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An Empirical Examination of the Relationship Between Data Storytelling Competency and Business Performance:
The Mediating Role of Decision-Making Quality

Mohammad Kamel Daradkeh, Yarmouk University, Irbid, Jordan

ABSTRACT

With the proliferation of big data and business analytics practices, data storytelling has gained increasing importance as an effective means for communicating analytical insights to the target audience to support decision-making and improve business performance. However, there is a limited empirical understanding of the relationship between data storytelling competency, decision-making quality, and business performance. Drawing on the resource-based view (RBV), this study develops and validates the concept of data storytelling competency as a multidimensional construct consisting of data quality, story quality, storytelling tool quality, storyteller skills, and storyteller domain knowledge. It also develops a mediation model to examine the relationship between data storytelling competency and business performance, and whether this relationship is mediated by decision-making quality. Based on an empirical analysis of data collected from business analytics practitioners, the results of this study reveal that the data storytelling competency is positively linked to business performance, which is partially mediated by decision-making quality. These results provide a theoretical basis for further investigation of possible antecedents and consequences of data storytelling competency. They also offer guidance for practitioners on how to leverage data storytelling capabilities in business analytics practices to improve decision-making and business performance.

KEYWORDS

Business Analytics, Business Performance, Data Quality, Data Storytelling Competency, Decision-Making Quality, Partial Least Squares, Resource-Based View, Story Quality, Storytelling Tool

INTRODUCTION

In today's business environment, organizations accumulate massive amounts of data, and their ability to make informed decisions and drive business performance depends in a part on their acumen and competency in analyzing these data and converting them into actionable insights (Daradkeh, 2019a, 2019b). To this end, various business analytics solutions are increasingly being leveraged by organizations to extract meaningful and relevant insights from the data they accumulate and support decision-making at both strategic and operational levels (Delen & Zolbanin, 2018). However, business

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analytics endeavors do not end when patterns, trends and business-critical insights are discovered. The effective articulation, presentation and communication of these insights to the relevant audience at the right time in the right format is crucial to guide the decision-making process and influence actions that create value to business performance (Dykes, 2019).

As business analytics usually deals with complex data and uses sophisticated algorithms and statistical models to generate insights (Davenport & Harris, 2007), there are often times issues with interpreting and digesting the analytical insights presented and contextualizing the analytics to the overall decision-making process (S. Chen et al., 2020). Low adoption rates of business analytics, as shown in various studies and reports (e.g., Daradkeh, 2019b; Ghasemaghaei, Ebrahimi, & Hassanein, 2018; Richardson, Sallam, Schlegel, Kronz, & Sun, 2020; Rouhani, Ashrafi, Ravasan, & Afshari, 2018; Sallam & Howson, 2017), and the benefits organizations expect from the pervasive usage of their information assets prove that there is a huge gap between obtaining analytical insights and presenting them to the relevant audience in a simple, compelling and impactful way (S. Chen et al., 2020; Vidgen, Shaw, & Grant, 2017). As a result, business analytics capabilities may not get used effectively, and decision-makers who usually lack analytical skills and expertise may fall back on their intuition or experience for decision-making (Herschel & Clements, 2017). As organizations create a culture of analytics, decision-makers and business partners are required to not only understand the insights generated from business analytics, but also be participants in the entire analytics workflow—from the moment of generating insights to the final decision or action (Daradkeh, 2019c).

To bridge the gap between analytical insights and resulting business decisions, and to create a pervasive culture of analytics, data storytelling has increasingly become a trending practice that many organizations are adopting to communicate and share business analytics insights with the non-technical audience in order to inform, guide, and influence decision-making and business performance (Dykes, 2019). The literature on data storytelling has already emphasized the importance and value of narrative and anecdotal information conveyed in the form of data stories to support decision-making at both strategic and operational levels (Boldosova & Luoto, 2019; Dykes, 2016; Herschel & Clements, 2017). Data storytelling has also a profound impact on business performance and productivity when aligned with business processes and strategic objectives of organizations (Davenport, 2015; Dykes, 2019; Knaflic, 2015; Vora, 2019). The key question is thus whether, after the adoption of data storytelling in business analytics practices, users actually accept, use, and take full advantage of its potential. Davenport (2015) argue that data storytelling is inextricably linked to the success of business analytics initiatives because it provides an effective means for sharing analytical results with decision-makers and business stakeholders in a way that is memorable, persuasive, and engaging. However, to reap the full benefits of leveraging data storytelling in business analytics practices, organizations need to build and improve their data storytelling competency (i.e., the organization's capability to effectively use storytelling-based resources in combination with other related resources and capabilities) to support decision-making and improve business performance.

While data storytelling is increasingly being recognized as a critical competency for data-driven organizations (Dykes, 2019), the praxis shows that the success attained from adopting data storytelling in business analytics initiatives is still questionable (Boldosova, 2019). Many organizations are not able to make data storytelling an effective tool for decision-making and communication (Herschel & Clements, 2017). A study by Tischler, Mack, and Vitsenko (2017) addressing the adoption state of data storytelling in European organizations shows that only one in ten organizations use data storytelling in a regular basis to communicate their analytical insights with concluding decisions or recommended actions to internal and external stakeholders. Likewise, only 15% of organizations stated that they have already started to implement or currently evaluating potential advantages of using data storytelling in their business analytics and reporting initiatives. Amini, Brehmer, Bolduan, Elmer, and Wiederkehr (2018) argue that the lack of maturity or the widespread use of data storytelling in business analytics practices is due to a variety of reasons such as the presence of low-quality data and the failure to use appropriate storytelling tools and techniques.

Notwithstanding the low coverage of storytelling in many specialized business analytics tools, the technical challenges are not the primary inhibitors of adoption; lack of storytelling skills, knowledge, and resources are among the most frequently cited barriers to the effective application of data storytelling in business analytics practices (Morgan, Pittenger, & McIntyre, 2018; Riche, Hurter, Diakopoulos, & Carpendale, 2018). Although self-service business analytics tools have evolved and improved to provide storytelling-focused features, the organization's competency required to create and tell compelling data stories has not been given sufficient attention (Amini et al., 2018). Furthermore, understanding the mechanisms through which data storytelling capabilities contribute to decision-making and business performance has been a complex issue (Adegboyega & Bahareh, 2018) and still remains a challenging task for both business and research communities (Behera & Swain, 2019). Therefore, the dimensions that characterize the data storytelling competency and the underlying mechanisms through which data storytelling competency may affect decision-making and business performance deserve careful theoretical analysis and empirical investigation.

Arguably, three significant research gaps remain in the literature. First, while prior research (Elias, Aufaure, & Bezerianos, 2013; Herschel & Clements, 2017) has emphasized the importance of data storytelling for the success of business analytics initiatives, no research has conceptualized, operationalized and validated the concept of data storytelling competency in business analytics. Conceptualizing and validating the concept of data storytelling competency and its impact on business outcomes offer new insights into the IT competency literature in general and data storytelling in particular. Second, while prior research has suggested that data storytelling is positively associated with business performance (Adegboyega & Bahareh, 2018; Dykes, 2019; Knaflic, 2015), no research appears to have examined the relationship between data storytelling competency and business performance. Third, although conceptual work has suggested that decision-making quality may mediate the relationship between data storytelling competency and business performance (Gustomo, Febriansyah, Ginting, & Santoso, 2019; Vora, 2019), almost no empirical evidence exists to examine this relationship and its mediating role. These research gaps can be attributed to the fact that most of the work on data storytelling in business analytics practices is conceptual and has been mainly contributed by industrial reports and consultants, which generally lack both theoretical and empirical validity. In order to better understand the interrelationship between data storytelling competency, decision-making quality and business performance, more empirical research is needed.

Drawing on the resource-based view (RBV) (Barney, 1991; Bharadwaj, 2000; Grant, 1991), which classifies key IT-based resources as IT infrastructure, human IT resources, and IT-enabled intangibles, this study develops and validates the concept of data storytelling competency as a multidimensional construct that consists of storytelling tool quality (IT infrastructure), storyteller skills, storyteller domain knowledge (human IT resources), and data quality and story quality (IT-enabled intangibles). It also develops a mediation model to examine the relationship between data storytelling competency and business performance, and whether this relationship is mediated by decision-making quality. To test the research model, data were collected through a questionnaire survey from 182 business analytics practitioners working in different businesses in Jordan. The collected data were analyzed using partial least squares-structural equation modeling (PLS-SEM) method. The results showed that the effective use of data storytelling as a means of communicating insights gleaned from business analytics can contribute positively to improving business performance by enabling effective, timely and informed decision-making. The findings from this study contribute to the literature on data storytelling, business analytics and RBV by providing an empirical understanding of, and new insight into, the mechanisms through which data storytelling may support decision-making and improve business performance. This study also provides a theoretical and practical basis for further research into possible antecedents and consequences of leveraging data storytelling as a mechanism for unlocking the value of business analytics insights and bridging the knowledge gap between business analytics practitioners and the target audience and consumers of analytics.

The remainder of this article is organized as follows. The next section presents a theoretical background, in which it describes the concept of data storytelling in business analytics, and its impact on decision-making and business performance. It also describes the research model and associated hypotheses. The following section explains the instrument development, data collection and analysis procedures. The section that follows reports on the empirical results of this study. The final part of this article discusses the results and their implications for research and practice in data storytelling. It also highlights the limitations of this study and suggests directions for future research.

THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

Data Storytelling in Business Analytics Practices

In the context of business analytics, Boldosova and Luoto (2019) describe data storytelling as a narrative sensemaking heuristic that helps business analytics practitioners to make sense of the big data and guides them though the process of interpreting and translating complex data patterns into a sequence of coherent and meaningful insights, which in turn, can lead to improved decision-making and performance. Similarly, Dykes (2019) defines data storytelling as a structured approach for conveying and communicating insights resulting from the data analysis process in a way that allows the relevant audience to easily and quickly understand the analytical insights, understand the context of these insights, and draw conclusions from them. Typically, data storytelling in business analytics consists of a combination of three key components: data, visuals, and narrative (Dykes, 2016). When a narrative is combined with data, it helps to explain to the target audience what is happening in the data and why a particular insight is critical to business performance. By applying visuals to data, the analytical insights become clearer, easier to understand, and more concrete for the target audience. Combining the right visual and narrative elements with the right data creates data stories that can engage the target audience and influence their decisions (Dykes, 2019; Lee, Nathalie, Petra, & Sheelagh, 2015).

The purpose of developing data stories in business analytics practices is to inform, persuade, engage and guide non-technical audience who may not be in the technical domain, such as marketing and sales personnel, chief executive officer, chief operating officer, and chief financial officer (Gutiérrez, Pérez, Castro, Chávez, & de Vega, 2017; Herschel & Clements, 2017; Riche et al., 2018). As the analytics process moves from data collection to the generation and communication of business insights, data storytelling provides a pivotal context and meaning for the analytical insights and helps business stakeholders to understand what business analytics contributes to a decision, even if they cannot understand the details and intricacies of the analytics process (Davenport, 2015). It is thus not surprising that business analytics practitioners, who make sense of data, are interested in data storytelling because it makes analytical insights meaningful, coherent, and interesting to the target audience. Elias et al. (2013) suggest that the business analytics process must be supported by the construction of stories and narratives, both during sensemaking and during the presentation of analytical results. They argue that the story structure provides a powerful abstraction to conceptualize threats and understand complex data patterns, and data storytelling is an effective means not only for informing discussion and guiding decision-making but also for facilitating and simplifying the business analytics process itself.

While data storytelling is often viewed as the last mile of analytics, it is not a single step or activity. Instead, data storytelling is an iterative process that involves multiple related activities and requires both technical and business knowledge (Lee et al., 2015). Amini et al. (2018) describe the data storytelling process as consisting of three main phases—exploring data, making a story and telling a story. The data exploration phase involves extracting the most relevant data excerpts that contain discovered insights, variations, or interesting ideas within the data. The story making phase involves turning discovered insights into a narrative and constructing a storyline or plot to fit the analytical insights and key story points identified in the data exploration phase. The main activities of the story making phase involve ordering, connecting story pieces, developing flow, and formulating main and concluding thoughts. These activities are often carried out over multiple iterations, through which specific data excerpts are extracted and assembled in a sequence that forms a coherent, meaningful and compelling narrative (Gratzl, Lex, Gehlenborg, Cosgrove, & Streit, 2016). The result of the story making phase is the plot that describes the structure of the story, the logical connections among the story pieces, and their meaning in an overall context. The telling part of the storytelling process includes activities that focus on communicating the data story to the target audience. This phase involves three main activities: building a representation by choosing appropriate materials and medium; communicating the story using the story medium; and finally receiving and responding to the feedback from the target audience (Chevalier et al., 2018). The telling part of the data storytelling process requires some sort of controlled presentation and communication of analytical insights to the target audience (Lee et al., 2015). This controlled presentation and communication involves components that shape the structures, elements and context of the data story. It also involves a set of factors relates to people, tools, and competencies that may influence the effectiveness of the data storytelling process (Mathisen, Horak, Klokmose, Grønbæk, & Elmqvist, 2019).

With the influx of big data and the growing demand for data-driven decision-making, the ability to turn data into engaging and compelling stories has become an essential competency and critical skill for all types of data analysts and explorers. These include business professionals looking for timely and intuitive analytics and insights to incorporate into their work, data analysts and scientists sharing their analytical results with non-technical users, and even vendors who claim their solutions tell better data stories. However, the techniques and tools used to create and tell data stories in business analytics practices have varied substantially (Dourish & Gómez Cruz, 2018; Riche et al., 2018). The dearth of empirical research on many aspects of data storytelling also means that less evidence is available to provide solid guidance to business analytics practitioners (Adegboyega & Bahareh, 2018). The practice of data storytelling in business analytics has been associated with the creation of different types of visualizations; from data charts and infographics to interactive dashboards and detailed visual reports (S. Chen et al., 2020). Dashboards provide collections of multiple visual representations linked and coordinated on a single view, that enable analysts to explore their data and intuitively view different aspects of complex datasets. However, simple collections of data visualizations cannot exhibit a clear, deep perception or understanding; to become meaningful they require contextualization and explanation, often presented in a story narrative (S. Chen et al., 2020). Elias et al. (2013) argue that dashboards and other data visualizations used for communicating analytical results cannot simply tell data stories. They need to be tailored and customized to accommodate data stories that can guide intended recipients toward a better understanding and appreciation of complex data patterns and insights, ultimately leading to better decisions and performance.

Some of commercial self-service business analytics tools, such as Tableau[1], QlikView[2], and Microsoft Power BI[3] can be used for creating sharable data-driven stories via data visualizations and interactive dashboards and reports. These platforms lay the foundations for constructing narrative elements and exploratory visuals of data storytelling (Daradkeh, 2019b, 2019c). However, business analytics platforms with dedicated features for developing data stories are not yet as advanced and still used less frequently than the aforementioned alternatives (Tischler et al., 2017). Still, the praxis shows that effective data storytelling can be achieved without significant investment in business analytics platforms; but fostering the organization's competency will bring with it improvements in current data storytelling practices to support decision-making and improve business performance. Therefore, studying the main resources that contribute to building data storytelling competency in organizations is essential to understanding the specifics and nuances of data storytelling and its relationship to decision-making quality and business performance, which can be explained through the data storytelling literature and the resource-based view of the organization (Bharadwaj, 2000; Grant, 1991).

Resource-Based View and Data Storytelling Competency

The resource-based view (RBV) theory (Barney, 1991) posits that business performance can be improved through organization-specific resources and capabilities that are valuable, rare, non-substitutable and difficult to imitate by competitors. Based on Grant (1991), the resources of an organization can be classified into three categories: tangible, intangible and personal-based resources. Tangible resources include the physical IT infrastructure components in the organization, while intangible resources include assets such as data and product quality, and personnel-based resources include technical know-how and skills set and employee training. From the perspective of the RBV, organizations can achieve better levels of business performance by assembling resources that work together to create the organization's competencies (Mills, Platts, & Bourne, 2003). Competency, thus, refers to the organization's ability to assemble, integrate and deploy different resources and capabilities to reach a desired and superior business performance (Bharadwaj, 2000; Ghasemaghaei et al., 2018).

Drawing on the RBV and building on previous studies (Amini et al., 2018; Boldosova, 2019; Boldosova & Luoto, 2019) that have established criteria for evaluating data storytelling in the context of business analytics, in this study, the dimensions that form the data storytelling competency are categorized as data quality, story quality (IT intangibles), storyteller skills and storyteller domain knowledge (human IT resources), and storytelling tool quality (IT infrastructure). While many other factors may contribute to the success or failure of data storytelling, these have not been included in the scope of this study due to them being highly context-specific, varying greatly according to the type and scope of the business, and thus deserving more in-depth analysis. Some of these factors might include synergy issues, audience orientation and relations, data governance, and management support and culture (Bharadwaj, 2000; Mills et al., 2003). These factors also vary greatly according to the story types and decision-making styles (Vora, 2019), so while it is possible to take a combined approach to different sectors at a strategic level, such an approach is not possible at an operational level. In view of the distinctive characteristics of the data storytelling competency, its dimensions are constituents rather than antecedents or consequences. The presence of these dimensions functioning constitutively is a necessary condition for building the data storytelling competency.

Data quality refers to the attributes that determine the ability of a dataset to serve an intended purpose such as planning, decision-making, and performance management (Nelson, Todd, & Wixom, 2005). Wang and Strong (1996) developed a hierarchical framework to categorize data quality attributes into four major dimensions: intrinsic, contextual, representational, and accessibility. The intrinsic category refers to the innate correctness of data regardless of the context in which they are being used such as accuracy and objectivity of data. The contextual category represents the quality of data that may vary according to the task at hand, such as relevancy, completeness, and timeliness of data. The representational category refers to the degree to which the data is presented in a clear and concise format, such as representational consistency and ease of interpretation and understanding. Finally, the accessibility category refers to the ease with which the data are located and obtained when needed.

In the context of data storytelling, data quality is an important requirement for what this communication mechanism delivers—information, knowledge, and data insights (Adegboyega & Bahareh, 2018). Data storytelling relying on practices and tools of business analytics can adopt heterogeneous forms of structured and unstructured data generated through analytics applications, statistical analysis and automated contents generation like charts, maps or textual content. Obviously, not all raw data are useful for creating story content. That is, data have to match with (have the coverage of the specifics for) the story for which it is intended to be used. Thus, the relevant data used throughout the data storytelling process should comply with the quality and quantity requirements. In other words, the data must be easily accessible to the story creator, and these data must be complete, relevant, and in a usable format. Chevalier et al. (2018) pointed out that data preparation, i.e., collection, cleaning, and integrity-checking are crucial tasks for handling data quality issues during the data storytelling process. The data storytelling process that ignores data-related tasks often ends up with the wrong story for the right problem, and these unwittingly created, seemingly good, stories may eventually lead to a misleading interpretation of the data insights, and therefore biased and inaccurate decisions. Hence, drawing on the RBV (Bharadwaj, 2000; Grant, 1991), data quality, an intangible IT-enabled resource, is considered as a key dimension of data storytelling competency.

Story quality is another important dimension of data storytelling competency. In business analytics practices, the concept of story quality relates to the different aspects and characteristics of a data story that determine its ability to serve the intended purpose anticipated by the target audience. According to the intention of data storytelling, Vora (2019) classified data stories in business analytics practices into four types: reporting, decision, probing, and pitching stories. Reporting and probing stories often provide information or exploratory analysis related to different aspects of business that can facilitate decision-making. Conversely, the decision and pitching stories are intended to present a complete set of analytical insights with a concluding decision or recommendation to the target audience and compel them to take action. Dykes (2019) identified five attributes that describe the story quality in business analytics practices, namely: insightful, explanatory, concrete, finite and curated. Similarly, proposed a set of criteria for evaluating the perceived quality of a data story in the analytics environment. These criteria include memorability, engagement, persuasiveness, ease of comprehension, understandability, increased knowledge, and impactful. Memorability represents one of the most interesting characteristics of data story quality. It refers to whether or not the intended audience can recall the (1) the content (e.g., different components, story units, and visualizations), (2) the message(s) conveyed, and (3) the reasoning behind the story (Amini et al., 2018; Tong et al., 2018). Engagement is another important dimension of data story quality as, during the communication of analytical results, it becomes a challenge to hold the audience's attention and increase their participation in the analytical conversation during the delivery of a story (Chevalier et al., 2018). Data stories are also intrinsically persuasive, which offers the storyteller tactics to persuade otherwise resistant audiences and encourage them to act based on the analytical insights delivered (Dahlstrom, 2014). At the same time, data stories are effective in expressing the tacit knowledge and quickly disseminating the analytical insights to reach a wider range of audiences within or outside the organization (Amini et al., 2018). Hence, based on the RBV, data story quality, an intangible IT-enabled resource, is considered as a key dimension of data storytelling competency.

As the process of developing high-quality data stories is often time-consuming, tedious, and requires different skills (Dahlstrom, 2014), business analytics practitioners and story creators need tools and dedicated features that assist them at every stage of the data storytelling process, from collecting key story points and data insights, to assembling identified data insights into a sequence of coherent and meaningful narrative, to delivering the story to the target audience (Knaflic, 2015; Riche et al., 2018). Therefore, the data storytelling tool quality, an IT infrastructure resource, is considered as a key dimension of data storytelling competency. Amini et al. (2018) describe the storytelling tool quality as the specific characteristics and features that determine the tool's ability to produce data stories that are useful to the target audience. They proposed a number of criteria for assessing the quality of the storytelling tool in the context of business analytics. These criteria include efficiency, effectiveness, learnability, integration, collaboration, and expressiveness. The efficiency of a storytelling tool relates to how quickly a storyteller or team of storytellers can produce data stories using the storytelling tool and how many stories can be produced using the tool. The effectiveness of a storytelling tool refers to whether storytellers can achieve their goal of producing data stories using the tool. This also includes the usefulness of features and capabilities of the storytelling tool to support the series of activities or tasks required to develop and deliver data stories to the target audience. Learnability relates to the ease with which the features are identified in a tool's interface and the time needed to learn how to appropriately use them. Integration, in the context of storytelling tools, refers to how well the tool integrates into existing analytics workflows, and other tools in the organization. The storytelling tool should also be extensible or modular in such a way that allows story authors to customize or repurpose the existing features of the tool to increase its expressiveness or integration. Collaboration, in the context of storytelling tool quality, relates to whether multiple storytellers can use a tool to generate their stories and share them with others. Finally, expressiveness is related to the range and types of stories that storytellers can create using the tool, individually or collaboratively (Amini et al., 2018).

During the data storytelling process, storytellers often participate in multiple roles and activities as they turn raw data into coherent and compelling data stories (Lee et al., 2015). For example, the storyteller is required to select and assemble the data excerpts and insights, build up a storyline around data insights, create the story material and elements, and then deliver the story to the target audience. The development of accessible and engaging data stories requires a broad range of skills related to communication, data analysis, information visualization, interaction design, and software engineering (Riche et al., 2018). However, business analytics practitioners are often skilled at collecting and conducting in-depth analysis of data, but lack the knowledge, experience and skills in how to communicate the business value hidden in the analytical insights (Davenport, 2015; Davenport & Kim, 2013). Indeed, the sophistication of the business analytics tools and the complexity of statistical analysis do not really matter if business analytics practitioners are not adept at delivering and communicating the derived insights to the right audience at the right time in the right format. If the insights gleaned from business analytics applications could help in improving business performance, then those derived insights must help the stakeholders to make decisions and take suitable actions. When business analytics practitioners lack the required storytelling skills, they may want to postpone their tasks, it might take them longer to create value from analytics, they may make mistakes and, as such, they will not be able to solve business problems (Vidgen et al., 2017). Therefore, drawing on the RBV, the storyteller's skills and competencies, a human IT resource, is considered as a key dimension of data storytelling competency.

Additionally, the storyteller needs to understand the audience's processes in arriving at a decision or conclusion from a data story. Similarly, the storyteller has a responsibility to have the subject knowledge necessary to present and deliver the analytical insights in a way that best meets the audience's needs, expectations, backgrounds, and preferences (Al-Kassab, Ouertani, Schiuma, & Neely, 2014; Amini et al., 2018). Data stories are more impactful and useful when they are crafted with the motivations, goals and decision-making styles of the target audience (Costa & Santos, 2017). Therefore, to increase the adaptability of data storytelling to the needs and styles of different audiences, story authors need to possess the appropriate domain knowledge and think carefully about how to articulate, present, and deliver their analytical insights to the target audience. The required domain knowledge includes a deep understanding of the procedures, facts, and processes involved in a given organization and industry (Bassellier & Benbasat, 2004; Ghasemaghaei et al., 2018). It also includes a deep understanding of the different levels of knowledge and expertise of the target audience (Riche et al., 2018). Having the appropriate domain knowledge enables the storyteller to better identify the key points to deliver and solve business problems of interest to the organization and customers more effectively. This also shapes the breadth and depth of the data story as well as the delivery method, style and presentation of the data story to the target audience (Amini et al., 2018). Therefore, drawing on the RBV, the business and domain knowledge of the storyteller, a human IT resource, is considered as a key dimension of the data storytelling competency.

Data Storytelling Competency and Business Performance

The stream of research on data storytelling that has contributed to business analytics and business performance has gradually drawn more attention from the academic community. In positioning the relevance of data storytelling in this way, several conceptual and practice-oriented studies suggest that the effective use of data storytelling as a means for conveying and communicating analytical insights to business stakeholders is likely to help improving different areas of business performance (Dessart, 2018; Southekal, 2020; Suzuki, Feliú-Mójer, Hasson, Yehuda, & Zarate, 2018; Vora, 2019). For example, a study by Tischler et al. (2017) on the benefits of data storytelling in business analytics practices demonstrated that 74 percent of organizations surveyed were able to increase their revenue by adopting data storytelling as part of their business analytics initiatives. Likewise, 20 percent of organizations claimed that with data storytelling they were able to distinguish themselves from competition, and 85 percent reported that they were able to allocate resources more efficiently. Another study by Boldosova (2019) found that the use of data storytelling in combination with big data analytics techniques can improve customers' adoption of services and products and enhance the relationship between organizations and their customers, thereby developing innovative solutions to meet growing market needs and enhancing existing business processes. Recent studies have also emphasized the pivotal role that data storytelling plays in augmenting business analytics initiatives and assisting individuals in interpreting and making sense of complex data patterns and insights (Boldosova & Luoto, 2019). Sharda, Delen, and Turban (2019) argue that when insights generated from business analytics are integrated into compelling stories, organizations can see a marked change in their performance across key areas of the business, such as return on investment (ROI), return on sales (ROS), customer retention and satisfaction, employees' productivity, employees' growth and professional development, and market share (Aydiner, Tatoglu, Bayraktar, Zaim, & Delen, 2019).

With the increased focus on data-driven business performance, extant research (Barker & Gower, 2010; Mirkovski, Gaskin, Hull, & Lowry, 2019; Sharda et al., 2019) has viewed data storytelling in organizations as a feasible solution to develop an effective communication environment. This communication environment can help develop a better understanding of customer-related business problems and build a strong connection between technical data and business value, thereby increasing business productivity and efficiency. It also can bridge the gap between employees from an experiential perspective, leading to actions that benefit the business performance (Davenport & Kim, 2013; Mirkovski et al., 2019). These benefits include improved understanding of and participation in the business analytics workflow, increased cohesiveness among team members, and higher quality relationships among both internal and external stakeholders. Therefore, by raising the quality and efficiency of data storytelling in business analytics practices, it can help lead to more effective and long-standing business relationships both within and between organizations—a significant pathway to achieving competitive advantage in today's fast-changing business ecosystem (Boldosova, 2019). Furthermore, effective data storytelling can help organizations to rapidly react in a competitive business environment, thereby enabling organizations to assess their overall performance and achievement level in terms of their defined strategy and objectives (Knaflic, 2015).

The literature has also demonstrated the value of storytelling to improve organizational processes and operations (Dykes, 2019; Elias et al., 2013) and collaboration quality, socialization and adaptation of new employees (Gustomo et al., 2019; Riche et al., 2018; Sundin, Andersson, & Watt, 2018), organizational and financial success (Vora, 2019; Welbourne, 2015), innovation capabilities and new product development and dissemination (Ciriello, Richter, & Schwabe, 2017; Dessart, 2018; Mirkovski et al., 2019), organizational knowledge management (Dalkir & Wiseman, 2004; Suzuki et al., 2018) and organizational learning and growth (Hedman, Bødker, Gimpel, & Damsgaard, 2018; Welbourne, 2015). While these studies provide conceptual evidence on the value and importance of using data storytelling in the organizational context, no research has been conducted to empirically test the relationship between data storytelling competency and business performance, and this is yet to be verified empirically through hypothesis testing. This clear justification of the relationship between data storytelling competency and business performance leads to proposing the following hypothesis:

H1: Data storytelling competency (which is characterized by the data quality, story quality, storytelling tool quality, storyteller skills, and storyteller domain knowledge) is positively linked to business performance.

The Mediating Role of Decision-Making Quality

Another way to understand the relationship between data storytelling competency and business performance is to examine whether and to what extent this relationship could be mediated by decision-making quality. Several conceptual studies suggest that the adoption of data storytelling in business analytics practices can contribute positively to business performance by enabling effective and timely data-driven decision-making (e.g., Damodaran, 2017; Davenport & Kim, 2013; Dessart, 2018; Dykes, 2019; Hedman et al., 2018; Herschel & Clements, 2017; Sundin et al., 2018; Vora, 2019). Building on these studies and considering how decision-making quality can mediate the relationship between data storytelling competency and business performance, the conceptual model developed by Boldosova and Luoto (2019) is particularly interesting as it postulates that the effective and appropriate use of data storytelling, resulting from the combined result of business analytics and data-driven environment, is positively related to decision-making quality. Boldosova and Luoto (2019) argue that the purpose of data storytelling is to guide the business analytics user through the process of interpreting and translating big data into valuable business insights, which in turn, can lead to improved decision-making quality and business performance. In enterprise scenarios where business analytics insights (often presented in reports, dashboards, and predictive models) have to be delivered to business stakeholders, data storytelling provides an effective means to illustrate, step-by-step, the use of business analytics to generate actionable insights; understanding the business problem it solves; and making evidence-based decisions that provide a solution to the business problem and ultimately lead to improvements in business processes and outcomes.

This process of illustrating the connection between data storytelling, decision-making and business performance offers an easy and detailed route for practitioners to realize and communicate the value of big data and business analytics solutions in their organizations. Given the amount of information and the complexity of numerical data, it is easier for business analytics users to bridge the gap between raw data and business value creation when organizations provide narratives about the actionable insights and what should be done to arrive at final decisions. As prior research on business analytics suggests (Brady, Forde, & Chadwick, 2017; Vidgen et al., 2017), to reap the full benefits of analytical insights, business analytics practitioners should not only possess technical skills but also have knowledge of the business value of insights for decision-making and performance optimization. Analytical insights are often too numerical and complex to process and interpret by decision-makers and business stakeholders who usually lack analytical skills and knowledge. Data storytelling simplifies the complex nature of technical data by translating them into coherent narratives. At the same time, it serves as a sensemaking heuristic that helps to process large amounts of raw data by aggregating them into meaningful and relevant insights (Boldosova, 2019). Data storytelling, therefore, provides a convenient format for capitalizing on big data and translating a large set of decision alternatives into simpler inferences that aid decision-making and business performance (Boldosova & Luoto, 2019).

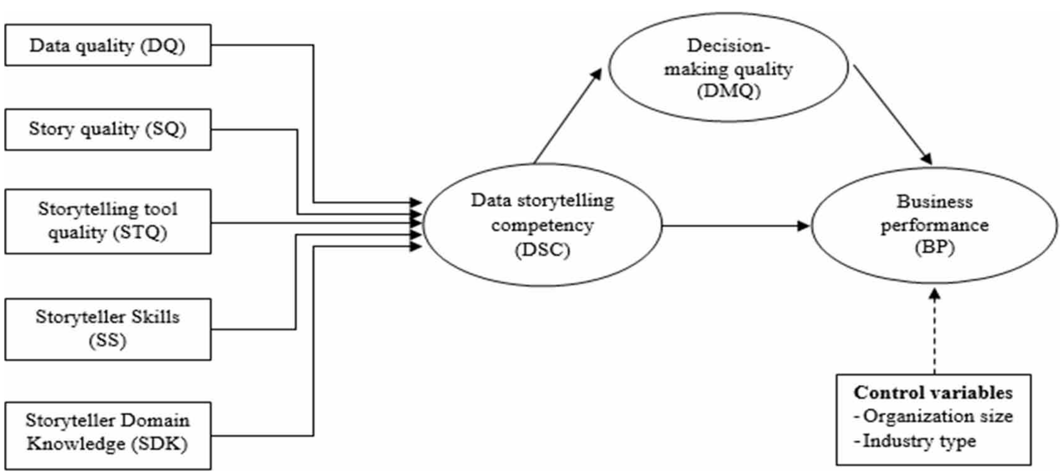
A key advantage of data storytelling is that it connects business analytics and business problems with the target audience by converting complex ideas into easily understandable and shareable visuals and adding context and meaning to the raw data. During data storytelling, business analytics practitioners associate visualizations and analytics with a business case, which positively affects their ability to integrate analytics results into the decision-making process and communicate results to the target audience. To be effective and impactful, data stories should explicitly reflect on how results from business analytics help in solving specific customer-related problems, thereby enhancing the quality of decision-making and business performance. Prior research (Brady et al., 2017) has emphasized the importance of data storytelling as a mechanism to bridge the knowledge gap between business analytics practitioners and the audience in understanding and interpreting analytical insights. At the same time, storytelling can help to fill in experiential gaps between employees by establishing a shared cognitive basis and collaborative work environment that enables them to develop their analytics and storytelling skills (Hedman et al., 2018). Given that human interaction and collaboration are critical to understanding and interpreting data insights (Riche et al., 2018), effective data storytelling in combination with business analytics techniques provide a powerful means for improving decision-making quality and business performance in organizations.

The literature on business analytics provides additional support for the relationship between decision-making quality and business performance. Knowledge accumulated in this area suggests that organizations having complete and accurate information about the likely relationship between choices and outcomes enable them to improve decision-making effectiveness (Cao, Duan, & Li, 2015), make consistently sound and rational decisions (Cao, Duan, & Cadden, 2019), or improve the quality of decision outcomes (Ghasemaghaei et al., 2018). Other studies (White, Burger, & Yearworth, 2016) suggest that organizations that are adept at extracting and communicating analytical insights to technical and non-technical audiences through telling compelling stories can extend the reach and scope of business analytics applications to address a wider range of business problems and needs. Such expansion must support the needs of the analytics audience for personalized and collaborative decision-making environment (Daradkeh, 2019b). It also enables organizations to build an analytics-driven culture and improve analytics literacy among employees, leading to a better productivity and performance (Boldosova, 2019; Dahlstrom, 2014). These studies suggest that data storytelling competency is closely associated with decision-making and business performance, though the exact interrelationship between them is unclear. Therefore, in addition to assuming a direct relationship between data storytelling competency and business performance, it is deemed plausible and pertinent to postulate that data storytelling competency improves the quality of decision making, which in turn becomes a driver of business performance. Thus, this study conjectures that:

H2: Decision-making quality mediates the relationship between data storytelling competency (which is characterized by data quality, story quality, storytelling tool quality, storyteller skills, and storyteller domain knowledge) and business performance.

As a result, a research model that shows the relationship between data storytelling competency and business performance mediated by decision-making quality is summarized and presented in Figure 1.

Figure 1. Research model



RESEARCH METHODOLOGY

To test the research model and hypotheses, this study used a quantitative research methodology based on a self-administered questionnaire to collect the data and PLS-SEM to analyze the data. The research steps including measures development, data collection, and data analysis are discussed in this section.

Measures Development

The research model proposed in this study (Figure 1) is composed of three main constructs: data storytelling competency (DSC), decision-making quality (DMQ), and business performance (BP). DSC is operationalized as a single higher-order multidimensional construct defined by five underlying subconstructs formatively and collectively: data quality (DQ), story quality (SQ), storytelling tool quality (STQ), storyteller skills (SS), and storyteller domain knowledge (SDK). While operationalizing DSC as a formative multidimensional construct may increase the complexity of the model, it may better describe the construct, measurement items, and underlying theory and relationships (Hair, Hult, Ringle, & Sarstedt, 2017). This parsimonious conceptualization of DSC seems to be pertinent based on the conceptualization of DSC presented in this study and the widely accepted assumption of the RBV that the improvement in business performance come from the level of IT competencies within the organization and the position of organization’s resources and capabilities (Barney, 1991; Bharadwaj, 2000; Ghasemaghaei et al., 2018).

To ensure content validity, all measurement items were derived from previous studies and adapted to suit the context of data storytelling in business analytics. The final set of measurement items and their associated constructs and sources is enclosed in the Appendix. DQ and STQ were measured as formative constructs using a 6-item scale adapted from Wang and Strong (1996) and a 7-item scale adapted from Amini et al. (2018), respectively. SQ, SS, and SDK were measured as reflective constructs using a 6-item scale adapted from Amini et al. (2018), a 4-item scale adapted from Tippins and Sohi (2003) and a 4-item scale adapted from Bassellier and Benbasat (2004), respectively. The constructs in this study were conceptualized as reflective or formative based on the four decision rules suggested by Petter, Straub, and Rai (2007): the direction of causality between constructs and their measures, the interchangeability of measures, the covariation among measures, and the nomological net for the measures. This helps define the constructs properly; thereby reducing the chances of inappropriate definition of constructs that may drastically affect the validity of the constructs and statistical conclusions and/or theory development and testing (Hair, Risher, Sarstedt, & Ringle, 2019; MacKenzie, Podsakoff, & Podsakoff, 2011).

DMQ and BP were operationalized as formative constructs. DMQ was measured in terms of whether the organization is effective and efficient at making accurate, reliable, precise, flawless, and timely decisions, which is consistent with the research on decision-making quality and business performance (Cao et al., 2015; Ghasemaghaei et al., 2018; Jarupathirun & Zahedi, 2007). BP was measured in terms of whether the organization is effective in terms of reducing cost, increasing sales, generating revenue and profits, improving productivity, and enhancing relationships with customers and stakeholders (Aydiner et al., 2019; Y. Chen et al., 2014; Loukis, Janssen, & Mintchev, 2019). Each measure captures different aspect of BP, and thus, this operationalization of the construct is formative; as the combination of these variant measures defines the construct of BP (Hair et al., 2017; Petter et al., 2007).

To further check for face and content validity, the measurement items and their associated constructs were sent to a panel of four respondents (three lecturers in MIS and one graduate student majoring in MIS) to obtain their feedback on appropriate measures for inclusion, following the methodology proposed by Moore and Benbasat (1991). After updating the measurement items based on the feedback and suggestions of the panel, all the measurement items in the survey were presented to another panel of three graduate students, who were then asked to categorize the measures for each construct. They were also asked to provide comments on unclear or ambiguous measures. In this process, only one measure related to story quality was found to be irrelevant and ambiguous. According to the comments of the judges, the rest of the measures were refined and retained for the next sorting round. In the second round, another five graduate students were asked to categorize and sort the retained measures based on the constructs' conceptualization. This round of sorting ended with an average agreement rate of 93%, indicating a very high reliability (Moore & Benbasat, 1991). This process has contributed to the establishment of reliable and valid measurement items for the constructs. The measurement items for each construct were further tested in the measurement model validation.

Two potentially relevant control variables were also included in the questionnaire. First, this study included organization size, operationalized with number of employees, as larger organizations have access to more resources than smaller organizations (Y. Chen et al., 2014), which may affect the relationship between DSC and BP. Based on a categorical description of organization size suggested by Judge and Elenkov (2005), organizations with fewer than 100 employees were classified as 'small', whereas organizations with more than 100 employees but fewer than 1000 employees were classified as 'medium', and organizations with more than 1000 employees as 'large'. Second, this study controlled for the industry type because different industries have different performance characteristics and involve different environmental factors, which may impact constructs and relationships in the research model (Ashrafi, Zare Ravasan, Trkman, & Afshari, 2019; Cao et al., 2015).

Sampling and Data Collection

As the purpose of this study is to examine the impact of data storytelling in the context of business analytics practices, the target population of this study consisted of business analytics practitioners as they could meaningfully answer technology-related and business-related questions in the questionnaire (Carter, Grover, and Thatcher 2011). Hence, the respondents were recruited via purposive sampling based on their work position and experience with business analytics within their organization; and should therefore be considered a convenience and representative sample. In particular, the sample in this study included employees whose primary job function involves working with data and analytics to solve business problems that impact business decisions and performance. Typically, a business analyst's job includes the collection of requirements and data for business problems across the organization to translate these data into analytical insights, coordination of the work with the business analytics team, and communication of their analytical findings with internal and external stakeholders (Daradkeh, 2019a). The participation in this study was on a voluntary basis with no financial incentive offered. The respondents were informed that the data gathered from questionnaires are strictly anonymous and confidential and will be used for research purposes only.

A total of 600 electronic questionnaires were mailed out to the addresses of the respondents. The responses received came from organizations of a diverse size and industry background in Jordan, as illustrated in Table 2. Jordan has a very high level of information and communication technology adoption, and a very dynamic business sector that places it in a good place in the Middle East to capitalize on digital transformation opportunities (Schwab, 2019). The sample was selected from the list of the 500 largest corporations in Jordan, published by Oxford Business Group (2018). The names and titles of respondents in the selected organizations were obtained from several sources, such as corporate directories, personal contacts, professional forums and LinkedIn profiles. Initially, the respondents were contacted informally by phone to explain to them about the purpose of the study, as well as the anonymity and confidentiality of data collected. After the phone contact, an email invitation to participate in the study was sent out to respondents followed by two reminder emails, each spaced about two weeks apart. The data collection process lasted for five months (September 2019 – January 2020). The average completion time of the questionnaire was 25 minutes.

After two follow-up emails and several personal and telephone contacts, 200 questionnaires were collected, constituting a response rate of 33%. Of these, 182 questionnaires were accepted as valid responses after discarding responses with incomplete or invalid answers. The usable response rate was well above the conventionally accepted level as suggested by Nulty (2008). Furthermore, in the structural model of this study, the largest number of formative items used to measure a single construct is nine; thus, a minimum sample size of 90 is required for PLS analysis, as suggested by Hair et al. (2017). The minimum sample size requirement was also assessed using G-Power software, and the results showed that the minimum sample size required is 88 in order to detect a minimum R^2 value of at least 0.25 in any of the constructs at a significant level of 5% and statistical power of 80%, which is consistent with the recommended minimum sample size estimations proposed by Hair et al. (2017) for PLS-SEM applications. Since 182 usable responses were collected in this study, the sample size met the common standards for PLS modeling.

Data Analysis

This study estimates the model using PLS-SEM which has recently received considerable attention in a variety of disciplines; and thus, proved to be more appropriate for estimating a hierarchical model than covariance-based SEM (CB-SEM) (Hair et al., 2017; Hair, Hult, Ringle, & Sartedt, 2014; Hair et al., 2019). PLS can successfully avert the constraints on distributional properties (i.e., assumptions of multivariate normality), sample size, measurement level, model complexity, model identification and sign indeterminacy of latent constructs. Furthermore, PLS path modeling is consistent with the prediction-oriented objective of this study, which aims to develop and test a theoretical model through exploration and prediction (Hair et al., 2019; Huang, 2020).

PLS analysis was conducted and reported in this study following a two-step approach as suggested by Hair et al. (2019). In the first step, the quality of the measurement model was assessed in terms of reliability, convergent and discriminant validity (measurement model evaluation). The second step involves the evaluation of the validity of the proposed theoretical model and assessing the strength of the hypothesized causal paths among constructs (structural model evaluation). SmartPLS 3.0 professional version (Ringle, Wende, & Becker, 2015) was used to execute all PLS analyses. Following the recommended guidelines by Hair et al. (2017), a non-parametric bootstrapping procedure with 5000 replications was used to obtain the standard errors of the estimates and calculate the level of significance of the regression coefficients.

RESULTS

Respondents

In addition to the items used to measure constructs in the proposed model (Figure 1), the questionnaire asked respondents to provide demographic data including their gender, age, industry type, experience in business analytics practices, and their position in the organization. Table 1 summarizes the demographic data of respondents. Around 68% of the respondents are male. 23% of the respondents fall in the 20-29 age group, 34% fall in the 30–39 age group, 30% fall in the 40–49 age group, and 13% of the respondents are above 50 years old. The respondents are working in organizations with different sizes ranging from less than 100 employees to more than 1000 employees. Specifically, 59% of the respondents are working in organizations with less than 100 employees, 27% are working in organizations with a size of between 100–1000 employees, and 14% of the respondents are working in organizations with more than 1000 employees. Regarding industry type, 36% of the respondents are working in the services and retail sector, 14% are working in the telecommunication sector, 13% are working in banks and financial sector, 8% are working in the healthcare sector, 8% are working in governmental organizations, and 11% are working in the manufacturing, transportation and energy sectors. The position of respondents shows that 69% of the respondents are in the business intelligence, analytics and data science positions, 15% of respondents identify themselves as application/product developers and engineers, and the rest of them (17%) hold managerial and executive positions in

Table 1. Demographics of respondents

Demographics		Frequency (n=182)	Percentage (%)
Gender	Male	123	68%
	Female	59	32%
Age	20 – 29	42	23%
	30 – 39	61	34%
	40 – 49	55	30%
	Above 50 years old	24	13%
Analytics experience	Under 2 years	5	03%
	2 – 5 years	22	12%
	6 – 10 years	65	36%
	11-15 years	60	33%
	16-20 years	19	10%
	Above 20 years	11	06%
Work position	Business/data analyst	41	23%
	BI Developer/ consultant	32	18%
	Data engineer/scientist	27	15%
	Sales/marketing/account/HR analyst	24	13%
	Application Engineer/developer	20	11%
	Manager/director of analytics	30	17%
	R&D/product developer	8	04%
Industry	Services	37	20%
	Retail	29	16%
	Telecommunications	25	14%
	Banks and Finance	23	13%
	Healthcare	15	08%
	Government	15	08%
	Manufacturing	10	05%
	Transportation	6	03%
	Energy and utilities	5	03%
	Education	5	03%
	Miscellaneous	12	07%
Organization Size (Number of employees in organization)	<100	108	59%
	100-1000	49	27%
	>1000	25	14%

analytics. The respondents have a mix of roles with different levels of analytical competency and domain knowledge; from analysts and data scientists who work with data and analytics on a daily basis, to analytics managers who need to provide guidance and feedback to analysts, to executives who need to incorporate analytics into their work and routinely deliver results to internal and external stakeholders. Overall, the sample of respondents seemed to be diverse, representing various industries, business analytics positions and experiences.

Evaluation of the Measurement Model

As the structural model includes both formative and reflective constructs, they were evaluated separately following different processes and criteria as suggested by (Hair et al., 2017; Hair et al., 2019). The evaluation is performed first for reflective constructs and then for formative constructs. The reflective constructs (i.e. SQ, SS, and SDK) were evaluated by examining their measures reliability, internal consistency, convergent validity (AVE) and discriminant validity, following the recommendations made by Hair et al. (2019). Measures reliability was assessed by examining the loading of each measure on its assigned construct. The results in Table 2 show that the measures loadings on their assigned construct are larger than the suggested threshold of 0.70; indicating acceptable measure reliability (Hair et al., 2019).

The internal consistency reliability, convergent and discriminant validity of reflective constructs were assessed using composite reliability, Cronbach's alpha, average variance extracted (AVE), and Fornell-Larcker criterion (Fornell & Larcker, 1981). As shown in Table 2, the composite reliability and Cronbach's alpha of all reflective constructs were large than the recommended threshold of 0.70 (Fornell & Larcker, 1981). Moreover, all average variance extracted (AVE) estimates were higher than 0.5, and the square root of the AVE value for each construct (the diagonal elements in Table 3) was larger than the correlation between that construct and any other construct in the model; indicating that all reflective constructs were sufficiently valid and reliable as each construct explains more than half of the variance of its measurement items (Fornell & Larcker, 1981; Hair et al., 2017; Hair et al., 2014; Hair et al., 2019).

The formative constructs in the structural model were evaluated based on examining the outer weights and outer loadings of measurement items, significance of weights, and multicollinearity (Hair et al., 2019). Based on bootstrapping (5000 samples), the outer weights of all formative items, outer loadings and their associated significance testing p-values were assessed, which are

Table 2. Assessment of reliability, convergent, and discriminant validity of reflective constructs

Construct	Items	Items Loadings*	Composite Reliability	Cronbach's Alpha	AVE
SQ	SQ1	0.881	0.847	0.773	0.682
	SQ2	0.873			
	SQ3	0.828			
	SQ4	0.848			
	SQ5	0.873			
	SQ6	0.848			
SS	SS1	0.835	0.885	0.741	0.658
	SS2	0.833			
	SS3	0.833			
	SS4	0.820			
SDK	SDK1	0.802	0.826	0.711	0.644
	SDK2	0.825			
	SDK3	0.803			
	SDK4	0.817			

* Items loadings are significant at $p < 0.001$.

Table 3. Inter-construct correlation matrix for reflective constructs

	Mean	S.D.	SQ	SS	SDK
SQ	2.76	0.90	0.826		
SS	2.62	1.08	0.34**	0.811	
SDK	2.06	1.04	0.38**	0.26**	0.802

summarized in Table 4. Following the procedure suggested by Hair et al. (2017), all outer weights of formative items were satisfactory; indicating that these items absolutely contribute to forming their associated constructs. Based on the statistical significance of outer weights and outer loadings, all items were retained. To assess the level of multicollinearity, the variance inflation factor (VIF) for each of the formative items was evaluated. Based on Hair et al. (2019), all VIF values were acceptable (below the critical value of 5.0); thus, there were no multicollinearity problems between the measurement items.

Common Method Bias

As all data for independent, dependent, and mediating constructs are collected at the same time using a self-reported questionnaire, there is a potential concern of common method bias (CMB) (Chin, Thatcher, & Wright, 2012; Jordan & Troth, 2020; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). To assess the potential occurrence of CMB, the Harman's one-factor and marker variables tests were conducted as recommended by Podsakoff et al. (2003). Evidence of CMB exists if a single factor can explain the majority of variance, or if un-rotated factor solutions result in a single factor (Jordan & Troth, 2020). An exploratory factor analysis was run on the items in the measurement model. The results yielded several factors with eigenvalues greater than 1.0, which accounted for 78.6% of the total variance. The first factor captured 40.3% of the variance in the data, which is well below the 50% threshold as recommended by Podsakoff et al. (2003). Thus, none of the identified factors explains the majority of variance.

The marker variable technique was also applied to further test for CMB (Roldán & Sánchez-Franco, 2012). CMB can be assessed based on the correlation between the marker variable and the theoretically unrelated variable (Bucic, Ngo, & Sinha, 2017; Jordan & Troth, 2020). A marker variable (gender) was implemented in the study that was theoretically unrelated to at least one other variable in the study (e.g. DMQ). The value of 0.009 was chosen as an estimate of the amount of method variance which was parceled out from other correlations, and the analysis was rerun. The results indicated no significant difference between the original correlation estimates and the adjusted ones. Given the results of the Harman's one-factor test and the marker variable test, the common method bias is not substantial in the collected data; therefore, is not likely to contaminate the results.

Evaluation of the Structural Model

With no serious problems detected in the psychometric properties of the measurement (or outer) model and instruments, this study next conducted a structural (inner) model analysis to find evidence supporting the theorized relationships between DSC, DMQ, and BP. Results of the structural model analysis are shown in Figure 2, which illustrates the explained variance of endogenous constructs $\left(R^2\right)$ and the standardized path coefficients (β). The significance values for path coefficients were obtained via a bootstrap re-sampling technique with 5000 subsamples (Hair et al., 2017; Hair et al., 2019; Hair, Sarstedt, Ringle, & Gudergan, 2018).

Based on the results in Figure 2, all path coefficients in the model were found to be significant. H1 postulates that DSC has a direct effect on BP, which was supported (β=0.198, $p < 0.001$). To verify H2, the mediating role of DMQ on the relationship between DSC and BP was analyzed and

Table 4. Outer weights, outer loadings and significance testing results of formative constructs

Constructs	Items	VIF	Outer weights	Outer loadings	p-values
DQ	DQ1	1.248	0.423	0.775	0.0000***
	DQ2	1.336	0.227	0.831	0.0136*
	DQ3	1.238	0.470	0.932	0.0000***
	DQ4	1.145	0.488	0.895	0.0000***
	DQ5	1.138	0.231	0.817	0.0000***
	DQ6	1.029	0.199	0.901	0.0091**
	DQ7	1.235	0.385	0.856	0.0000***
STQ	STQ1	1.285	0.327	0.795	0.0000***
	STQ2	1.281	0.338	0.872	0.0000***
	STQ3	1.081	0.405	0.928	0.0000***
	STQ4	1.097	0.457	0.902	0.0000***
	STQ5	1.135	0.365	0.743	0.0000***
	STQ6	1.836	0.467	0.773	0.0000***
	STQ7	1.438	0.444	0.896	0.0000***
DMQ	DME1	1.482	0.307	0.844	0.0000***
	DME2	1.154	0.307	0.917	0.0000***
	DME3	1.029	0.364	0.838	0.0000***
	DME4	1.602	0.207	0.828	0.0155*
	DME5	1.515	0.277	0.818	0.0301*
	DME6	1.168	0.308	0.862	0.0000***
BP	BP1	1.499	0.332	0.815	0.0000***
	BP2	1.398	0.302	0.797	0.0000***
	BP3	1.669	0.414	0.731	0.0000***
	BP4	1.694	0.512	0.715	0.0000***
	BP5	1.792	0.422	0.814	0.0000***
	BP5	1.847	0.375	0.801	0.0000***
	BP7	1.525	0.412	0.742	0.0000***
	BP8	2.015	0.388	0.802	0.0000***
	BP9	1.087	0.349	0.801	0.0000***

summarized in Table 5, following the recommendations made by (Baron & Kenny, 1986) Baron and Kenny (1986) state that a mediation effect of a construct exists when: 1) the independent construct significantly affects the mediator; 2) the mediator significantly affects the dependent construct; and 3) the direct effect from the independent to dependent constructs is reduced when the mediator is controlled for. A relationship is considered fully mediated when the direct path between independent and dependent constructs is significantly reduced to zero. Conversely, a partial mediating effect occurs when the mediator explains some, but not all, of the effect between the independent and dependent constructs (Kim, 2019).

Figure 2. Path analysis results

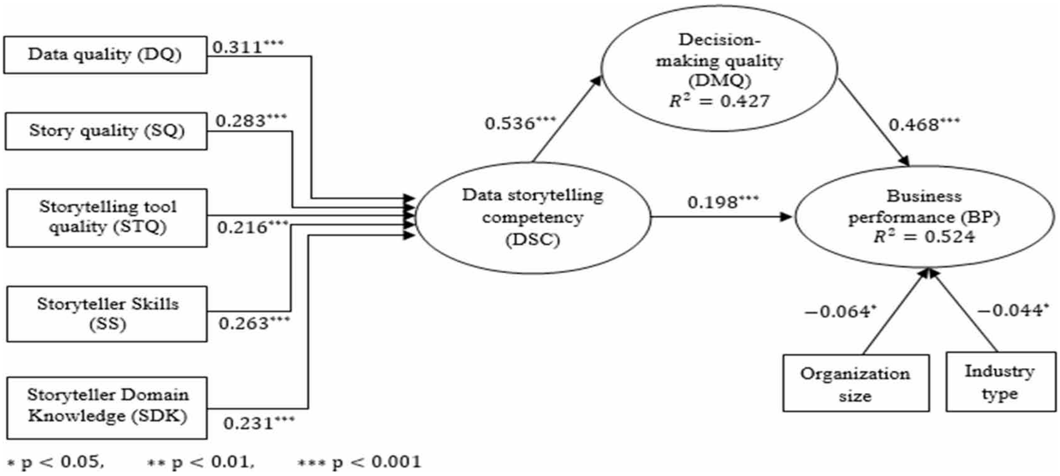


Table 5. The mediation of DMQ on the relationship between DSC and BP

Hypothesis	Direct effect without mediation	Direct effect with mediation	Indirect effect	VAF	Mediation type observed
H2	0.317***	0.198***	0.251***	0.652	Partial

$*p < 0.05, **p < 0.01, ***p < 0.001$
VAF > 0.80 full mediation, 0.20 <= VAF <= 0.80 partial mediation, VAF < 0.20 no mediation.

To analyze the mediating effect of DMQ, the direct relationship between DSC and BP was estimated, which was significant. Then the mediator, DMQ, was included to analyze whether the indirect effect of DSC via DMQ on BP was significant. The evaluation found a significant relationship between DSC and DMQ (β=0.536, p < 0.001) and between DMQ and BP (β=0.468, p < 0.001). Therefore, the indirect effect of DSC via DMQ on BP (i.e., the product of each indirect path coefficient in Figure 2) was 0.251 (0.536×0.468), and its significance was confirmed by calculating the empirical p-value of the indirect effect based on the 5000 bootstrap resamples. The magnitude of the mediating effect was examined by calculating the variance accounted for (VAF) based on Shrout and Bolger (2002), which demonstrated that DMQ partially mediates the effect of DSC on BP (VAF=0.652, p < 0.001); thus Hypothesis 2 is supported. These results lend empirical support to the theoretical proposition in this study that the DSC can explain substantial variance in BP through DMQ.

The explanatory power (or predictive accuracy) of the research model was determined by examining the coefficient of determination (R^2) value, of each dependent construct, which indicates to what extent the variance in the exogenous constructs explains the variance in the endogenous construct. When PLS-SEM is used, the acceptable values of R^2 is 0.75 (substantial), 0.50 (moderate) and 0.25 (weak) (Hair et al., 2019). In line with this, the R^2 values, as depicted in Figure 2, indicate that 52.4% of the variance in BP can be attributed to the mediation of DMQ on the relationship between DSC and BP; suggesting that the effect of DSC on BP is indirect as it is mediated by DMQ. Furthermore, the effect of DSC on DMQ is moderate (R^2 =0.427); suggesting that 42.7% of the variance in DMQ can be explained by the variance in DSC.

Table 6 shows the standardized path coefficients (β) for each hypothesized path of the theoretical model (excluding the control variables) and the full model including all variables. The results show

Table 6. Summary results of path analysis

Path	Path Coefficients	
	Theoretical model (a)	Full model (b)
	0.536***	0.536***
DMQ $\rightarrow$ BP	0.586***	0.468***
DSC $\rightarrow$ BP	0.238 ***	0.198 ***
Control variable	Firm size $\rightarrow$ BP	— .064*
	Industry type $\rightarrow$ BP	— .044*
ΔR^2 value for BP	$\Delta R^2 = 0.524b - 0.501a = 0.023$ ***	
$*p < 0.05, **p < 0.01, ***p < 0.001$ ns= not significant		

that the organization size did not significantly influence BP (β=−0.064; p > 0.05). Similarly, industry type did not significantly impact BP (β=−0.044; p > 0.05). Thus, the effect of the control variables was deemed marginal.

DISCUSSION

While data storytelling has been increasingly recognized as a critical competency for organizations seeking to leverage business analytics to improve their business performance (Davenport, 2015; Dykes, 2016, 2019; Herschel & Clements, 2017), empirical research that examines the relationship between data storytelling competency and business performance is still scarce. Rather than assuming a direct relationship between data storytelling competency and business performance that creates a black box issue, this study has examined this relationship by modeling decision-making quality as a mediator that intervenes the relationship between data storytelling competency and business performance. This study operationalized and validated the concept of data storytelling competency as a multidimensional construct consisting of five key dimensions: data quality, story quality, storytelling tool quality, storyteller skills, and storyteller domain knowledge. By operationalizing and testing the dimensions that constitute data storytelling competency, this study provides theoretical and empirical evidence on why data storytelling competency in business analytics practices is likely to be a key factor in improving the quality of decision making and business performance in organizations.

Implications for Research

This study mainly contributes to the limited body of empirical research linking data storytelling and business performance by developing a mediation model that not only shows a positive relationship between data storytelling competency and business performance, but this relationship can also be significantly mediated by decision-making quality. While conceptual research on data storytelling (Boldosova & Luoto, 2019; Elias et al., 2013; Herschel & Clements, 2017) generally suggests that data storytelling capabilities can help improving decision-making quality and business performance, such a belief has rarely been examined based on testable hypotheses underpinned by theories. The findings from this study make an original contribution to the data storytelling literature by providing an explanation for, and new insights into, how data storytelling competency creates a strategic value for business analytics practices and the resulting business decisions and performance.

Viewed from a resource-based perspective, the empirical findings of this study demonstrate the unique importance of all five dimensions of data storytelling competency (i.e., data quality, story quality, storytelling tool quality, storyteller skills, and storyteller domain knowledge) as they all significantly contribute to building the data storytelling competency in business analytics practices. Evidence of their contribution to building the data storytelling competency through measurement relations is strong; the strong predicted relationship observed with decision-making quality and business performance (identified through structural relations) further supports the validity of the data storytelling competency construct and related dimensions. Indeed, data storytelling in business analytics practices has been subject to little robust empirical examination to date, and a myriad of definitions, conceptualizations and uses circulate among practitioners (Dykes, 2019; Mathisen et al., 2019). The conceptualization and operationalization of the multifaceted and multidimensional concept of data storytelling competency in business analytics practices in such a way that encompasses the different functions and purposes presents a novel addition to the data storytelling literature. The observed strong positive relationships between data storytelling competency and related dimensions point to the importance of studying the avenues to enhance the status of each dimension in organizations.

Furthermore, the findings from this study adds to the limited body of empirical research on the impact of data storytelling and the role it can play to improve different aspects of business performance. The strong and positive relationship observed between data storytelling competency and business performance (H1: $\beta=0.198$, $p < 0.001$) suggests that the effective use of data storytelling in business analytics practices can positively contribute to improving business performance by enabling better communication of the analytical insights to reach a wider audience, guiding the audience towards key insights, and inciting interpretation, inferences, and decisions to a degree that would not be possible using purely visual or numerical-based communication formats. This empirical finding supports previous conceptual studies (Boldosova & Luoto, 2019; S. Chen et al., 2020; Mathisen et al., 2019) suggesting that data storytelling can help bridge the gap between discovering insights in the data and influencing business stakeholders to achieve optimum performance. By improving the quality and competency of data storytelling, the organization will be able to better understand business problems and the needs of customers and stakeholders, make informed and insightful business decisions, and respond quickly to changes (Vora, 2019; Welbourne, 2015). As a result, the organization could attract new customers, increase customer loyalty and retention, provide products and services that meet consumers' needs, and reduce the cycle time in all aspects of a business, thus providing greater value to its customers and improving the efficiency of internal processes (Davenport, 2015; Sundin et al., 2018; Suzuki et al., 2018).

The findings from this study also provide empirical evidence that the relationship between data storytelling and business performance could be mediated by decision-making quality. The result of the mediation model demonstrates that decision-making quality partially mediates the relationship between data storytelling competency and business performance (H2: VAF=0.652, $p < 0.001$). This finding implies that data storytelling competency has a positive effect on decision-making quality, which in turn has a positive impact on business performance. This mediating effect suggests that the quality of decision-making is an important intervening factor that helps to explain how data storytelling in business analytics indirectly improves business performance. This seems perfectly plausible because by effectively communicating analytical insights through data storytelling, the organization will be able to enhance its information processing and analysis capabilities to meet decision-making requirements (Rouhani et al., 2018), and therefore, to be more effective and efficient in making better, more informed, and high-quality decisions that lead to better business performance. This is consistent with and provides support for practice-oriented studies on data storytelling (e.g., Davenport, 2015; Davenport & Kim, 2013; Dykes, 2016, 2019) who suggest that organizations that are adept at capturing, analyzing and communicating analytical insights to the target audience can effectively integrate key insights into business processes; and hence, improve the quality of decision-making and overall performance. By linking the data storytelling capabilities to decision-making quality, this study may stimulate other researchers to further examine the relationship between data storytelling capabilities and dimensions of decision-making quality (e.g. efficiency, effectiveness, accuracy and correctness) as the impact of data storytelling capabilities in business analytics practices are rarely considered in the literature (Boldosova & Luoto, 2019).

Implications for Practice

The findings from this study have important implications for business analytics practitioners as well as organizations seeking to build or improve their data storytelling competency for extending the reach and impact of business analytics capabilities within their organizations. This study provides practitioners with a deeper understanding of the mechanism through which the potential value of data storytelling can be attained. The findings suggest that business analytics practitioners can help organizations to improve their decision-making process and business performance not only by collecting, processing and performing statistical analysis of data, but also by being skilled at communicating the analytical findings to the relevant audience in a compelling, engaging, and influential way. By developing their data storytelling competency, the business analytics practitioners will be able to better share, communicate, and utilize information and insights. This in turn will allow decision-makers, executives and other business stakeholders to have complete and accurate information about the likely relationship between choices and outcomes, such as better understanding of customers, serving them better by developing products and services that meet their needs; thereby, increasing the loyalty and retention of customers (Boldosova, 2020; Knaflic, 2015; Lee et al., 2015). Similarly, by adopting data storytelling in business analytics applications, organizations will be able to make consistently sound and rational choices, make decisions faster and timely than ever before, and act confidently and decisively in a fast-paced marketplace (Vora, 2019).

Furthermore, this study provides practical insights and guidance by deconstructing some of the key peculiarities and nuances of data storytelling competency and its relationship to decision-making quality. To improve data storytelling competency, organizations could, for example, embark on training to improve storytelling skills and competency of business analytics practitioners; when employees have the skills needed to fulfill their job demands, the results of their work are improved (Riche et al., 2018; Welbourne, 2015). As discussed in Knaflic (2015), part of the challenge to the business community is that data storytelling is often seen as a single step in the business analytics process. Those hired into analytical roles typically have quantitative backgrounds that suit them well for the other steps (i.e., finding the data, integrating them together, analyzing them, and building quantitative models), but not necessarily any formal training in data storytelling to help them when it comes to the communication of the analytical results to the non-technical audience. Likewise, managers need to ensure that employees who want to take advantage of data storytelling capabilities and tools for efficient decision-making have sufficient domain knowledge in order to accurately use the tools and deliver the results to the target audience. Furthermore, managers can employ a thorough selection process when acquiring business analytics tools to ensure that the selected tool is sophisticated enough to support the data storytelling process and activities (Amini et al., 2018). To increase data storytelling competency, managers also need to invest in data quality to reduce the information processing time and improve the quality of decision-making outcomes (Boldosova & Luoto, 2019).

LIMITATIONS AND AVENUES FOR FUTURE RESEARCH

Despite the theoretical and practical contributions of the current study, there are limitations that should be recognized and addressed in future research. First, while this study has demonstrated that there is a positive relationship between data storytelling competency and business performance, which is mediated by decision-making quality, this understanding could be further advanced by including more organizational and environmental factors. In the current study, there might be biases resulting from excluding other salient factors; consequently, the results of this study should be interpreted with this potential problem in mind. Future research could extend the research model in this study by incorporating factors that would provide better understanding of the impact of data storytelling capabilities on business performance, such as knowledge management, customer orientation, synergy, organizational culture and information processing capabilities.

Second, this study was conducted among business analytics practitioners within one developing country (Jordan), and thus the findings from this study should be generalized with some caution. Ashrafi et al. (2019) reported that several issues, such as cultural and structural differences between countries and employees, may cause variations in research outcomes. Given the potential impact of culture on users' perceptions regarding information technology, future research should examine the associations studied here, in other environments. The research model was also examined using cross-sectional data collected through a self-administered questionnaire at one specific point in time. Since some resources and capabilities in firms require a long period of time to develop (Ashrafi et al., 2019), to evaluate their stability, future studies could re-examine the findings using panel data. Subsequent studies could replicate findings from this study in other context (e.g., developed countries) and compare the results with this study or use a longitudinal study to address the limitations of the cross-sectional nature of this study.

Thirdly, data storytelling in the context of business analytics is a relatively new concept, and there seems to be no established academic definition (Mirkovski et al., 2019; Suzuki et al., 2018). The literature review shows that data storytelling incorporates several functions and techniques to support the decision-making process by preparing an appropriate decision environment and engaging stakeholders (Boldosova, 2019). The current study only mentioned data storytelling on a conceptual level an did not delve into the functional details. Thus, the findings could be criticized in terms of its discriminatory power for different types and techniques of data storytelling within an organization. In-depth case studies, such as those developed by Adegboyega and Bahareh (2018) and Boldosova (2019), would be beneficial to provide a more complete understanding of the impact of different types of data storytelling on decision-making and business performance.

Finally, Finally, this study did not specifically address the types, contexts or styles of decision-making. As the relative importance of data storytelling competency and its various dimensions may vary depending on the type of decisions being made, future research is warranted, focusing on examining the impact of data storytelling competency on organizational outcomes in specific contexts, such as marketing promotions, sales management and processes, and knowledge management. Such research would provide more specific guidance on what type of data storytelling an organization should focus on in a given situation to improve its decision-making quality and business performance.

CONCLUSION

With the proliferation of big data and business analytics applications, data storytelling has become increasingly important as an effective means of communicating analytical insights to non-technical audiences to support decision-making and improve business performance. However, empirical research investigating the relationship between data storytelling competency and business performance is rather limited. What is less understood is the mediating role of decision-making quality in the relationship between data storytelling competency and business performance. Drawing on the resource-based view, this study presents and validates the concept of data storytelling competency in business analytics practices as a multidimensional construct consisting of data quality, story quality, storytelling tool quality, storyteller skills, and storyteller domain knowledge. The nomological validity of these dimensions was confirmed by an empirical study based on a survey approach involving a relevant sample of business analytics practitioners. In addition, this study presents a research model for understanding the interrelationships among data storytelling competency, decision-making quality, and business performance. The findings from this study shows that there is a positive relationship between data storytelling competency and business performance, which is partially mediated by decision-making quality. This study provides useful implications for both theory and practice in the emerging field of data storytelling in business analytics, thus stimulating further research on possible antecedents and consequences of using data storytelling in business analytics practices for improving the quality of decision-making in organizations and achieving better business performance.

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REFERENCES

Adegboyega, O., & Bahareh, H. (2018). Patterns in Award Winning Data Storytelling. *Digital Journalism*, *6*(6), 693–718. doi:10.1080/21670811.2017.1403291

Al-Kassab, J., Ouertani, Z., Schiuma, G., & Neely, A. (2014). Information visualization to support management decisions. *International Journal of Information Technology & Decision Making*, *13*(2), 407–428. doi:10.1142/S0219622014500497

Amini, F., Brehmer, M., Bolduan, G., Elmer, C., & Wiederkehr, B. (2018). Evaluating Data-Driven Stories and Storytelling Tools. In N. Riche, C. Hurter, N. Diakopoulos, & S. Carpendale (Eds.), Data-Driven Storytelling (pp. 249-286). A K Peters/CRC Press. doi:10.1201/9781315281575-11

Ashrafi, A., Zare Ravasan, A., Trkman, P., & Afshari, S. (2019). The role of business analytics capabilities in bolstering firms' agility and performance. *International Journal of Information Management*, *47*(1), 1–15. doi:10.1016/j.ijinfomgt.2018.12.005

Aydiner, A., Tatoglu, E., Bayraktar, E., Zaim, S., & Delen, D. (2019). Business analytics and firm performance: The mediating role of business process performance. *Journal of Business Research*, *96*(1), 228–237. doi:10.1016/j.jbusres.2018.11.028

Barker, R., & Gower, K. (2010). Strategic Application of Storytelling in OrganizationsToward Effective Communication in a Diverse World. *Journal of Business Communication*, *47*(3), 295–312. doi:10.1177/0021943610369782

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. doi:10.1177/014920639101700108

Baron, R., & Kenny, D. (1986). The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182. doi:10.1037/0022-3514.51.6.1173 PMID:3806354

Bassellier, G., & Benbasat, I. (2004). Business Competence of Information Technology Professionals: Conceptual Development and Influence on IT-Business Partnerships. *Management Information Systems Quarterly*, *28*(4), 673–694. doi:10.2307/25148659

Behera, R., & Swain, A. (2019). *Big Data Real-Time Storytelling with Self-service Visualization.* Paper presented at the Emerging Technologies in Data Mining and Information Security, Singapore. doi:10.1007/978-981-13-1498-8_36

Bharadwaj, A. (2000). A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation. *Management Information Systems Quarterly*, *24*(1), 169–196. doi:10.2307/3250983

Boldosova, V. (2019). Deliberate storytelling in big data analytics adoption. *Information Systems Journal*, *29*(6), 1126–1152. doi:10.1111/isj.12244

Boldosova, V. (2020). Telling stories that sell: The role of storytelling and big data analytics in smart service sales. *Industrial Marketing Management*, *86*(1), 122–134. doi:10.1016/j.indmarman.2019.12.004

Boldosova, V., & Luoto, S. (2019). Storytelling, business analytics and big data interpretation: Literature review and theoretical propositions. *Management Research Review*, *43*(2), 204–222. doi:10.1108/MRR-03-2019-0106

Brady, C., Forde, M., & Chadwick, S. (2017). Why your company needs data translators. *MIT Sloan Management Review*, *58*(2), 14–16.

Bucic, T., Ngo, L., & Sinha, A. (2017). Improving the effectiveness of market-oriented organisation: Empirical evidence from an emerging economy. *Australian Journal of Management*, *42*(2), 308–327. doi:10.1177/0312896215611189

Cao, G., Duan, Y., & Cadden, T. (2019). The link between information processing capability and competitive advantage mediated through decision-making effectiveness. *International Journal of Information Management*, *44*(1), 121–131. doi:10.1016/j.ijinfomgt.2018.10.003

Cao, G., Duan, Y., & Li, G. (2015). Linking Business Analytics to Decision Making Effectiveness: A Path Model Analysis. *IEEE Transactions on Engineering Management*, *62*(3), 384–395. doi:10.1109/TEM.2015.2441875

Chen, S., Li, J., Andrienko, G., Andrienko, N., Wang, Y., Nguyen, P., & Turkay, C. (2020). Supporting Story Synthesis: Bridging the Gap between Visual Analytics and Storytelling. *IEEE Transactions on Visualization and Computer Graphics*, *26*(7), 2499–2516. doi:10.1109/TVCG.2018.2889054 PMID:30582542

Chen, Y., Wang, Y., Nevo, S., Jin, J., Wang, L., & Chow, W. (2014). IT capability and organizational performance: The roles of business process agility and environmental factors. *European Journal of Information Systems*, *23*(3), 326–342. doi:10.1057/ejis.2013.4

Chevalier, F., Tory, M., Lee, B., Dörk, M., Wijk, J., Santucci, G., & Hullman, J. (2018). *From analysis to communication: Supporting the lifecycle of a story*. New York: A K Peters/CRC Press.

Chin, W., Thatcher, J., & Wright, R. (2012). Assessing Common Method Bias: Problems with the ULMC Technique. *Management Information Systems Quarterly*, *36*(3), 1003–1019. doi:10.2307/41703491

Ciriello, R., Richter, A., & Schwabe, G. (2017). When prototyping meets storytelling: Practices and malpractices in innovating software firms. In *Proceedings of the 39th International Conference on Software Engineering: Software Engineering in Practice Track* (pp. 163-172). IEEE Press. doi:10.1109/ICSE-SEIP.2017.24

Costa, C., & Santos, M. (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*, *37*(6), 726–734. doi:10.1016/j.ijinfomgt.2017.07.010

Dahlstrom, M. (2014). Using narratives and storytelling to communicate science with nonexpert audiences. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(Supplement 4), 13614–13620. doi:10.1073/pnas.1320645111 PMID:25225368

Dalkir, K., & Wiseman, E. (2004). Organizational Storytelling and Knowledge Management: A Survey. *Storytelling, Self, Society*, *1*(1), 57–73. doi:10.1080/15505340409490258

Damodaran, A. (2017). *Narrative and numbers: The value of stories in business*. Columbia University Press., doi:10.7312/damo18048

Daradkeh, M. (2019a). Critical Success Factors of Enterprise Data Analytics and Visualization Ecosystem: An Interview Study. *International Journal of Information Technology Project Management*, *10*(3), 34–55. doi:10.4018/IJITPM.2019070103

Daradkeh, M. (2019b). Determinants of Self-Service Analytics Adoption Intention: The Effect of Task-Technology Fit, Compatibility, and User Empowerment. *Journal of Organizational and End User Computing*, *31*(4), 19–45. doi:10.4018/JOEUC.2019100102

Daradkeh, M. (2019c). Determinants of visual analytics adoption in organizations: Knowledge discovery through content analysis of online evaluation reviews. *Information Technology & People*, *32*(3), 668–695. doi:10.1108/ITP-10-2017-0359

Davenport, T. (2015). *Why Data Storytelling is So Important, and Why We're So Bad at It*. Retrieved from https://dupress.deloitte.com/dup-us-en/topics/analytics/data-driven-storytelling.html

Davenport, T., & Harris, J. (2007). *Competing on Analytics: The New Science of Winning*. Harvard Business School Press.

Davenport, T., & Kim, J. (2013). *Keeping Up with the Quants: Your Guide to Understanding and Using Analytics*. Harvard Business Review Press.

Delen, D., & Zolbanin, H. (2018). The analytics paradigm in business research. *Journal of Business Research*, *90*, 186–195. doi:10.1016/j.jbusres.2018.05.013

Dessart, L. (2018). Do ads that tell a story always perform better? The role of character identification and character type in storytelling ads. *International Journal of Research in Marketing*, *35*(2), 289–304. doi:10.1016/j.ijresmar.2017.12.009

Dourish, P., & Gómez Cruz, E. (2018). Datafication and data fiction: Narrating data and narrating with data. *Big Data & Society*, *5*(2), 1–10. doi:10.1177/2053951718784083

Dykes, B. (2016). *Data Storytelling: The essential data science skill everyone needs*. Retrieved from https://www.forbes.com/sites/brentdykes/2016/03/31/data-storytelling-the-essential-data-science-skill-everyone-needs/#740cb28652ad

Dykes, B. (2019). *Effective Data Storytelling: How to Drive Change with Data, Narrative and Visuals*. John Wiley & Sons, Inc.

Elias, M., Aufaure, M.-A., & Bezerianos, A. (2013). *Storytelling in Visual Analytics Tools for Business Intelligence.* Paper presented at the Human-Computer Interaction – INTERACT 2013, Berlin, Germany. doi:10.1007/978-3-642-40477-1_18

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable and measurement error. *JMR, Journal of Marketing Research*, *18*(1), 39–50. doi:10.1177/002224378101800104

Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *The Journal of Strategic Information Systems*, *27*(1), 101–113. doi:10.1016/j.jsis.2017.10.001

Grant, R. (1991). The Resource-Based Theory of Competitive Advantage: Implications for Strategy Formulation. *California Management Review*, *33*(3), 114–135. doi:10.2307/41166664

Gratzl, S., Lex, A., Gehlenborg, N., Cosgrove, N., & Streit, M. (2016). From Visual Exploration to Storytelling and Back Again. *Computer Graphics Forum*, *35*(3), 491–500. doi:10.1111/cgf.12925 PMID:27942091

Gustomo, A., Febriansyah, H., Ginting, H., & Santoso, I. (2019). Understanding narrative effects: The impact of direct storytelling intervention on increasing employee engagement among the employees of state-owned enterprise in West Java, Indonesia. *Journal of Workplace Learning*, *31*(2), 166–191. doi:10.1108/JWL-07-2018-0088

Gutiérrez, A., Pérez, C. B., Castro, L. A., Chávez, F., & de Vega, F. F. (2017). *Visual stories in business intelligence to support decision making*. Paper presented at the 12th Iberian Conference on Information Systems and Technologies (CISTI), Lisbon, Portugal. doi:10.23919/CISTI.2017.7975893

Hair, J., Hult, G., Ringle, C., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd ed.). Sage.

Hair, J., Hult, G., Ringle, C., & Sartedt, M. (2014). *A primer on partial least squares structural equation modeling*. Sage.

Hair, J., Risher, J., Sarstedt, M., & Ringle, C. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. doi:10.1108/EBR-11-2018-0203

Hair, J., Sarstedt, M., Ringle, C., & Gudergan, S. (2018). *Advanced Issues in Partial Least Squares Structural Equation Modeling*. Sage.

Hedman, J., Bødker, M., Gimpel, G., & Damsgaard, J. (2018). Translating evolving technology use into user stories: Technology life narratives of consumer technology use. *Information Systems Journal*, *29*(6), 1–23. doi:10.1111/isj.12232

Herschel, R., & Clements, N. (2017). The Importance of Storytelling in Business Intelligence. *International Journal of Business Intelligence Research*, *8*(1), 26–39. doi:10.4018/IJBIR.2017010102

Huang, C. (2020). User's Segmentation on Continued Knowledge Management System Use in the Public Sector. *Journal of Organizational and End User Computing*, *32*(1), 19–40. doi:10.4018/JOEUC.2020010102

Jarupathirun, S., & Zahedi, F. (2007). Exploring the influence of perceptual factors in the success of web-based spatial DSS. *Decision Support Systems*, *43*(3), 933–951. doi:10.1016/j.dss.2005.05.024

Jordan, P., & Troth, A. (2020). Common method bias in applied settings: The dilemma of researching in organizations. *Australian Journal of Management*, *45*(1), 3–14. doi:10.1177/0312896219871976

Judge, W., & Elenkov, D. (2005). Organizational capacity for change and environmental performance: An empirical assessment of Bulgarian firms. *Journal of Business Research*, *58*(7), 893–901. doi:10.1016/j.jbusres.2004.01.009

Kim, H. (2019). Investigating the Mediating Role of Social Networking Service Usage on the Big Five Personality Traits and on the Job Satisfaction of Korean Workers. *Journal of Organizational and End User Computing*, *31*(1), 110–123. doi:10.4018/JOEUC.2019010106

Knaflic, C. (2015). *Storytelling with Data: A Data Visualization Guide for Business Professionals*. John Wiley & Sons, Inc. doi:10.1002/9781119055259

Lee, B., Nathalie, H., Petra, I., & Sheelagh, C. (2015). More than Telling a Story: Transforming Data into Visually Shared Stories. *IEEE Computer Graphics and Applications*, *35*(5), 84–90. doi:10.1109/MCG.2015.99 PMID:26416365

Loukis, E., Janssen, M., & Mintchev, I. (2019). Determinants of software-as-a-service benefits and impact on firm performance. *Decision Support Systems*, *117*(1), 38–47. doi:10.1016/j.dss.2018.12.005

MacKenzie, S., Podsakoff, P., & Podsakoff, N. (2011). Construct Measurement and Validation Procedures in MIS and Behavioral Research: Integrating New and Existing Techniques. *Management Information Systems Quarterly*, *35*(2), 293–334. doi:10.2307/23044045

Mathisen, A., Horak, T., Klokmose, C. N., Grønbæk, K., & Elmqvist, N. (2019). InsideInsights: Integrating Data-Driven Reporting in Collaborative Visual Analytics. *Computer Graphics Forum*, *38*(3), 649–661. doi:10.1111/cgf.13717

Mills, J., Platts, K., & Bourne, M. (2003). Applying resource-based theory: Methods, outcomes and utility for managers. *International Journal of Operations & Production Management*, *23*(2), 148–166. doi:10.1108/01443570310458429

Mirkovski, K., Gaskin, J. E., Hull, D. M., & Lowry, P. B. (2019). Visual storytelling for improving the comprehension and utility in disseminating information systems research: Evidence from a quasi-experiment. *Information Systems Journal*, *29*(6), 1153–1177. doi:10.1111/isj.12240

Moore, G., & Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research*, *2*(3), 192–222. doi:10.1287/isre.2.3.192

Morgan, S., Pittenger, K., & McIntyre, N. (2018). Storytelling-An effective tool for moving the needle towards engaged learning. *Paper presented at the Developments in Business Simulation and Experiential Learning: Proceedings of the Annual ABSEL Conference*.

Nelson, R., Todd, P., & Wixom, B. (2005). Antecedents of information and systems quality: An empirical examination within the context of data warehousing. *Journal of Management Information Systems*, *21*(4), 199–235. doi:10.1080/07421222.2005.11045823

Nulty, D. (2008). The adequacy of response rates to online and paper surveys: What can be done? *Assessment & Evaluation in Higher Education*, *33*(3), 301–314. doi:10.1080/02602930701293231

Oxford Business Group. (2018). *The Report: Jordan 2018*. Retrieved 16 September 2019, from https://oxfordbusinessgroup.com/jordan-2018

Petter, S., Straub, D., & Rai, A. (2007). Specifying Formative Constructs in Information Systems Research. *Management Information Systems Quarterly*, *31*(4), 623–656. doi:10.2307/25148814

Podsakoff, P., MacKenzie, S., Lee, J., & Podsakoff, N. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *The Journal of Applied Psychology*, *88*(5), 879–903. doi:10.1037/0021-9010.88.5.879 PMID:14516251

Richardson, J., Sallam, R., Schlegel, K., Kronz, A., & Sun, J. (2020). *Magic Quadrant for Analytics and Business Intelligence Platforms*. Retrieved 11 May, 2020, from https://www.gartner.com/en/documents/3980852/magic-quadrant-for-analytics-and-business-intelligence-p

Riche, N., Hurter, C., Diakopoulos, N., & Carpendale, S. (Eds.). (2018). Data-Driven Storytelling (1st ed.). New York: A K Peters/CRC Press.

Ringle, C., Wende, S., & Becker, J. (2015). *SmartPLS 3* [Computer software]. SmartPLS GmbH. http://www.smartpls.com

Roldán, J. L., & Sánchez-Franco, M. J. (2012). *Variance-Based Structural Equation Modeling: Guidelines for Using Partial Least Squares in Information Systems Research*. IGI Global. doi:10.4018/978-1-4666-0179-6.ch010

Rouhani, S., Ashrafi, A., Ravasan, A. Z., & Afshari, S. (2018). Business Intelligence Systems Adoption Model: An Empirical Investigation. *Journal of Organizational and End User Computing*, *30*(2), 43–70. doi:10.4018/JOEUC.2018040103

Sallam, R., & Howson, C. (2017). *Survey Analysis: Why BI and Analytics Adoption Remains Low and How to Expand Its Reach*. Retrieved 25 February, 2020, from https://www.gartner.com/en/documents/3753469/survey-analysis-why-bi-and-analytics-adoption-remains-lo

Schwab, K. (2019). *The Global Competitiveness Report*. World Economic Forum.

Sharda, R., Delen, D., & Turban, E. (2019). *Analytics, Data Science, & Artificial Intelligence: Systems for Decision Support* (11th ed.). Pearson.

Shrout, P., & Bolger, N. (2002). Mediation in experimental and nonexperimental studies: New procedures and recommendations. *Psychological Methods*, *7*(4), 422–445. doi:10.1037/1082-989X.7.4.422 PMID:12530702

Southekal, P. (2020). *Analytics Best Practices: A Business-Driven Playbook for Creating Value Through Data Analytics*. Technics Publications, LLC.

Sundin, A., Andersson, K., & Watt, R. (2018). Rethinking communication: Integrating storytelling for increased stakeholder engagement in environmental evidence synthesis. *Environmental Evidence*, *6*(7), 1–6. doi:10.1186/s13750-018-0116-4

Suzuki, W., Feliú-Mójer, M., Hasson, U., Yehuda, R., & Zarate, J. (2018). Dialogues: The science and power of storytelling. *Journal of Neuroscience, 38*(44), 9468–9470. 10.1523/JNEUROSCI.1942-18.2018

Tippins, M., & Sohi, R. (2003). IT competency and firm performance: Is organizational learning a missing link? *Strategic Management Journal*, *24*(8), 745–761. doi:10.1002/smj.337

Tischler, R., Mack, M., & Vitsenko, J. (2017). *BARC Research Study: Interactive Analytical Storytelling*. Retrieved 20 February, 2020, from https://www.pac-online.com/25919/185961#:~:text=Interactive%20analytical%20storytelling%20is%20an,storytellers%20by%20explaining%20their%20story.&text=Storybooks%20are%-20an%20integral%20part%20of%20interactive%20storytelling.download/

Tong, C., Roberts, R., Borgo, R., Walton, S., Laramee, R., Wegba, K., & Xiaojuan, M. et al. (2018). Storytelling and Visualization: An Extended Survey. *Information (Basel)*, *9*(3), 1–42. doi:10.3390/info9030065

Vidgen, R., Shaw, S., & Grant, D. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, *261*(2), 626–639. doi:10.1016/j.ejor.2017.02.023

Vora, S. (2019). *The Power of Data Storytelling* (1st ed.). Sage Publications. doi:10.4135/9789353885946

Wang, R., & Strong, D. (1996). Beyond Accuracy: What Data Quality Means to Data Consumers. *Journal of Management Information Systems*, *12*(4), 5–33. doi:10.1080/07421222.1996.11518099

Welbourne, T. (2015). Data-Driven Storytelling: The Missing Link in HR Data Analytics. *Employment Relations Today*, *41*(4), 27–33. doi:10.1002/ert.21471

White, L., Burger, K., & Yearworth, M. (2016). Big data and behavior in operational research: towards a "smart OR". In M. Kunc, J. Malpass, & L. White (Eds.), *Behavioral Operational Research: Theory, Methodology and Practice* (pp. 177–193). Palgrave Macmillan. doi:10.1057/978-1-137-53551-1_9

ENDNOTES

[1] https://www.tableau.com/
[2] https://www.qlik.com/us/
[3] https://powerbi.microsoft.com/en-us/

APPENDIX

Table 7. Constructs and measurement items

Construct	Item	Measure	Sources
Data Storytelling Competency (DSC)			
	The data used for creating data stories in our analytics practice are:		
	DQ1	Accurate	
	DQ2	Complete	
Data Quality (DQ)	DQ3	Current	
	DQ4	Reliable	
	DQ5	Relevant to the analysis task at hand	
	DQ6	Appropriate in terms of level of details	
	The data stories used in our analytics practice:		
	SQ1	Provides audience with a comprehensive understanding of key insights gleaned from analytics	
	SQ2	Helps audience to recall the analytical insights during meetings	
Story Quality (SQ)	SQ3	Keeps the audience's attention during the delivery of a story and increase their level of engagement	Amini et al. (2018)
	SQ4	Facilitates the dissemination of analytical insights among audience and shareability with peers	
	SQ5	Increases the audience's knowledge of the insights gleaned from analytics	
	SQ6	Influences audience's behaviour and beliefs; ultimately resulting result in an action	
	The storytelling tool and dedicated features used in our analytics practice:		
	STQ1	Enables me to create a range of possible data stories	
	STQ2	Enables me to quickly produce data stories	
	STQ3	Enables me to accomplish my goals of producing data stories (Effectiveness)	
Stortelling tool Quality (STQ)	STQ4	Does not require too much effort from me to discover the features I need in the interface and learn how to appropriately use them	
	STQ5	Integrates well into existing workflows, workplace contexts, and other tools in the firm	
	STQ6	Can be extensible in such a way that allows me to customize the existing features of the tool or add new features to the tool (Extensibility)	
	STQ7	Can be used by multiple users to generate data stories together	

continued on following page

Table 7. Continued

Construct	Item	Measure	Sources
Storyteller skills (SS)	The users of storytelling tools in our analytics practice are:		(Tippins & Sohi, 2003)
	SS1	Skilled at using tools, techniques and strategies to tell data stories	
	SS2	Skilled at recognizing the needs, goals, and knowledge of the intended audience	
	SS3	Present a high degree of expertise in techniques and strategies of data storytelling	
	SS4	Knowledgeable when it comes to leveraging data storytelling tools for telling compelling and effective data stories	
Storyteller domain knowledge (SDK)	The users of storytelling tools in our analytics practice:		(Bassellier & Benbasat, 2004)
	SDK1	Have a high level of knowledge of the external environment (e.g., government, competitors, suppliers, and customers)	
	SDK2	Have a high level of knowledge of the organization's goals and objectives.	
	SDK3	Have a high level of knowledge of the core capabilities and competitive differentiation of the organization	
	SDK4	Have a high level of knowledge of the key factors that must go right for the organization to succeed	
Decision-making quality (DMQ)	The use of data storytelling in analytics practice has enabled my organization to make:		Jarupathirun and Zahedi (2007), Cao et al. (2015), and
	DMQ1	Informed decisions	
	DMQ2	Rational decisions	
	DMQ3	Reliable decisions	
	DMQ4	Timely decisions	
	DMQ5	Fast decisions	
	DMQ6	Effective decisions	
	DMQ7	Flawless decisions	
	DMQ8	Satisfactory decisions	
Business performance (BP)	The use of data storytelling in analytics practice has enabled my organization to:		Y. Chen et al. (2014), Aydiner et al. (2019), and
	BP1	Achieve a higher level of return on investment (ROI)	
	BP2	Reduce the cost	
	BP3	Achieve a higher level of return on sales.	
	BP4	Achieve a higher level of productivity	
	BP5	Improve the Internal business processes	
	BP6	Improve its capability to innovate new products	
	BP7	Improve its relationships with customers and stakeholders	
	BP8	Achieve a higher level of customer loyalty.	
	BP9	Increase its market share	

Mohammad Daradkeh is an Associate Professor of Business and Data Analytics in the Faculty of Information Technology and computer Sciences, Yarmouk University. Before joining Yarmouk University, Dr. Daradkeh has been working as a Lecturer in the Department of Informatics and Enabling Technologies at Lincoln University, New Zealand for two years. He received his PhD in Software and Information Technology from Lincoln University, New Zealand, and MSc. and BSc. in Computer Science from Yarmouk University, Jordan. His research interests lie primarily in the areas of Business Intelligence and Analytics, Visual Analytics, Decision Support Systems, and Uncertainty and Risk Management. He is currently teaching in undergraduate and graduate courses related to Decision Support systems, Business Intelligence and Analytics, Software Project Management, and Data Analytics. Dr. Daradkeh has published in Int. J. of Decision and Information Sciences, Int. J. of Business Information Systems, Int. J. of Decision Support Systems Technology, Journal of Organizational and End User Computing, Information Technology and People, and Int. J. of Information Systems in the Service Sector.