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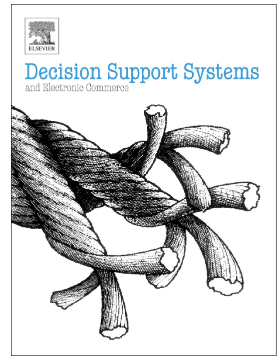

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Does Data Analytics Use Improve Firm Decision Making Quality? The Role of Knowledge Sharing and Data Analytics Competency

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Abstract

Despite the huge investment in data analytics tools, the necessary conditions required to obtain benefit from such investment deserves close investigation. In this study we utilize the knowledge-based view and data analytics competency literature to address two important research questions: (1) Does knowledge sharing have a mediating role on the impact of data analytics usage on the quality of firm decisions?; and (2) What is the role of data analytics competency in enhancing the quality of firm decisions through increasing knowledge sharing? Survey data collected from top and middle-level managers from 133 U.S.-based firms indicates that: the impact of data analytics use on the quality of firm decisions is fully mediated by knowledge sharing; the impact of knowledge sharing on firm decision quality is not significant and it is moderated by data analytics competency; and data analytics competency does not moderate the impact of data analytics use on knowledge sharing. Collectively, the findings provide a theory-based understanding of how data analytics use improves firm decision quality. The results also provide actionable guidelines for firms regarding the critical resources they need to invest in order to obtain benefits from using data analytics tools.

Keywords: Data analytics use, knowledge sharing, decision making quality, data analytics competency

Introduction

Decision making quality, which refers to a firm's ability to make accurate and correct decisions, is considered a firm vital capability (Janssen et al., 2017; Sharma et al., 2014). Decision-making in firms is a knowledge-intensive activity and knowledge is its raw material (Bose, 2003). With the availability of data with high variety, volume, and velocity, a lot of firms have invested in data analytics tools to generate and share knowledge which may help firms to improve the quality of their decisions. The ability to take advantage of data analytics tools has become a critical factor for firm success (Janssen et al., 2017; Müller et al., 2016; Olszak, 2016) as it enables firms to better sense threats and opportunities, shape them, and seize them (Côrte-Real et al., 2017). However, only twenty-seven percent of firms reported that their investment in data analytics has been successful (Ghasemaghaei et al., 2017b). One reason for the failure is that many firms still do not know the necessary conditions they need to utilize data analytics tools effectively (Ghasemaghaei et al., 2017a; Ghasemaghaei et al., 2017b). Existing research focuses on anecdotal evidence about the impact of data analytics usage on the quality of firm decisions and there is a lack of understanding about the conditions required to improve firm decision quality through utilizing data analytics tools; this study is an attempt to address this "unknown" in the literature.

Knowledge sharing, which is defined as activities of disseminating knowledge within the firm, enables firms to have better access to the information required in making decisions and thus improve the quality of their decisions (Bose, 2003). Data analytics tools are a source of knowledge sharing which allow firms to share the knowledge obtained through analyzing data integrated from internal and external sources (Côrte-Real et al., 2017). A firm that extensively uses data analytics may have a better ability to share knowledge within the firm and improve its decision quality. However, despite the potential benefits of data analytics usage, many firms have failed to improve their outcomes by utilizing analytics tools (Johnson et al., 2017), and others are still uncertain whether using data analytics tools will positively impact their outcomes (Ghasemaghaei et al., 2017a; Ghasemaghaei et al., 2017b; Grover et al., 2018; Kwon et al., 2014). According to a recent survey (Van der Meulen, 2016), although 48% of firms invested in utilizing advanced analytical tools in 2016, the number of firms that have planned to capitalize in this area in the next two years fell by 6%. In this study, the first objective is to explore the influence of data analytics usage on firm decision quality and investigate whether knowledge sharing has a mediating role in this relationship.

Data analytics competency, which refers to firm's capability in utilizing data analytics-based resources (Ghasemaghaei et al., 2017b), is an important factor in successfully using data analytics tools (Janssen et al., 2017). Bharadwaj (2000) developed a framework in which the resources relevant to Information Technology (IT) is categorized as IT-enabled intangibles, IT infrastructure, and human IT resources. Drawing from Bharadwaj's (2000) framework, Ghasemaghaei et al. (2017b) classified data analytics-based resources as big data utilization and data quality (IT-enabled intangibles), employee analytical capabilities (human IT resource), and tools sophistication (IT infrastructure). Firms with different levels of data analytics competency may have a different ability to integrate and disseminate the knowledge in the firm (Janssen et al., 2017). However, there is still a lack of knowledge about how data analytics competency impacts the quality of firm decisions. Therefore, the second objective of this study is to address this gap by investigating the moderating role of data analytics competency on the influence of data analytics use on the quality of firm decisions through enhancing knowledge sharing.

To address these objectives, we used the knowledge-based view (Grant, 1996) and data analytics competency literature to understand (1) Does knowledge sharing have a mediating role on the impact of data analytics usage on the quality of firm decisions?; and (2) What is the role of data analytics competency in enhancing the quality of firm decisions through increasing knowledge sharing? We adopted the knowledge-based view which states that a firm's knowledge resources are inimitable and unique which enable firms to enhance the quality of their decisions (Côrte-Real et al., 2017). The data analytics competency literature helps us to understand the essential conditions firms need to enhance their decision quality through using data analytics tools. To answer the main research questions, we collected data from 133 top and middle-level managers and empirically assessed the relationships in the proposed research model. The findings of this study help researchers and managers to better understand the conditions required to improve the quality of firm decisions through data analytics usage.

Relevant literature

Knowledge-based view

Sprouting from the resource-based view (Wernerfelt, 1984), the knowledge-based view focuses on the role of knowledge in obtaining competitive advantage (Erickson & Rothberg, 2014). According to this view, because knowledge-based resources are often difficult to imitate, knowledge assets may create a long-term competitive advantage for firms (Alavi & Leidner, 2001). This view argues that a firm's knowledge is a critical firm resource which enables the firm to improve its outcomes (Côrte-Real et al., 2017; Grant, 1996). Thus, firms need to identify and manage their knowledge assets effectively in order to obtain competitive advantage (Erickson & Rothberg, 2014). Employees are the best source of knowledge in firms. In fact, knowledge resides within individuals, and in particular, in the employees that generate and apply knowledge in performing their tasks (Bock et al., 2005). Firms with knowledgeable employees can better identify opportunities and threats in the market and thus make better decisions (Côrte-

Real et al., 2017). Therefore, the movement of knowledge across organizational and individual boundaries is eventually dependent on employees' knowledge sharing behaviour in the firm.

Alavi & Leidner (2001) argue that IT may play a vital role in effectuating the knowledge-based view of the firm. In particular, IT enables firms to generate and disseminate knowledge in the firm (Lee & Hong, 2002). For example, advanced information technologies (e.g., data analytics tools) can be used to integrate and analyze large volumes of data and expedite the knowledge sharing process within the firm (Erickson & Rothberg, 2014). Pavlou et al., (2005) argue that the knowledge-based view can help to conceptualize the impact of IT investments on firm outcomes. Firms need to explore new knowledge and exploit their existing knowledge to manage uncertain market conditions (Gupta & George, 2016). The stocks of knowledge (old and new) can be combined with the insights generated from the use of data analytics tools to make informed decisions (Gupta & George, 2016; Chae et al., 2014; Horita et al., 2017). Côrte-Real et al. (2017) argue that firm knowledge assets are critical firm resources in generating value from utilizing data analytics tools. Given the importance of organizational knowledge in improving firm outcomes, we utilize the knowledge-based view to understand how the sharing of the knowledge obtained through using data analytics tools could improve the quality of the decisions in the firms.

Data analytics competency

Data analytics competency refers to a firm's capability in utilizing data analytics-based resources (Ghasemaghaei et al., 2017b). The data analytics competency of each firm influences its outcomes (Gupta & George, 2016). Firm competencies include the processes and skills that transform inputs into outputs of better value (Nwankpa & Datta, 2017; Wade & Hulland, 2004). Lee (2001) argues that firm competency depends on the existence of valuable resources that are unsubstitutable, and inimitable by the competitors. Using the resource-based view, researchers have identified different IT relevant resources in the literature (Wamba et al., 2015). One of the most popular IT related resource classifications has been developed by Bharadwaj (2000) who classified the main IT-based resources as (1) intangible resources (e.g., knowledge assets), (2) human resources (e.g., analytics skills), and (3) tangible resources (e.g., IT infrastructure). While tangible firm resources comprise communication and computer technologies, human resources involve the capabilities and skills of employees, and intangible resources tend to be tacit (Bharadwaj, 2000). Firm competency is enhanced by assembling relevant firm resources which could create competitive advantage (Bharadwaj, 2000).

In the context of data analytics, Ghasemaghaei et al. (2017b) adopted the IT-based resource framework, which was developed by Bharadwaj (2000), and classified data analytics competency as big data utilization and data quality (IT intangibles), employee analytics capabilities (human IT resource), and tools sophistication (IT infrastructure). Ghasemaghaei et al. (2017b) suggest that the assembling of these resources forms data analytics competency in firms. Big data utilization is defined as the ability of a firm to integrate data that has high variety, high velocity, and high volume (Lycett, 2013; Raghupathi & Raghupathi, 2014). Whereas the velocity of data is the speed in integrating and analyzing data, variety refers to the analysis of different types of data, and volume refers to the integration of large amounts of data (Ghasemaghaei, 2018). Data quality is identified as another critical data analytics competency resource which refers to the quality of the data that is being used in the analyses. Wang & Strong (1996) argue that the accuracy and reliability of data, as well as the relevancy of data, how it is represented, and the accessibility of data are critical factors that need to be considered to improve the quality of the data. According to Popovič et al. (2014), the value that data analytics tools generate is considerably influenced by its data quality. Employee analytics capability is identified as another critical data analytics competency resource which refers to the skills of employees in integrating and analyzing data while using data analytics tools (Ghasemaghaei et al., 2017a). Having employees with the right skills and talent is an important resource for firms to generate value from data analytics tools (Ghasemaghaei et al., 2017b). Tools sophistication is the maturity of the analytics tools in providing in-depth analyses and it is considered another vital resource that forms data analytics competency in firms (Davenport, 2013). Tools that have high levels of sophistication can provide analyses regarding current and past events, projections of future happenings, and the possible best courses of actions and the outcome of each (Ghasemaghaei et al., 2017b).

In this study, we use Ghasemaghaei et al. (2017b)'s framework to identify the relevant resources that form the competency of data analytics. Firm's data analytics competency could have an important role in improving the firm's decision quality through data analytics usage and knowledge sharing in the firm.

Research model

The proposed research model is shown in Figure 1 which maps the hypothesized relationships between data analytics use, knowledge sharing, data analytics competency, and decision making quality.

Figure 1 about here

Decision making quality refers to the correctness and accuracy of decisions (Janssen et al., 2017). Decision quality improves if the decision maker has sufficient knowledge about problem variables. However, if the decision maker does not have the required knowledge about the relationships among problem variables, the quality of the decision may decrease (Raghunathan, 1999). Therefore, decision quality depends on the inputs. Previous studies emphasized the importance of the interaction between the employees who collect and analyze data and those who make decisions (Brynjolfsson et al., 2011; Burleson et al., 1984). For example, Janssen et al. (2017) argue that the ability of the decision maker to collaborate with others in the data analysis chain to better understand the relationships among problem variables may result in better decision quality. This could be due to the fact that decision making is a knowledge-intensive activity for which knowledge is a raw material. Therefore, the ability of the decision maker to have access to the required knowledge for making decisions is a vital factor in improving the quality of the decisions (Bose, 2003). Côrte-Real et al. (2017) argue that firms that enhance knowledge sharing behaviour enable their employees to better share insights and know-how with each other in the firm. Such interaction enhances the capabilities of decision makers to better identify threats and opportunities in the market (Della Corte & Del Gaudio, 2012). According to the knowledge-based view, firms need to manage their knowledge assets effectively in order to improve the quality of their decisions. Hence,

H1: *Knowledge sharing increases firm decision making quality.*

In order to create a knowledge environment and improve the quality of firm decisions by utilizing data analytics tools, employees need to share the knowledge that is required to make high-quality decisions. One of the key sources of successful knowledge sharing is a firm competency in creating, integrating, and leveraging knowledge (Lee, 2001). As discussed earlier, Ghasemaghaei et al. (2017b) developed a framework in which they found that firm data analytics competency is formed by big data utilization, data quality, analytical capabilities, and tools sophistication. Big data utilization, which is considered an important firm intangible resource, helps firms to develop sharper insights about their marker by discovering unforeseen patterns (Fernández et al., 2014; Demirkan & Delen 2013). Thus, it is considered an important factor in shaping firm data analytics competency. In particular, utilizing large volumes of heterogeneous data in a timely manner helps firms to learn more about their customers, business, market, and environment (Akter et al., 2016). For example, with the advancement of new technologies, firms can obtain data from different sources (e.g., Internet of Things, social media) about their customers (Calantone et al., 2002). This rich information may facilitate improving decision quality through sharing knowledge among employees. Another important factor that forms data analytics competency is tools sophistication (Ghasemaghaei et al., 2017b). Firms that use sophisticated analytical tools can obtain deep insights about past, current, and future happenings (Davenport, 2013). Thus, using sophisticated tools may help firms to share more insightful knowledge with the decision makers which can improve the quality of their decisions. Employee analytics capability is also considered a vital factor in shaping data analytics competency in firms (Ghasemaghaei et al., 2017b). Employees need to be able to interpret the data and deeply understand the processes and procedures involved in the industry/firm to better identify the key knowledge that needs to be shared with decision makers (Wong, 2012). If employees do not have sufficient analytics capabilities, they may not be able to obtain useful insights from analytical tools and they may not properly share the knowledge they obtained from the use of data analytics with decision makers. Ghasemaghaei et al. (2017b) also found data quality as an important factor in forming data analytics competency in firms. Previous studies argue that data quality is one of the main requirements for making effective decisions (Baesens et al., 2014; Ghasemaghaei & Hassanein, 2016; Ghasemaghaei & Hassanein, 2018; Hazen et al., 2014). As the knowledge that is obtained from data analytics usage depends on the quality of the data used, the value of using such tools will be impacted by the data being used (Lycett, 2013). Sharing knowledge that is generated by analyzing low-quality data may decrease the quality of the decisions make in firms. Hence, based on Ghasemaghaei et al. (2017b)'s data analytics competency framework, we hypothesize that:

H2: *Data analytics competency moderates the influence of knowledge sharing on firm decision quality, such that the effect is stronger with higher competencies.*

Data analytics use is the extent of utilizing the technologies that are designed to economically extract value from large amounts of different types of data (Gantz & Reinsel, 2012; Ghasemaghaei, 2018; Ghasemaghaei, 2019). Firms need to manage the data analytics findings proficiently and deliver them appropriately to the decision makers (Rajpathak & Narsingpurkar, 2013). The use of analytical tools is the key source of knowledge sharing in firms which help knowledge to flow efficiently to improve the quality of firm decisions (Chau & Xu, 2012). Data analytics tools have the potential to add value to firms by providing transparent results to support decision-makers in different business functions (Manyika & Roxburgh, 2011). The data analytics utilization enables firms to process, and sense the data and convert it into knowledge (Rajpathak & Narsingpurkar, 2013). Côrte-Real et al. (2017) suggest that the use of analytical tools may help to improve organizational knowledge by enhancing knowledge sharing among employees. Bose (2003) also argues that the extensive use of data analytics tools may improve the ease of access to new knowledge for employees; this may enhance the dissemination of knowledge in firms. Therefore, many firms have begun to take advantage of new analytical tools to facilitate knowledge sharing (Lin, 2007). Based on the knowledge-based view, the use of data analytics tools is a potential knowledge asset that should be appropriately used to improve knowledge management in the firm (Erickson & Rothberg, 2014). Hence,

H3: *Data analytics use increases knowledge sharing within firms.*

Data analytics competency could be an important factor in sharing the knowledge obtained from utilizing data analytics tools. In particular, competency in processing and analyzing data may facilitate the dissemination of the knowledge and insights generated from the use of data analytics. Therefore, the factors (i.e., tools sophistication, data quality, big data utilization, and analytical capabilities) that are found to form data analytics competency (Ghasemaghaei et al., 2017b) could potentially impact the sharing of the knowledge obtained from data analytics utilization. For example, analyzing large volumes of different types of data in a timely manner provides detailed findings for firms (Manyika & Roxburgh, 2011). Processing such big data allows firms to continually obtain new knowledge about their business, market, and customers (Zheng et al., 2011). Therefore, the ability of firms to utilize big data may improve knowledge sharing within the firm. In addition, employees need to have sufficient capability to disseminate the insights they obtain from data analytics tools (Ghasemaghaei et al., 2017a). Janssen et al. (2017) argue that knowledge sharing may degrade if employees are not able to interpret and understand the findings they obtain when they use IT. Previous studies also argue that employees who analyze data that is accurate, complete, and relevant obtain a higher quality of outputs. Obtaining high-quality insights makes it easier for employees to share it with other members of the firm (Dyer & Nobeoka, 2000). Furthermore, using sophisticated tools that provide deep knowledge about past and future happenings enables firms to obtain detailed information and deep knowledge about their partners, competitors, and customers. Having access to such detailed information may motivate employees to share more knowledge with others in the firm (Davison et al., 2013). Hence, based on Ghasemaghaei et al. (2017b)'s data analytics competency framework, we hypothesize that:

H4: *Data analytics competency moderates the influence of data analytics use on knowledge sharing, such that the effect is stronger with higher competencies.*

Methodology

This study uses the positivist research approach to investigate the causal relationships in the proposed research model (Straub et al., 2004). Using the positivist approach, we used survey measures to investigate the mediating role of knowledge sharing on the impact of data analytics use on the quality of firm decisions. Further, we explored the role of data analytics competency in enhancing the quality of firm decisions through increasing knowledge sharing. Based on the knowledge-based view and data analytics competency literature, we conceptualized the research model and validated the hypothesized relationships in the model, using partial least squares (PLS).

Sampling and scaling

In this study, we adopted the questionnaire-based survey method which captures the causal relationships between the variables in the proposed research model and thus provides generalizable statements on the research setting (Pinsonneault & Kraemer, 1993; Wamba et al., 2017). Straub et al. (2004) suggest the use of the survey method for predictive and explanatory theory in order to obtain confidence in the generalizability of the findings. Gable (1994) argues that the survey method can provide associations between the constructs and identify in-depth information. In this study, we used a survey questionnaire that includes previously validated scales (see Appendix A). Particularly, we measured data analytics use as a reflective variable and we used a 3-item scale adapted from Venkatesh et al. (2008). Likewise, we measured decision making quality as a reflective variable and we used a 6-item scale adapted from Ghasemaghaei et al. (2017b). Data analytics competency was considered as a second-order variable which was formed by big data utilization, tools sophistication, analytics capability, and data quality. The scale for measuring data analytics competency was adapted from Ghasemaghaei et al. (2017b). Knowledge sharing was measured as a reflective variable using a 5-item scale adapted from Cummings (2004). We also included the number of employees, industry type, high-tech industry, and revenue as control variables to account for differences among firms.

An invitation to participate in the survey was sent to the sample of 572 middle and top-level managers in the United States who had sufficient knowledge to answer the questions regarding the data analytics utilization and its impact on their firm outcomes (Abbasi et al., 2016). This approach has been used in previous studies (e.g., Akter et al., 2016; Sun, 2012). After careful analysis of all responses, 133 valid surveys were considered appropriate[1] for further analysis, resulting in having a response rate of about 23%. The response rate is in the upper half of Churchill and Iacobucci's (2006) guidance of 12–20% for acceptability in cross-sectional surveys, and it is consistent with extant research (e.g., Johnson et al., 2017; Joshi, 2016; Reid et al., 2015; Schleimer & Faems, 2016). We also followed Armstrong & Overton's (1977) guideline to assess nonresponse bias. We conducted a wave analysis to compare the last and first quartiles of respondents in terms of key study variables and demographic characteristics. The findings showed no significant differences between early and late respondents. Therefore, nonresponse bias was not a concern in these data. Table 1 displays the characteristics of respondents' firms and their demographic characteristics.

Table 1 about here

Results

Measurement model

[1] Some participants terminated the survey at the beginning and some did not complete the survey.

To examine the proposed model, we first evaluated the measurement model prior to the structural model to assess internal consistency, discriminant validity, and item loadings. Table 2 displays the correlation, and the square roots of average variance extracted (AVE) (i.e., diagonal values) of the reflective variables (i.e., data analytics use, knowledge sharing, decision quality, analytics capability). Table 2 illustrates that the correlation between each variable with other variables is less than the square root of the AVE, indicating sufficient discriminant validity (Barclay et al., 1995). Moreover, the table shows that the composite reliability of all the constructs is larger than 0.70 (Fornell & Larcker, 1981). The loadings of the items and their assigned constructs are shown in Table 3. This table indicates that all the items load highly (i.e., large than the threshold of 0.70 (Chin, 1998) on their theoretical assigned factor and the load is at least 0.10 larger than the loads on other factors in the model (Gefen & Straub, 2005).

Table 2 about here

Table 3 about here

To assess if the formative variables (i.e., tools sophistication, data quality, and big data utilization) are correlated highly, as suggested by Petter et al. (2007), we measured the Variance Inflation Factor (VIF). The findings indicate that the VIF value for all the formative variables was less than 3.3 (Diamantopoulos & Siguaw, 2006), indicating that multicollinearity is not an issue for the formative constructs. To measure the properties of data analytics competency (i.e., the second-order formative construct), we used Bagozzi & Fornell's (1982) guideline. As Bagozzi & Fornell (1982) suggested, for each first order variable, we used weights to multiply item values and then we summed them up. To create the composite indices, we then used the weighted sum of the first order variables. Next, we used the composite indices to measure the data analytics competency. The VIF for the data analytics competency was lower than 3.3. Thus, multicollinearity is not a problem for our second-order construct (Diamantopoulos & Siguaw, 2006). Moreover, as suggested by Gefen & Straub (2005), to further ensure the validity of the second-order construct, we examined the outer model loadings for each first order construct. The findings show that the loadings for big data utilization, data quality, tools sophistication, and analytics capability are significant at the 0.05 alpha level (0.70, 0.78, 0.74, 0.83, respectively), and the loadings are all higher than the threshold of 0.70 which shows the importance of each first order construct in forming the data analytics competency (Dwivedi et al., 2006).

We also conducted Harman's single-factor test (Podsakoff, 2003) and marker-variable technique (Lindell & Whitney, 2001) in order to identify the potential common method bias. For Harman's single-factor test, which is suggested by several prior studies (e.g., Luo et al., 2012; Sun, 2012), the unrotated solution revealed several factors and none of the variables contributed more than 50 percent of the variance. For marker-variable technique, which is also recommended by many previous studies (e.g., Malhotra et al., 2006; Pavlou et al., 2007; Xu et al., 2014), we used theoretically irrelevant construct (a marker variable) to adjust the correlation among the main variables in the research model. Having a high correlation between the main constructs and the marker variable (here gender) indicates common method bias. The findings display that the average correlation between gender and the main variables is -0.02. Hence, the findings of the Harman's single-factor and the marker-variable tests indicate that this study does not have an issue regarding the common method bias.

Structural model

As shown in Figure 2, the structural model shows that while knowledge sharing does not enhance decision making quality ($\beta = 0.121$; $p > 0.05$), which rejects H1, data analytics competency significantly moderates the impact of knowledge sharing on decision quality ($\beta = 0.128$; $p < 0.05$), which supports H2. Moreover, while data analytics use significantly enhances knowledge sharing ($\beta = 0.282$; $p < 0.001$), which supports H3, data analytics competency does not moderate the impact of data analytics use on knowledge sharing ($\beta = 0.029$; $p > 0.05$), which rejects H4. The impacts of control variables (i.e., firm size, firm industry, high-tech industry, and revenue[2]) on firm decision making quality were also examined. Findings indicated that firm size, firm industry, high-tech industry, and revenue did not significantly impact firm decision making quality ($\beta = 0.019$; $p > 0.05$; $\beta = 0.081$; $p > 0.05$; $\beta = 0.027$; $p > 0.05$; $\beta = -0.029$; $p > 0.05$, respectively).

Figure 2 about here

Further, we followed the procedure suggested by Baron and Kenny (1986) to examine whether the effect of data analytics usage on the quality of decisions is fully or partially mediated by knowledge sharing. We first assessed the direct effect of data analytics use on firm decision making quality in the absence of knowledge sharing. The findings showed the significant impact of data analytics use on the quality of decisions ($\beta = 0.317$, $p < 0.001$). We then added knowledge sharing as a mediator between data analytics use and quality of firm decisions. The findings showed that the impact of data analytics use on the quality of firm decisions was no longer significant ($\beta = -0.028$, $p > 0.05$). Therefore, the findings indicate that knowledge sharing fully mediates the impact of data analytics use on the quality of firm decisions.

Post hoc analysis

[2] Firm size, firm industry, high-tech industry, and revenue were coded as dummy variables using the categories shown in Table 1.

Interaction plot for the moderating effect of data analytics competency on knowledge sharing-decision making quality

As discussed, the findings of the structural model indicated that data analytics competency moderates the relationship between knowledge sharing and firm decision making quality. To further understand this moderating impact, we used the Interaction software package[3] to understand the role of big data utilization, data quality, analytics capability, and tools sophistication on the relationship between knowledge sharing and firm decision making quality. The findings are presented in Figure 3 which shows the t-values and the level of significance for each regression line. As shown in Figure 3a, when knowledge sharing enhances, firm decision quality is at its highest level when firms utilize high levels of big data. Interestingly, at low levels of big data utilization, the impact of knowledge sharing on firm decision making quality is not significant. Figure 3b displays that the impact of knowledge sharing on firm decision making quality is at its highest when employee analytics capability is at its highest level. Most importantly, the impact of knowledge sharing on decision making quality is not significant at low levels of analytics capability. Figure 3c illustrates that the impact of knowledge sharing on decision making quality is very high when firms utilize sophisticated tools. The impact of knowledge sharing on decision making quality is not significant at low levels of tools sophistication and, interestingly, the impact of knowledge sharing on firm decision making quality is significantly negative when firms use unsophisticated tools. Figure 3d shows that while the impact of knowledge sharing on firm decision making quality is at its highest when firms utilize high data quality, the impact of knowledge sharing on decision making quality is not significant below the mean level of data quality. In general, Figure 3 indicates that knowledge sharing within a firm does not necessarily enhance the quality of the decisions made in the firm;

[3] See www.danielsoper.com

a firm's data analytics competency has a vital role in the impact of knowledge sharing on firm decision making quality.

Figure 3 about here

Discussion

With the availability of large amounts of data, many firms have capitalized in utilizing data analytics tools to generate and share the knowledge they obtain from the use of analytical tools to improve their decision making quality (Ghasemaghaei et al., 2017b). However, only a few firms reported success in investing in data analytics use (Ghasemaghaei et al., 2017a). One of the main reasons for the failure is that many firms still do not know the necessary conditions required to successfully utilize data analytics tools. Existing literature has mainly focused on anecdotal evidence and there is a lack of understanding about the conditions required to improve the quality of firm decisions through utilizing data analytics tools. In this study, the above gap was addressed by utilizing the knowledge-based view and data analytics competency literature to investigate the role of data analytics competency and knowledge sharing in improving the quality of firm decisions through utilizing data analytics tools.

The findings indicate that while the use of data analytics tools enhances knowledge sharing within firms, data analytics competency does not moderate this relationship. This finding could be due to the fact that, as Chau & Xu (2012) argue, the use of analytical tools is the main source of knowledge sharing in firms which helps knowledge to flow efficiently within different firm functions. Thus, regardless of the data analytics competency of firms, the use of analytical tools enhances the knowledge sharing within firms. Interestingly, the findings reveal that sharing knowledge is not sufficient to enhance the quality of a firm's decisions; in fact, data analytics competency plays a critical role in this regard. This means that big data utilization, data quality, tools sophistication, and employee analytics capability all have an important role in enhancing firm decision making quality through sharing the knowledge obtained from using analytical tools. Specifically, the findings of the interaction plot display that when firms share knowledge, they can improve their decision making quality only at high levels of data quality, tools sophistication, big data utilization, and analytics capability. In other words, at low levels of these data analytics-based resources, the impact of knowledge sharing on enhancing decision making quality is not significant. Interestingly, the impact of knowledge sharing on firm decision making quality is significantly negative when firms use unsophisticated tools. Therefore, having competency in data analytics-based resources plays a vital role in improving firm decision making quality through knowledge sharing in firms. The findings are theoretically important given the need to have an understanding of the necessary conditions required to improve the quality of firm decisions through data analytics usage. This research also contributes to the knowledge-based view literature by understanding how sharing knowledge within firms could improve decision making quality.

To summarize, this is the first study that explored the mediating role of knowledge sharing on the impact of data analytics use on the quality of firm decisions. The findings indicate that knowledge sharing fully mediates the above relationship. In addition, this study investigated the role of data analytics competency in enhancing the quality of firm decisions through sharing knowledge within firms. The findings reveal that while many firms capitalized in utilizing data analytics, they can not necessarily improve their decision making quality. Firms should improve their competency in utilizing data analytics tools to improve their decision making quality through knowledge sharing. We believe that the findings of this study provide valuable guidelines for researchers interested in better understanding the influence of data analytics utilization and knowledge sharing on improving firm decision making quality.

Theoretical contributions

The results of this study inform various theoretical perspectives on data analytics, knowledge sharing, and knowledge-based view. First, the findings extend the data analytics literature by showing the importance of data analytics competency on influencing the impact of knowledge sharing on decision making quality. Most importantly, the findings show that just sharing the knowledge in the firm could not considerably enhance the quality of the decisions; firms need to enhance their big data utilization, data quality, tools sophistication, and employee analytical capability in order to increase their decision making quality. The findings of the interaction plot provide interesting insights regarding the impact of knowledge sharing on firm decision making quality at different data analytics-based resources levels. The results also extend the knowledge-based view by showing the necessary conditions required to enhance decision making quality through sharing the knowledge in the firm. The findings of this study are first strides toward understanding the role of knowledge sharing and data analytics competency on enhancing firm decision making quality through the use of data analytics. We call for future research to open the black boxes we unravel here and examine the mechanism through which different attributes of data analytics competency influence the impact of knowledge sharing on decision making quality.

Second, this study extends the data analytics literature by examining the mediating role of knowledge sharing on the impact of data analytics use on firm decision making quality. This unique perspective can explain one possible reason for the mixed findings about data analytics value in firms (Ghasemaghaei, 2018; Ghasemaghaei et al., 2017a; Ghasemaghaei et al., 2017b).

Specifically, the findings show that knowledge sharing fully mediates the impact of data analytics use on the quality of firm decisions. This also represents an extension of the knowledge-based view to the new context of data analytics. This theory has been mainly used in organizational settings, but rarely in IS and particularly data analytics contexts. This paves the way for further integrating the organizational behaviour literature with information systems and data analytics research. Moreover, the findings suggest that future studies should consider not only the influence of data analytics use on firm decision making quality, but also explore the possible factors that facilitate this impact. In addition, future research can extend our study by examining the possible mediating role of knowledge sharing on the impact of data analytics use on other firm outcomes (e.g., firm performance, and firm agility).

Third, while the role of data analytics competency on influencing the impact of data analytics use on firm outcomes has been emphasized by previous studies (e.g., Ghasemaghaei et al., 2017a; Ghasemaghaei et al., 2017b), to the best of our knowledge, there is not any empirical study that has examined the moderating role of data analytics competency on the impact of data analytics use on firm outcomes. Interestingly, our findings show the non-significant impact of data analytics competency on the effect of data analytics use on knowledge sharing, while the results indicate the significant impact of data analytics competency on the influence of knowledge sharing on decision making quality. These findings reinforce the need to understand the role of data analytics competency on influencing the impact of data analytics use on firm outcomes. The findings extend prior research that point to the importance of data analytics competency within firms (Ghasemaghaei et al., 2017a; Ghasemaghaei et al., 2017b; Wamba et al., 2017).

Practical contribution

Given that investment in data analytics utilization continues to grow, firms are keen to know how they can improve their decision quality from such investment. Our findings inform firms about the vital role of knowledge sharing in enhancing the quality of the decisions by utilizing analytical tools. Thus, firms should train employees about how to share and disseminate the knowledge they obtained through the use of analytical tools. Firms can also emphasize the importance of knowledge sharing in firms by informing their employees how sharing the knowledge may save time as other employees do not need to 'reinvent the wheel' when the required knowledge is shared by their colleagues (Connelly et al., 2014).

However, the findings showed that sharing knowledge is not sufficient to enhance firm decision making quality. We identified the necessary conditions needed to enhance the quality of firm decisions when firms use data analytics tools. The findings emphasized the importance of data quality, big data utilization, tools sophistication, and employee analytics capability; thus, firms need to invest in these resources to successfully improve the quality of their decisions. For example, firms can collect both structured and unstructured data from various sources such as customers' clickstream and social media in a timely manner to better generate insights about the products that fit best with customers' needs; this will better help them to improve their decisions regarding new product developments. The findings also revealed that investing in utilizing sophisticated tools is an important factor in improving decision making quality. Therefore, firms need to use a proper data analytics tools that help them to gain deep insights into prior and current events, future happenings, and the best course of actions that can be taken by firms in the future (Delen & Demirkan, 2013). For example, firms should not only focus on generating insights from descriptive analytics (e.g., dashboards, scorecards), but they also need to conduct prescriptive analytics (e.g., optimization, simulation), and predictive analytics (e.g., text mining, forecasting).

Given the importance of data quality in improving decision making quality, firms should focus on increasing the correctness of data. For example, firms can conduct different tasks such as filtering, cleansing, matching, and pruning to improve the quality of the data they collect from various sources. Firms can also provide clear policies about how employees can collect and process data (Hazen et al., 2014). Further, firms should hire knowledgeable employees who are skillful in monitoring and controlling the quality of the data that is used in the firms (Jones-Farmer et al., 2014). The results also indicate that having skillful employees that have appropriate analytics capabilities enables firms to improve their decision making quality. To do so, firms should hire employees who have sufficient knowledge in the area of data analytics. They can also initiate training programs to teach their employees how to effectively analyze data (Ghasemaghaei et al., 2017a). Employees that do not have the ability to perform their tasks are likely to postpone or avoid conducting the required analyses (Ghasemaghaei, 2018).

To summarize, the findings of this study demonstrate how firms can improve the quality of their decisions by sharing the knowledge obtained from the use of data analytics tools. In order to improve the decision making quality, just sharing knowledge is not sufficient to reap the full benefit of investing in utilizing data analytics tools. The findings reveal that it is necessary to pay careful attention to the data analytics-based resources to make accurate and flawless decisions. Leveraging the findings of this study provides actionable guidelines for firms regarding the essential conditions required to improve their decision making quality.

Limitations and future research

We note several limitations of the research. First, we assessed the research model using cross-sectional data. Future studies could conduct longitudinal research to provide additional support for the relationships in the model. A longitudinal study could provide insights into the importance of each data analytics-based resources over a period of time. Second, the participants in this study were managers from firms in the United States. Future studies could recruit participants from different countries to explore the impact of culture on the relationships in the research model. Third, the impact of data analytics use on the quality of firm decisions could be mediated by constructs other than knowledge sharing. Future studies could assess the mediating role of other constructs (e.g., value generation) on the impact of data analytics use on the quality of firm decisions. Fourth, the effect of knowledge sharing on decision making quality could be moderated by factors (e.g., management support) other than data analytics competency, which warrants future studies. Finally, in this study, perceptual measures were adopted to evaluate the dependent variables. Future studies could collect more objective measures to show a more concrete picture of the impact of data analytics use on firm outcomes.

Conclusion

This study provides a nomological network that investigates the impact of data analytics use on the quality of firm decisions, mediated through knowledge sharing. Further, this study highlights the necessary conditions required to enhance decision making quality through knowledge sharing. Collectively, the results provide actionable guidelines for firms regarding the critical resources they need to invest in order to benefit from using data analytics tools. The findings also provide a theory-based understanding of how data analytics use improves firm decision making quality. In summary, the findings indicate that: (1) using data analytics significantly improves knowledge sharing within firms; (2) the effect of data analytics use on the quality of firm decisions is fully mediated by knowledge sharing; (3) knowledge sharing does not necessarily improve firm decision quality; its impact is moderated significantly by data analytics competency; (4) firms that have low levels of data analytics-based resources could not improve their decision making quality through utilizing data analytics tools. In general, the findings of this study help firms to better understand the data analytics-based resources they need to invest in order to obtain benefits from utilizing data analytics tools and sharing knowledge in their firms.

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Appendix A

Survey items

Table A1 about here

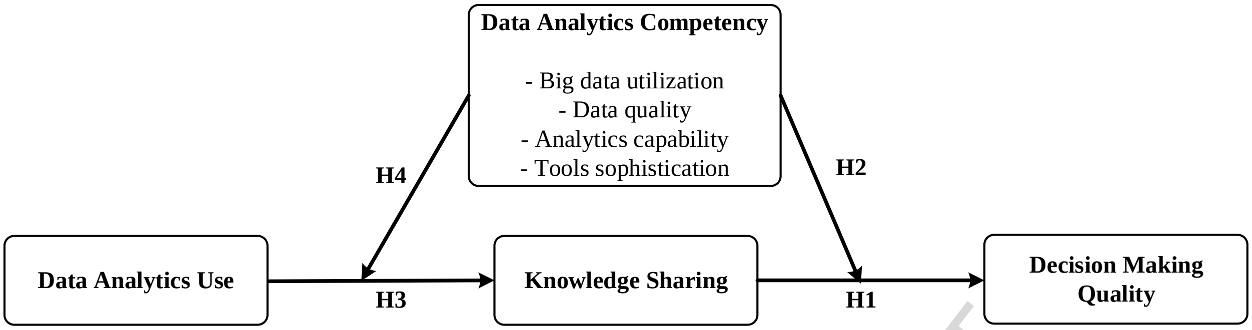

Figure 1. Research model

Table 1. Sample characteristics

Dimension	Category	Percentage (%)
Firm Size	< 100 employees	4.5
	100-500 employees	15.8
	501-1000 employees	15.8
	1001-5000 employees	29.3
	> 5001 employees	34.6
Industry Type	Manufacturing (producer goods)	7.5
	Manufacturing (consumer goods)	15
	Services	57.2
	Financial	12
	Utilities	8.3
Firm Revenue	< 1 million	9
	Between 1 million & 5 million	7.5
	Between 5 million and 10 million	9.8
	Between 10 million & 20 million	12.8
	Between 20 million & 50 million	6
	Between 50 million & 500 million	9
	Between 500 million & 1 billion	17.3
	> 1 billion	28.6
High-Tech Industry	Low-tech	47.4
	High-tech	52.6
Age	Between 20 and 30 years old	9
	Between 31and 50 years old	60.2
	Above 51 years old	30.8
Gender	Female	58.6
	Male	41.4

Education	High School	3.7
	College diploma	28.6
	Bachelor's degree	47.4
	Master's degree	18
	Ph.D. degree	2.3

Table 2. Correlation matrix

	Relib	Data Analytics Use	Decision Making Quality	Knowledge Sharing	Analytics Capability
Data Analytics Use	0.94	**0.92**			
Decision Making Quality	0.94	0.32	**0.84**		
Knowledge Sharing	0.93	0.54	0.62	**0.86**	
Analytics Capability	0.96	0.40	0.65	0.64	**0.95**

Note: Relib: composite reliability

Table 3. Loading of measures

	Data Analytics Use	Analytics Capability	Decision Making Quality	Knowledge Sharing
Data Analytics Use1	**0.93**	0.36	0.29	0.51
Data Analytics Use2	**0.94**	0.37	0.28	0.48
Data Analytics Use3	**0.89**	0.37	0.30	0.51
Analytics Capability1	0.38	**0.93**	0.60	0.61
Analytics Capability2	0.37	**0.95**	0.64	0.62
Analytics Capability3	0.37	**0.96**	0.62	0.60
Decision Making Quality1	0.25	0.59	**0.89**	0.52
Decision Making Quality2	0.26	0.64	**0.87**	0.55
Decision Making Quality3	0.25	0.56	**0.87**	0.52
Decision Making Quality4	0.22	0.39	**0.79**	0.45
Decision Making Quality5	0.20	0.39	**0.75**	0.44
Decision Making Quality6	0.39	0.65	**0.88**	0.60
Knowledge Sharing1	0.46	0.59	0.57	**0.88**
Knowledge Sharing2	0.46	0.54	0.50	**0.88**
Knowledge Sharing3	0.48	0.48	0.50	**0.82**
Knowledge Sharing4	0.48	0.55	0.50	**0.82**
Knowledge Sharing5	0.45	0.59	0.58	**0.88**

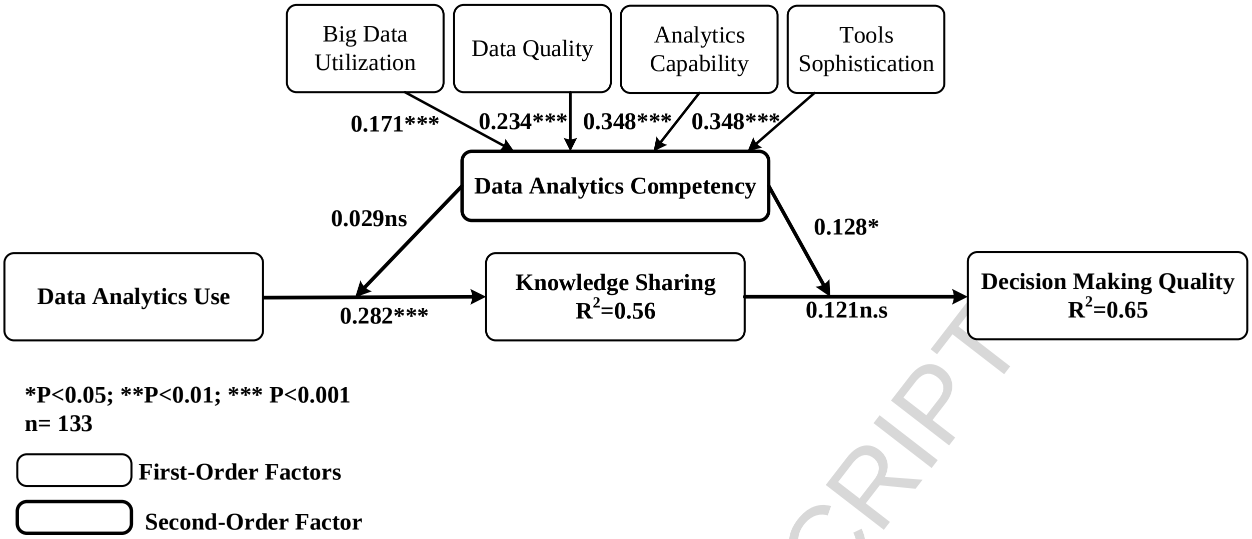

Figure 2. Results of research model

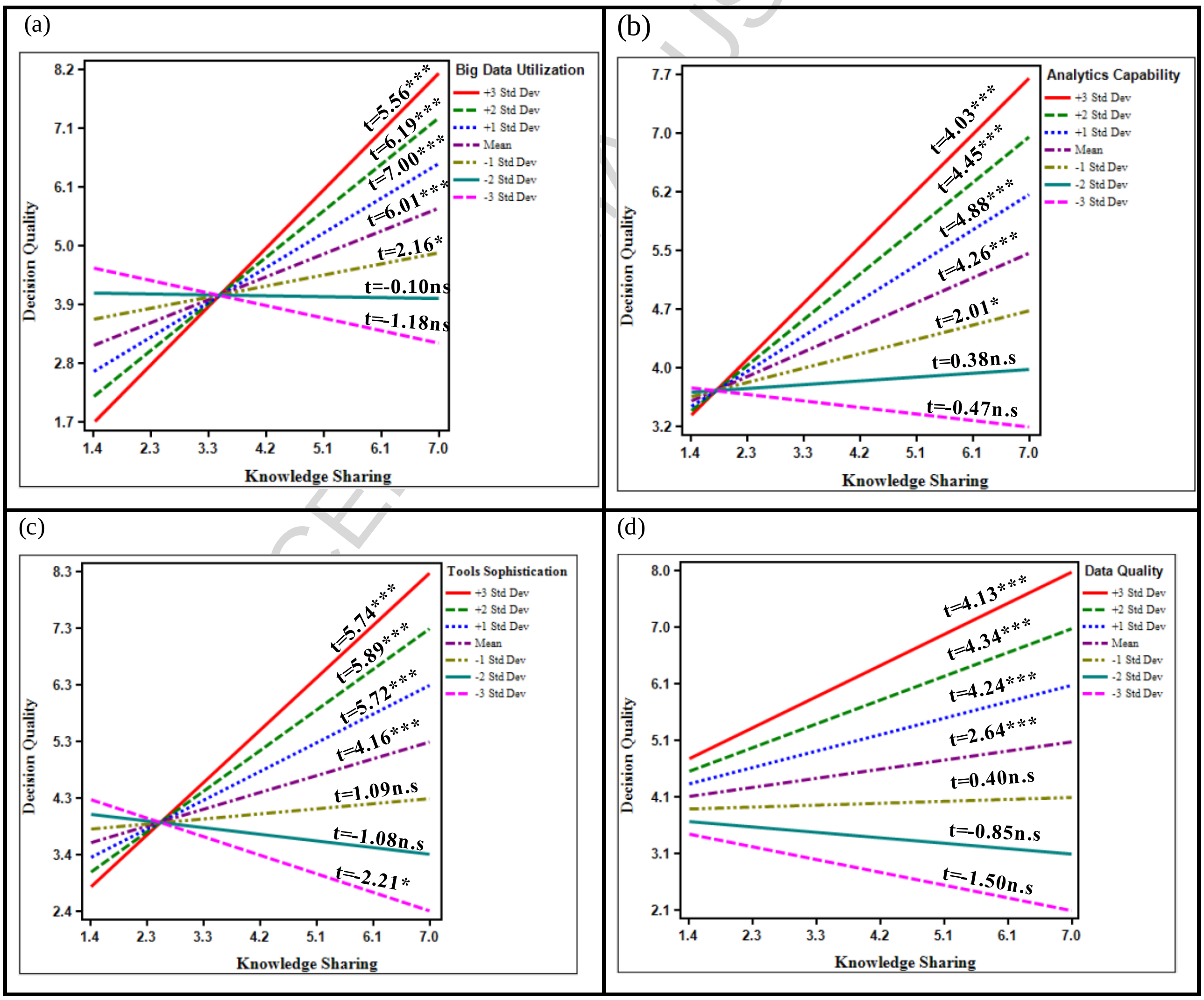

Figure 3. The interaction plots

Table A1. Measurement items

Construct Names	Measurement Items (7-point scale)	Mean	SD
Tools Sophistication	In my organization, we use tools that • Perform modeling and simulation • Evaluate different alternatives • Provide information processing and retrieval capabilities • Perform natural language analytics • Identify problems • Provide real-time insight	4.89	1.12
Knowledge Sharing	On average, how often do your data analysts exchange information/knowledge with the rest of your organization in the following areas in relation to the use of data analytics tools? • General overviews (e.g., business goals, external environment, etc.) • Specific requirements of a given analysis (e.g., numerical projections, market forecasts) • Analytical techniques (e.g., statistical tools, detailed methods, or testing procedures) • Progress reports (e.g., status updates, resource problems) • Analysis results (e.g., preliminary findings, unexpected outcomes, or clear recommendations)	4.63	1.0
Data Quality	In my organization, data used in data analytics: • is secure • is reliable • is relevant to the task at hand • is timely • is accurate • has an appropriate level of details	5.25	0.95
Big Data Utilization	My organization processes • Real time data. • High volumes of data. • Different types of data.	5.47	1.16
Decision Making Quality	In my organization, decision outcomes are often • Precise • correct • error-free • flawless • reliable • accurate	4.73	0.97
Analytics Capability	• Our data analytics users possess a high degree of data analytics expertise. • Our data analytics users are knowledgeable when it comes to utilizing such tools. • Our data analytics users are skilled at using data analytics tools.	5.12	1.18

Data Analytics Use	• On average, please specify the duration to which data analytics users employ such tools in your organization. • Please indicate how often data analytics tools are used in your organization. • Please indicate to what extent data analytics tools are used in your organization.	4.44	1.48

Biographical Note

Dr. Maryam Ghasemaghaei is an Assistant Professor of Information Systems at DeGroote School of Business at McMaster University. Her research interests relate to technology adoption, and the use of data analytics in organizations. Her research activities have resulted in over 30 peer-reviewed articles in academic journals, and conference proceedings such as MIS Quarterly, Journal of Strategic Information Systems, Information & Management, Decision Support Systems, Computers in Human Behavior, Journal of Computer Information Systems, International Journal of Information Management, Enterprise Information Systems, Behaviour & Information Technology, and Communications of the Association for Information Systems.

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Highlights

- Using data analytics significantly improves knowledge sharing within firms
- Knowledge sharing fully mediates data analytics usage impact on decision quality
- Knowledge sharing does not necessarily improve firm decision quality
- Data analytics competency moderates knowledge sharing impact on decision quality