (Provost and Fawcett, 2013) has encouraged researchers to concentrate on examining the underlying principles of extracting knowledge from data. While some prior research has focused on the importance of data scientists (Costa and Santos, 2017; Davenport and Patil, 2012; Harris and Mehrotra, 2014; Provost and Fawcett, 2013), relying mainly on data-analytic thinking, other research has criticized the role of data scientists for their lack of business orientation, thus emphasizing the relevance of data translators (Brady *et al.*, 2017). To harness the power of data, data translators need to speak the same language as that of data scientists and executive decision makers (Brady *et al.*, 2017).

Despite the diversity of phenomena addressed in prior research, many studies lack an explanation of how organizations should extract business meaning from complex data and embed analytics into decision-making – assuming that hiring expensive data scientists or data translators is not an option. Prior research suggests that a number of factors influence decision-making quality in big data technologies, including people analytics skills, data quality and information visualization quality (Bose, 2009; Janssen *et al.*, 2017; Zabukovec and Jaklič, 2015). Nevertheless, existing studies lack extensive discussions of other potential factors facilitating the relationship between data interpretation and data-driven decision-making. However, understanding how to improve interpretation of complex BA data will provide useful insights for practitioners who aim to successfully integrate and use BA in organizations. The present study therefore contributes to filling the abovementioned research gaps by theorizing storytelling as an alternative strategy that improves quality in BA data interpretation and subsequent decision-making.

3.4 Storytelling from big data in operational research

A growing number of researchers has examined the role of storytelling and narratives as powerful management tools in OR (Klein, 2009; Klein *et al.*, 2007; White and Taket, 2000), information systems literature (Davison, 2016) and psychology (Yang, 2013).

Given the amount of information and the complexity of numerical data, storytelling is seen as a sensemaking tool (Yang, 2013) for further data processing from charts and bars; storytelling transforms raw data into memorable visual insights easily understood by non-analytical people (Gershon and Page, 2001). The use of narrative visualization and the generation of "data stories" are challenging processes requiring both technical and business knowledge (Segel and Heer, 2010). The ability to tell a compelling story with data is considered to be one of the most relevant skills in the current age of digital analytics (Brady *et al.*, 2017; Costa and Santos, 2017).

OR has addressed the role of storytelling in creative problem solving (Klein, 2009) and introduced the concept of *narrative engineering* (Klein *et al.*, 2007). OR scholars encourage managers to become narrative engineers who should systematically and deliberately use storytelling to facilitate and make sense of organizational change (Klein *et al.*, 2007).

While some of the research has focused on exploring storytelling in OR interventions (Klein *et al.*, 2007), deliberate storytelling in managing technological change (Boldosova, 2019), scientific storytelling as a process of telling stories from scientific data (Ma *et al.*, 2012) and the effects of information presentation on decision-making (Kuechler and Vaishnavi, 2006), other researchers have primarily addressed storytelling as an effective data visualization technique supporting decision-making (Gershon and Page, 2001; Kosara and Mackinlay, 2013). Although Boldosova (2019) demonstrates the importance of deliberate storytelling in facilitating individual-level BDA adoption, prior research does not offer insights on how storytelling supports employees' big data interpretation and decision making. Nevertheless, extant research has highlighted the relevance of complementing data visualization with storytelling to maximize the value of BA data for decision-making (Al-Kassab *et al.*, 2014; Vidgen *et al.*, 2017).

Despite the growing interest in the concept of storytelling, scholars in the Information Systems (IS) and OR literatures have neglected the role of storytelling as a verbal narrative technique generating business insights from data. Moreover, prior research largely overlooks the way in which storytelling affects the human mind and human behavior in big data interpretation. This study therefore explores storytelling as the process of generating verbal stories from BA data to improve decision-making quality. This study is built upon extant research recommendations (Costa and Santos, 2017; Klein *et al.*, 2007; Vidgen *et al.*, 2017) to explore the implications of storytelling in BA and OR.

4. Conceptual framework: business analytics data-driven storytelling

Thus far, we have focused on synthesizing prior research and identifying current research gaps. We now turn our attention to extending existing BOR knowledge and advancing theory on the role of storytelling in BA data interpretation. This section introduces the concept of *BA data-driven storytelling* and reveals new ways of:

- improving BA data interpretation quality;
- enhancing decision-making quality from BA; and
- facilitating individual intention to use BA in organizations; which
- results in increased actual use of BA.

We develop propositions (P1-P3b) about the relationship between BA data-driven storytelling and the intention to use BA (Figure 2). This framework and set of propositions are then elaborated on using theoretical arguments from existing literature.

4.1 Definition

This article focuses on an underresearched form of storytelling in BOR – *BA data-driven storytelling* – a term that we coin to describe a narrative sensemaking heuristic. Building upon the definition of storytelling used by Gabriel (2000), BA data-driven stories consist of a plot that narrates about:

- interpreting raw technical data;
- incorporating that data into a particular business context; and
- identifying solution(s) to previously identified business challenge(s).

Given the growth of unstructured data and evolving needs in processing and interpreting knowledge (Sivarajah *et al.*, 2017; White *et al.*, 2016), we suggest BA data-driven storytelling as a novel method of interpreting patterns and trends for improved decision-making, thus contributing to an organization's big data-driven decision-making culture. We propose that organizations that deliberately harness the power of storytelling over time will be able to reach high levels of daily BA use and BA-driven decision-making among employees; thus,

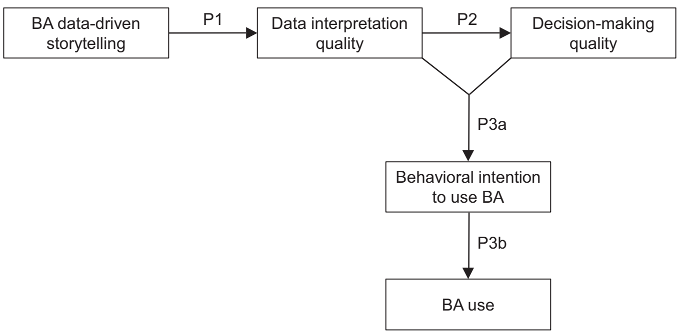


Figure 2.
The relationship between BA data-driven storytelling and BA use

they should be able to build a data-driven decision-making mindset in the long term. In an organizational context, storytelling has been widely used as a strategic business narrative technique for aligning human behavior with an organization's business goals (Baker, 2014; Barker and Gower, 2010). Building on existing insights into storytelling (James and Minnis, 2004; SunWolf and Frey, 2001), we propose that BA data-driven storytelling is able to trigger emotions and cognitive patterns regarding improved data interpretation and decision-making, ultimately transforming employees' views regarding BA use.

4.2 Story development and dissemination

As a standardized tutorial for BA data-driven storytelling, we recommend that organizations follow certain guidelines when developing and disseminating BA data-driven stories. We suggest that the process of storytelling begins with the development of deliberate stories by an organizational department, depending on where BA will be incorporated into daily activities. Given the complexity of BA content, we suggest that the number and/or complexity of disseminated stories be proportional to the number of data visualization tools and types of analytics (descriptive, predictive, prescriptive analytics) comprising BA. Thus, every new type of data visualization tool and every new type of analytical approach should be accompanied by a discrete data-driven story.

Prior to the development of stories, it is crucial to assign a corresponding business challenge to each type of BA functionality. This approach ensures that while hearing stories, employees will vividly remember which business purpose different visualizations and analytics can be used for. When preparing a simple, compelling and engaging BA data-driven story, it is important to start the story with a description of what kind of knowledge the visualized data conveys and continue the story by contextualizing it in a business setting, thus exemplifying the customer problem(s) that these data solve and the operational decision(s) that the story triggers.

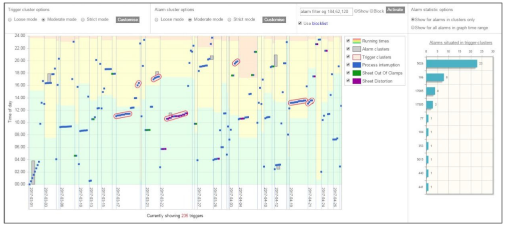
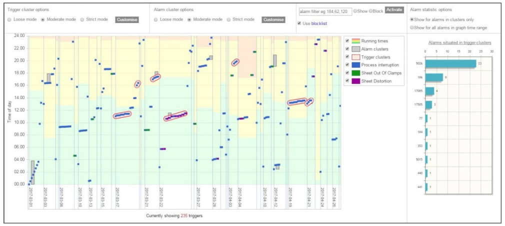
Next, stories should be consistently disseminated through different channels (e.g. training workshops, online training platforms) that enable employees to interact with BA. The context where deliberate stories are disseminated should provide a positive learning environment where employees are able to learn, collaborate and reflect upon BA use. To maximize the value of storytelling, the deliberate dissemination of stories should be carried out by business experts at the department where BA is introduced (e.g. Service, Sales, Marketing) in cooperation with the technical development team building the BA technical infrastructure.

The difference between a traditional data interpretation approach and data interpretation supported by BA data-driven storytelling is reflected in the experience that the user has while interpreting data and making decisions. Additionally, the intention to regularly use BA depends on the positive or negative experiences that users have while interacting with it (Figure 3).

Our example describes how storytelling can be utilized in operations and maintenance (O&M) analytics for remote machine diagnostics and maintenance in the sheet metal working industry, which is characterized by a frequent use of BA by the Service unit (Figure 3).

The example story in Figure 3 can be explicitly divided into several interrelated clauses. First, the story starts with visual data interpretation: *"The Trigger Graph illustrates a customer's machine performance and utilization rate over the period of 2 months."* Then, the story continues by putting these data into a business context, illustrating what value the data have to customers: *"These data can be used to determine what causes machine interruption and how we can improve the customer's machine performance."* Prior to

Figure 3.
BA user experience map: a comparison of data interpretation approaches

Stage of the journey	Traditional visual data interpretation	Visual data interpretation supported by BA data-driven storytelling
Doing	 Interpreting data	 Interpreting data + "The Trigger Graph illustrates a customer's machine performance and utilization rate over the period of 2 months. These data can be used to determine what causes machine interruption and how we can improve…" Listening to story
Thinking	- How do I use this data? - What customer problem can I solve with this data? - How much time it will take for me to make a decision?	- I know how I can use this data. - I have an understanding of which customer problem can I solve with this data. - I know it will not take a long time to make a decision.
Feeling	- Annoyed: Data is too complex to understand. - Anxious: What if I misinterpret data and make a wrong decision? - Frustrated: I can't waste too much time on this. - Skeptical: Will this data really help me do my job? - Disappointed: I don't know where to start analyzing this data.	- Confident: I know how to analyze this data. - Surprised: It is easier to use it than I expected. - Satisfied: This data will help me do my job better and make decisions faster.
User experience	- I do not enjoy using this BA. - I will not use this BA for decision-making on daily basis. - I will not recommend using this BA to other colleagues.	- I enjoy using this BA. - I will use this BA for decision-making on a daily basis. - I will recommend using this BA to other colleagues.

Notes: Traditional (left) and data-driven storytelling (right)[a]; [a]The screenshot of a BA software was kindly provided by an international sheet metal processing organization, which is facing the challenges of complex data interpretation and decision-making. The organization preferred to remain anonymous providing a solution to the problem and encouraging a particular decision, the story narrates a more in-depth interpretation of the data: *"Data show repeating trigger clusters (process interruption, sheet out of clamps, sheet distortion) between 10:00-12:00. Clusters represent the areas where the machine's automatic operations are continuously interrupted."* Finally, based on an in-depth analysis of the data, the story suggests further steps that should be taken regarding the customer case: *"After checking which manual machine operations (e.g., wrong placement of the sheet on the loading table) cause machine interruption and decline of productivity, we should contact the customer and help to correctly perform the sheet loading"*.

In conclusion, the story repeats the value of these data in a business setting and specifically to customers, thus capturing the lessons learned from BA data interpretation: *"When a customer regularly wastes 4 hours of production time per week – it costs money. Fixing this problem can help improve the customer's production efficiency and increase machine performance by 7-10%"*.

Through this somewhat simplified example of deliberate data-driven storytelling (models are only approximations of reality, after all), we hope to have illustrated the nature of a symbolically charged narrative with a plot that translates data into business insights, supports employees' visual data interpretation and facilitates employees' decision-making.

4.3 Research propositions

While prior research highlights the importance of hiring data scientists (Costa and Santos, 2017; Davenport and Patil, 2012; Harris and Mehrotra, 2014; Provost and Fawcett, 2013) or data translators (Brady *et al.*, 2017), we believe that deliberate dissemination of data-driven stories can enhance *existing employees'* skills in translating BA data into valuable business insights. Thus, extensive and correct use of storytelling eliminates the need to hire new expensive labor. Instead, company experts in R&D, Service or Sales can be trained to give meaning to raw data and deliberately disseminate data interpretation stories to colleagues who are dealing with BA-driven decision-making on a daily basis.

Data-driven stories connect data science, analytics and business problems with the target audience by adding easily interpretable business meaning to raw data. Building on prior research (Chen *et al.*, 2012; Li *et al.*, 2016), we suggest that stories should explicitly reflect on how data help to solve specific customer-related business problems, thus enhancing decision-making quality. As prior research on big data analytics in BOR suggests (White *et al.*, 2016), to reap the full benefits of BA data, employees should not only possess technical skills but also have knowledge of the economic value of data for decision-making. Raw data presented with BA visualization tools is too numerical and complex to process and interpret for efficient decision-making. While some organizations may acquire BA software from a third party, others with strong R&D expertise develop BA internally within an organization. In the latter case, a BA tool developed by R&D can be excessively technical or analytical, making it difficult to communicate the meaning of data to nontechnical users. Hence, storytelling provides a common sensemaking instrument (Yang, 2013) that translates data into business insights. By incorporating data into the business context, BA data-driven stories reduce the ambiguity and uncertainty caused by big data and make it easier to understand the meaning and practical implications of data. For maximum efficacy, such stories should also be *memorable*.

Data-driven storytelling simplifies the complex nature of technical data and provides cognitive linearity for the human mind by narrating key memorable data insights. Human interaction and human understanding are crucial to interpreting data (Yaqoob *et al.*, 2016), which is why we argue that data visualization techniques *in combination with* data-driven storytelling provide a powerful means for improving decision-making quality. The purpose of data-driven stories is to take the BA user on an interpretive journey through the data. The intention of stories is to illustrate, step-by-step, the use of BA by guiding the user through the process of:

- interpreting data;
- grasping the business challenge(s) it solves; and
- making the right decision, thus providing a solution to the problem.

This process of illustrating how BA data can be used for problem solving and decision-making provides a precise data interpretation journey map instead of mere coordinates. It is easier for BA users to bridge the gap between raw data and business insights when organizations provide narratives about the BA data interpretation journey and what should be done to reach the final destination. Summarizing our arguments (Figure 2), we propose the following:

P1. The use of BA data-driven storytelling in organizations enhances the quality of individual employees' data interpretation.

P2. The improvement in an individual's BA data interpretation quality improves the quality of that individual's decision-making.

Given the complexity of the information overload that employees face, it is challenging to comprehend and recall all structured and unstructured data. Organizations that aim to adopt BA on an individual level should not overburden employees attending BA training with complex time-consuming descriptions of BA functionalities. Instead, deliberate use of storytelling helps BA users relate to the stories and remember the key takeaways after leaving the training session. Individuals can subsequently use these story-driven takeaways for real-time problem solving and decision-making. Data-driven storytelling creates a connection between technical data and a business case, and it provides a clearer mental map for a user than mere data or data visualization would. Stories serve as an explanatory tool for understanding and interpreting how BA data works as well as how to derive useful insights and make decisions based on data. Hence, BA data-driven storytelling should be viewed as a way to help employees make sense of BA and facilitate individual-level BA adoption in organizations.

Supported by behavioral theories on the acceptance and use of technology (Venkatesh *et al.*, 2003), we further propose that as storytelling leads to improvements in both data interpretation quality and decision-making quality, employees become more willing to accept and use BA on a daily basis. Accordingly, we posit the following:

P3a and P3b. In organizations that place a relatively greater emphasis on data-driven storytelling, the improvement in data interpretation quality and decision-making quality positively enhances individual intention to use BA and actual use of BA.

4.4 Microfoundations from linguistics, psychology and neuroscience

Further insight into BA data-driven storytelling can be gleaned from linguistics, psychology and neuroscience. How the human brain operates during storytelling is the neuropsychological *proximate mechanism* (Laland *et al.*, 2011) that enables the effectiveness of data-driven storytelling. That is why an improved understanding of the neuropsychology underlying storytelling sheds light on the effectiveness of storytelling as a sensemaking OR heuristic.

Synthesizing insights from neurolinguistics (Dor, 2015, 2017) and deliberate storytelling research (Boldosova, 2019; Klein *et al.*, 2007), we propose that organizations should use deliberate data-driven storytelling as an internal communication heuristic that aims to bridge the experiential gap between the storyteller and the audience by activating the recipients' imagination. *Experiential gaps* within the context of this study refer to the different knowledge gaps that employees have in comprehending and interpreting BA data. Given that organizations introduce data-driven stories to employees during the BA adoption process, deliberate storytelling creates a shared cognitive basis among employees regarding the perceived ease-of-use and usefulness of BA. As in the evolutionary history of human language (Boyd, 2017; Dor, 2015, 2017), storytelling fills in the experiential gaps between the storyteller and the audience by instructing the audience's imagination in the manner that the storyteller intends.

From an evolutionary psychological perspective, storytelling is a more powerful cognitive device compared with abstract images, simple gestures or sounds (Yang, 2013). The human mind finds stories appealing because a story with a clear plot enhances the audience's ability to make sense of unstructured scattered information (Yang, 2013). BA data-driven storytelling is a communicative sensemaking heuristic that helps employees to better understand the data interpretation process by connecting different data patterns into meaningful insights with *coherence* and *sequence* (Riessman, 1993). As a cognitive heuristic, data-driven storytelling helps employees to make sense of BA and assists them in BA-driven decision-making during organizational adoption of BA.

Prior research on cognitive mechanisms that promote learning through storytelling (Swap *et al.*, 2001) highlights the importance of an *availability heuristic* (MacLeod and Campbell, 1992; Tversky and Kahneman, 1973), a mental shortcut that helps employees interpret data and make decisions based on the latest important information that can be recalled. During data-driven storytelling, BA users begin to associate visualizations and analytics with particular business cases, which positively affects their availability heuristics during real-time decision-making or problem solving. It is easier to make a decision based on a story associated with specific business knowledge as opposed to complex technical data. Storytelling acts as an enabling factor that facilitates the ease with which BA users recall from memory past events associated with big data interpretation, thus reducing the likelihood of forgetting relevant information. Under uncertainty during data interpretation and decision-making, availability heuristics provided by stories support BA users in avoiding complex and time-consuming in-depth judgment. Instead, the human mind uses mental shortcuts for faster decision-making operations (Kahneman, 2011) that are enabled by data-driven storytelling.

In addition to the availability heuristic, *elaboration* is another cognitive mechanism (Swap *et al.*, 2001) that explains why storytelling in combination with BA visualizations enhances an individual's ability to interpret data and make decisions. BA data-driven stories comprise both technical data and business knowledge that employees can relate to based on their personal experience. Employees will remember these stories because elaborating on visual technical data with verbal business information stimulates the development of *conceptually* coherent mental images. Correspondingly, during real-time data interpretation and decision-making, stories provide a way to recall meaningful information that is associated with these vivid mental images (Swap *et al.*, 2001). Finally, when BA users hear stories, the received knowledge from this experience is stored immediately in episodic memory (Swap *et al.*, 2001), and it is easily retrievable when needed during later data interpretation and decision-making.

Cognitive psychologists have found that problem solving and decision-making quality decrease with information overload (Eppler and Mengis, 2004). To decrease the information overload that BA users encounter when interpreting data and making decisions, storytelling provides a heuristic that helps to process large amounts of raw data by compressing it into precise, valuable business insights. Data-driven storytelling therefore provides a convenient format for dealing with big data, reducing a large set of data alternatives to simpler heuristics (Gigerenzer *et al.*, 1999) that aid decision-making.

When BA users hear a story, that experience activates Broca's and Wernicke's areas – regions of the brain responsible for processing linguistic information; other brain regions are also activated, including the sensory, visual, motor and frontal cortices (Gazzaniga *et al.*, 2014; Snyder, 2016). Storytelling activates the human brain in such a way that listeners respond and relate to the information being told on a deeper level, hence retaining this knowledge in long-term memory (Snyder, 2016). Storytelling creates a *neural coupling effect* (Hasson *et al.*, 2012; Stephens *et al.*, 2010) that activates similar patterns in the brain of the storyteller and the listener, thus enabling the listener to connect to the storyteller and relate to the story both mentally and emotionally. During storytelling, listeners' brain activity mirrors the storyteller's brain activity, which, under optimal circumstances, leads to improved perception of BA data ease-of-use and usefulness. Correspondingly, BA data-driven stories are more effective in enhancing data interpretation and decision-making compared with reading a written technical document or following a technical BA demonstration.

5. Discussion

5.1 Theoretical implications

Synthesizing theoretical insights from BA, storytelling, behavioral research, linguistics, psychology and neuroscience, the present article introduces the new concept of *BA data-driven storytelling* and developed a model with propositions for future research. The study's theoretical contribution is threefold.

First, this study extends existing BA literature on *individual*-level adoption (Shahbaz *et al.*, 2019; Verma *et al.*, 2018) by illustrating how data-driven storytelling can facilitate BA use in organizations. While extant research has focused mainly on *organization*-level adoption of analytics (Caesarius and Hohenthal, 2018; Gunasekaran *et al.*, 2017; Kwon *et al.*, 2014; Lai *et al.*, 2018; Moktadir *et al.*, 2019), this study takes an opposite approach by exploring factors facilitating BA use at the *individual* level. Drawing on the increasing role of psychology in existing behavioral research (Abraham *et al.*, 2013; Bettiga and Lamberti, 2017; Kroenung *et al.*, 2017), this study is an attempt to stimulate further research on the psychological microfoundations of technology adoption, whether approached from a cognitive, an evolutionary or a behavioral neuroscience point of view.

Second, the present article contributes to extant BOR studies on BA (Hämäläinen *et al.*, 2013; White *et al.*, 2016) with a novel behavioral theory of the relationship between BA data-driven storytelling and BA use (Figure 2). Given the increasing importance of BA and challenges organizations face when integrating BA into daily operations (Agarwal and Dhar, 2014; Sivarajah *et al.*, 2017), this study responds to research calls for interdisciplinary OR studies (Becker, 2016; Brocklesby, 2016; Franco and Hämäläinen, 2016) by using linguistics, psychology and neuroscience to explain how storytelling improves data interpretation and decision-making quality. Contributing to the discussion on the challenges of BA-driven decision-making (Al-Kassab *et al.*, 2014; Kuechler and

Vaishnavi, 2006; Vidgen *et al.*, 2017), this study enriches existing knowledge (Bumblauskas *et al.*, 2017; Li *et al.*, 2016) on the importance of improving data interpretation quality for decision-making. Whereas previously scholars have addressed the impact of information visualization (Zabukovec and Jaklič, 2015), data quality and people skills (Bose, 2009; Janssen *et al.*, 2017) on decision-making, we draw attention to storytelling as an *alternative* factor affecting BA data interpretation and decision-making quality. Although we acknowledge the importance of data scientists (Costa and Santos, 2017; Harris and Mehrotra, 2014; Provost and Fawcett, 2013) and data translators (Brady *et al.*, 2017), we suggest that BA data-driven storytelling is an alternative approach that can be used to improve current employees' skills in turning data into business insights, hence reducing the need to hire new labor.

Third, our study extends the current state of storytelling literature in OR (Klein, 2009; Klein *et al.*, 2007; White *et al.*, 2016) by proposing and defining *BA data-driven storytelling* as a strategic sensemaking OR heuristic. The present study goes beyond the earlier understanding of storytelling as a creative problem-solving tool (Klein, 2009) or a narrative engineering tool (Klein *et al.*, 2007). Instead, we introduce a new implication of storytelling in supporting employees in BA data interpretation and data-driven decision-making. While prior studies have primarily explored storytelling as a visualization instrument (Gershon and Page, 2001; Kosara and Mackinlay, 2013; Ma *et al.*, 2012), this study extends the literature by taking the opposite approach, highlighting the importance of storytelling as a social communication technology (Dor, 2017) and as a verbal narrative heuristic that facilitates the transfer of technology as human social tradition (Boyd, 2017). As a result, this study increases the research field's attention to diverse implications of storytelling, and it encourages future research to continue exploring storytelling in an interdisciplinary OR context.

5.2 Managerial implications

To become successful in the digital age and to maximize the business potential of BA, managers should aim to understand behavioral and psychological factors influencing individual-level BA adoption. This article recommends that BA data-driven stories be disseminated within an organization to help BA users better interpret data and make informed decisions. We argue that deliberate storytelling can influence individuals' intentions to use BA daily in their jobs. The storytelling instructions and example of the BA data-driven story provided in the study should support and encourage managers in their own storytelling activities.

5.3 Limitations and future research directions

Although this article has provided preliminary insights into the role of storytelling in BA use and decision-making quality, it has a number of limitations. First, given the theoretical nature of this study, rigorous empirical research is needed to test the model and better understand the role of BA data-driven storytelling. Second, modeling human behavior is a challenging process involving unpredictable human behavior (Greasley and Owen, 2016). As a result, the behavioral model proposed in this study necessarily simplifies reality. Finally, we suggest that further BOR on BA is important not only for building theory on this emerging phenomenon but also for increasing this research field's attention to the practical challenges that practitioners face. We hope the present article stimulates new discussions and encourages scholars to invest further efforts into cross-disciplinary BA research.

6. Conclusion

The current synthesis of insights from OR, behavioral studies, linguistics, psychology, neuroscience, BA and storytelling has formed a theoretical framework on the basis of which we introduced the concept of *BA data-driven storytelling*. We suggest that organizations using BA data-driven storytelling as a narrative sensemaking heuristic are able to support employees in BA data interpretation and data-driven decision-making, with the additional benefit of positively influencing employees in adopting BA and using it on a daily basis.

Note

1. Despite the main focus of this study being on business analytics, it is important to include prior research on big data analytics into the literature review. Given the similar nature of these concepts and the interchangeable use of these terms in the literature (Chen *et al.*, 2012), the incorporation of extant BDA research increases the breadth of the literature review and provides additional insights into BA within the context of this study.

References

Abraham, C., Boudreau, M.-C., Junglas, I. and Watson, R. (2013), "Enriching our theoretical repertoire: the role of evolutionary psychology in technology acceptance", *European Journal of Information Systems*, Vol. 22 No. 1, pp. 56-75.

Agarwal, R. and Dhar, V. (2014), "Editorial – big data, data science, and analytics: the opportunity and challenge for IS research", *Information Systems Research*, Vol. 25 No. 3, pp. 443-448.

Al-Kassab, J., Ouertani, Z.M., Schiuma, G. and Neely, A. (2014), "Information visualization to support management decisions", *International Journal of Information Technology and Decision Making*, Vol. 13 No. 2, pp. 407-428.

Aydiner, A.S., Tatoglu, E., Bayraktar, E., Zaim, S. and Delen, D. (2019), "Business analytics and firm performance: the mediating role of business process performance", *Journal of Business Research*, Vol. 96, pp. 228-237.

Baker, B. (2014), "Use storytelling to engage and align employees around your strategic plans", *Industrial and Commercial Training*, Vol. 46 No. 1, pp. 25-28.

Barker, R.T. and Gower, K. (2010), "Strategic application of storytelling in organizations: toward effective communication in a diverse world", *Journal of Business Communication*, Vol. 47 No. 3, pp. 295-312.

Becker, K.H. (2016), "An outlook on behavioural or–three tasks, three pitfalls, one definition", *European Journal of Operational Research*, Vol. 249 No. 3, pp. 806-815.

Bettiga, D. and Lamberti, L. (2017), "Exploring the adoption process of personal technologies: a cognitive-affective approach", *The Journal of High Technology Management Research*, Vol. 28 No. 2, pp. 179-187.

Boldosova, V. (2019), "Deliberate storytelling in big data analytics adoption", *Information Systems Journal*, pp. 1-27.

Bose, R. (2009), "Advanced analytics: opportunities and challenges", *Industrial Management and Data Systems*, Vol. 109 No. 2, pp. 155-172.

Boyd, B. (2017), "The evolution of stories: from mimesis to language, from fact to fiction", *Wiley Interdisciplinary Reviews: Cognitive Science*, Vol. 9 No. 1, pp. 1-16.

Brady, C., Forde, M. and Chadwick, S. (2017), "Why your company needs data translators", *MIT Sloan Management Review*, Vol. 58 No. 2, pp. 14-16.

Brocklesby, J. (2016), "The what, the why and the how of behavioural operational research – an invitation to potential sceptics", *European Journal of Operational Research*, Vol. 249 No. 3, pp. 796-805.

Bumblauskas, D., Nold, H., Bumblauskas, P. and Igou, A. (2017), "Big data analytics: transforming data to action", *Business Process Management Journal*, Vol. 23 No. 3, pp. 703-720.

Caesarius, L.M. and Hohenthal, J. (2018), "Searching for big data", *Scandinavian Journal of Management*, Vol. 34 No. 2, pp. 129-140.

Calvard, T.S. (2016), "Big data, organizational learning, and sensemaking: theorizing interpretive challenges under conditions of dynamic complexity", *Management Learning*, Vol. 47 No. 1, pp. 65-82.

Carillo, K.D.A. (2017), "Let's stop trying to be "sexy" – preparing managers for the (big) data-driven business era", *Business Process Management Journal*, Vol. 23 No. 3, pp. 598-622.

Chen, H., Chiang, R.H.L. and Storey, V.C. (2012), "Business intelligence and analytics: from big data to big impact", *MIS Quarterly*, Vol. 36 No. 4, pp. 1165-1188.

Corley, K.G. and Gioia, D.A. (2011), "Building theory about theory building: what constitutes a theoretical contribution?", *Academy of Management Review*, Vol. 36 No. 1, pp. 12-32.

Cornelissen, J. (2017), "Editor's comments: developing propositions, a process model, or a typology? Addressing the challenges of writing theory without a boilerplate", *Academy of Management Review*, Vol. 42 No. 1, pp. 1-9.

Costa, C. and Santos, M.Y. (2017), "The data scientist profile and its representativeness in the European E-competence framework and the skills framework for the information age", *International Journal of Information Management*, Vol. 37 No. 6, pp. 726-734.

Cunha, M.P. and Rego, A. (2010), "Complexity, simplicity, simplexity", *European Management Journal*, Vol. 28 No. 2, pp. 85-94.

Davenport, T.H. and Harris, J.G. (2007), *Competing on Analytics: The New Science of Winning*, Harvard Business School Press, Boston, MA.

Davenport, T.H. and Patil, D.J. (2012), "Data scientist: the sexiest job of the 21st century", *Harvard Business Review*, Vol. 90 No. 10, pp. 70-76.

Davenport, T.H., Barth, P. and Bean, R. (2012), "How 'big data' is different", *MIT Sloan Management Review*, Vol. 54 No. 1, pp. 43-46.

Davison, R.M. (2016), "The art of storytelling", *Information Systems Journal*, Vol. 26 No. 3, pp. 191-194.

Dor, D. (2015), *The Instruction of Imagination: Language as a Social Communication Technology*, Oxford University Press, Oxford.

Dor, D. (2017), "From experience to imagination: language and its evolution as a social communication technology", *Journal of Neurolinguistics*, Vol. 43, pp. 107-119.

Eppler, M.J. and Mengis, J. (2004), "The concept of information overload: a review of literature from organization science, accounting, marketing, MIS, and related disciplines", *The Information Society*, Vol. 20 No. 5, pp. 325-344.

Franco, L.A. and Hämäläinen, R.P. (2016), "Behavioural operational research: returning to the roots of the or profession", *European Journal of Operational Research*, Vol. 249 No. 3, pp. 791-795.

Gabriel, Y. (2000), *Storytelling in Organizations: Facts, Fictions, and Fantasies*, Oxford University Press, Oxford.

Gazzaniga, M., Ivry, R.B. and Mangun, G.R. (2014), *Cognitive Neuroscience: The Biology of the Mind*, W. W. Norton and Company, New York, NY.

Gershon, N. and Page, W. (2001), "What storytelling can do for information visualization", *Communications of the Acm*, Vol. 44 No. 8, pp. 31-37.

Gigerenzer, G. and Todd, P.M. and ABC Research Group (1999), *Simple Heuristics That Make Us Smart*, Oxford University Press, Oxford.

Greasley, A. and Owen, C. (2016), "Behavior in models: a framework for representing human behavior", in Kunc, M., Malpass, J. and White, L. (Eds), *Behavioral Operational Research: Theory, Methodology and Practice*, Palgrave Macmillan, London, pp. 47-63.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S.F., Childe, S.J., Hazen, B. and Akter, S. (2017), "Big data and predictive analytics for supply chain and organizational performance", *Journal of Business Research*, Vol. 70, pp. 308-317.

Hämäläinen, R.P., Luoma, J. and Saarinen, E. (2013), "On the importance of behavioral operational research: the case of understanding and communicating about dynamic systems", *European Journal of Operational Research*, Vol. 228 No. 3, pp. 623-634.

Harris, J.G. and Mehrotra, V. (2014), "Getting value from your data scientists", *MIT Sloan Management Review*, Vol. 56 No. 1, pp. 15-18.

Hasson, U., Ghazanfar, A.A., Galantucci, B., Garrod, S. and Keysers, C. (2012), "Brain-to-brain coupling: a mechanism for creating and sharing a social world", *Trends in Cognitive Sciences*, Vol. 16 No. 2, pp. 114-121.

Hindle, G.A. and Vidgen, R. (2017), "Developing a business analytics methodology: a case study in the foodbank sector", *European Journal of Operational Research*, Vol. 268 No. 3, pp. 836-851.

James, C.H. and Minnis, W.C. (2004), "Organizational storytelling: it makes sense", *Business Horizons*, Vol. 47 No. 4, pp. 23-32.

Janssen, M., van der Voort, H. and Wahyudi, A. (2017), "Factors influencing big data decision-making quality", *Journal of Business Research*, Vol. 70, pp. 338-345.

Kahneman, D. (2011), *Thinking, Fast and Slow*, Farrar, Straus and Giroux, New York, NY.

Katsikopoulos, K.V. (2016), "Behavior with models: the role of psychological heuristics in operational research", in Kunc, M., Malpass, J. and White, L. (Eds), *Behavioral Operational Research: Theory, Methodology and Practice*, Palgrave Macmillan, London, pp. 27-45.

Klein, J. (2009), "Ackoff's fables revisited: stories to inform operational research practice", *Omega*, Vol. 37 No. 3, pp. 615-623.

Klein, J.H., Connell, N.A.D. and Meyer, E. (2007), "Operational research practice as storytelling", *Journal of the Operational Research Society*, Vol. 58 No. 12, pp. 1535-1542.

Kosara, R. and Mackinlay, J. (2013), "Storytelling: the next step for visualization", *Computer*, Vol. 46 No. 5, pp. 44-50.

Kroenung, J., Eckhardt, A. and Kuhlenkasper, T. (2017), "Conflicting behavioral paradigms and predicting IS adoption and non-adoption – the importance of group-based analysis", *Computers in Human Behavior*, Vol. 67, pp. 10-22.

Kuechler, W.L. and Vaishnavi, V. (2006), "So, talk to me: the effect of explicit goals on the comprehension of business process narratives", *MIS Quarterly*, Vol. 30 No. 4, pp. 961-979.

Kunc, M. and O'Brien, F.A. (2019), "The role of business analytics in supporting strategy processes: opportunities and limitations", *Journal of the Operational Research Society*, Vol. 70 No. 6, pp. 974-985.

Kwon, O., Lee, N. and Shin, B. (2014), "Data quality management, data usage experience and acquisition intention of big data analytics", *International Journal of Information Management*, Vol. 34 No. 3, pp. 387-394.

Lai, Y., Sun, H. and Ren, J. (2018), "Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management: an empirical investigation", *The International Journal of Logistics Management*, Vol. 29 No. 2, pp. 676-703.

Laland, K.N., Sterelny, K., Odling-Smee, J., Hoppitt, W. and Uller, T. (2011), "Cause and effect in biology revisited: is mayr's proximate-ultimate dichotomy still useful?", *Science*, Vol. 334 No. 6062, pp. 1512-1516.

Li, Y., Thomas, M.A. and Osei-Bryson, K.-M. (2016), "A snail shell process model for knowledge discovery via data analytics", *Decision Support Systems*, Vol. 91, pp. 1-12.

Liberatore, M.J. and Luo, W. (2010), "The analytics movement: implications for operations research", *Interfaces*, Vol. 40 No. 4, pp. 313-324.

MacLeod, C. and Campbell, L. (1992), "Memory accessibility and probability judgments: an experimental evaluation of the availability heuristic", *Journal of Personality and Social Psychology*, Vol. 63 No. 6, pp. 890-902.

Ma, K.-L., Liao, I., Frazier, J., Hauser, H. and Kostis, H.N. (2012), "Scientific storytelling using visualization", *IEEE Computer Graphics and Applications*, Vol. 32 No. 1, pp. 12-19.

Moktadir, M.A., Ali, S.M., Paul, S.K. and Shukla, N. (2019), "Barriers to big data analytics in manufacturing supply chains: a case study from Bangladesh", *Computers and Industrial Engineering*, Vol. 128, pp. 1063-1075.

Mortenson, M.J., Doherty, N.F. and Robinson, S. (2015), "Operational research from taylorism to terabytes: a research agenda for the analytics age", *European Journal of Operational Research*, Vol. 241 No. 3, pp. 583-595.

Provost, F. and Fawcett, T. (2013), "Data science and its relationship to big data and data-driven decision making", *Big Data*, Vol. 1 No. 1, pp. 51-59.

Ranyard, J.C., Fildes, R. and Hu, T.-I. (2015), "Reassessing the scope of or practice: the influences of problem structuring methods and the analytics movement", *European Journal of Operational Research*, Vol. 245 No. 1, pp. 1-13.

Riessman, C.K. (1993), *Narrative Analysis*, Sage, Thousand Oaks, CA.

Royston, G. (2013), "Operational research for the real world: big questions from a small island", *Journal of the Operational Research Society*, Vol. 64 No. 6, pp. 793-804.

Seddon, P.B., Constantinidis, D., Tamm, T. and Dod, H. (2017), "How does business analytics contribute to business value?", *Information Systems Journal*, Vol. 27 No. 3, pp. 237-269.

Segel, E. and Heer, J. (2010), "Narrative visualization: telling stories with data", *IEEE Transactions on Visualization and Computer Graphics*, Vol. 16 No. 6, pp. 1139-1148.

Shahbaz, M., Gao, C., Zhai, L., Shahzad, F. and Hu, Y. (2019), "Investigating the adoption of big data analytics in healthcare: the moderating role of resistance to change", *Journal of Big Data*, Vol. 6 No. 1, pp. 1-20.

Sivarajah, U., Kamal, M.M., Irani, Z. and Weerakkody, V. (2017), "Critical analysis of big data challenges and analytical methods", *Journal of Business Research*, Vol. 70, pp. 263-286.

Snyder, R.A. (2016), *The Social Cognitive Neuroscience of Leading Organizational Change: TiER1 Performance Solutions' Guide for Managers and Consultants*, Routledge, New York, NY.

Stephens, G.J., Silbert, L.J. and Hasson, U. (2010), "Speaker-listener neural coupling underlies successful communication", *Proceedings of the National Academy of Sciences*, Vol. 107 No. 32, pp. 14425-14430.

SunWolf and Frey, L.R. (2001), "Storytelling: the power of narrative communication and interpretation", in Robinson, W.P. and Giles, H. (Eds), *The New Handbook of Language and Social Psychology*, Wiley, New York, NY, pp. 119-135.

Swap, W., Leonard, D., Shields, M. and Abrams, L. (2001), "Using mentoring and storytelling to transfer knowledge in the workplace", *Journal of Management Information Systems*, Vol. 18 No. 1, pp. 95-114.

Tversky, A. and Kahneman, D. (1973), "Availability: a heuristic for judging frequency and probability", *Cognitive Psychology*, Vol. 5 No. 2, pp. 207-232.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "User acceptance of information technology: toward a unified view", *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478.

Verma, S., Bhattacharyya, S.S. and Kumar, S. (2018), "An extension of the technology acceptance model in the big data analytics system implementation environment", *Information Processing and Management*, Vol. 54 No. 5, pp. 791-806.

Vidgen, R., Shaw, S. and Grant, D.B. (2017), "Management challenges in creating value from business analytics", *European Journal of Operational Research*, Vol. 261 No. 2, pp. 626-639.

Wamba, S.F., Akter, S., Edwards, A., Chopin, G. and Gnanzou, D. (2015), "How 'big data' can make big impact: findings from a systematic review and a longitudinal case study", *International Journal of Production Economics*, Vol. 165, pp. 234-246.

Whetten, D.A. (1989), "What constitutes a theoretical contribution?", *Academy of Management Review*, Vol. 14 No. 4, pp. 490-495.

White, L. and Taket, A. (2000), "Exploring the use of narrative analysis as an operational research method: a case study in voluntary sector evaluation", *Journal of the Operational Research Society*, Vol. 51 No. 6, pp. 700-711.

White, L., Burger, K. and Yearworth, M. (2016), "Big data and behavior in operational research: towards a "smart OR", in Kunc, M., Malpass, J. and White, L. (Eds), *Behavioral Operational Research: Theory, Methodology and Practice*, Palgrave Macmillan, London, pp. 177-193.

Yang, C. (2013), "Telling tales at work", *Business Communication Quarterly*, Vol. 76 No. 2, pp. 132-154.

Yaqoob, I., Hashem, I.A.T., Gani, A., Mokhtar, S., Ahmed, E., Anuar, N.B. and Vasilakos, A.V. (2016), "Big data: from beginning to future", *International Journal of Information Management*, Vol. 36 No. 6, pp. 1231-1247.

Zabukovec, A. and Jaklič, J. (2015), "The impact of information visualisation on the quality of information in business decision-making", *International Journal of Technology and Human Interaction*, Vol. 11 No. 2, pp. 61-79.

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