Dec 10th, 12:00 AM

Analytics, Innovativeness, and Innovation Performance

Steffen Wölfl
_University of Bamberg_, steffen.woelfl@uni-bamberg.de

Alexander Leischnig
_Queen Mary University of London_, a.leischnig@qmul.ac.uk

Björn Ivens
_University of Bamberg_, bjoern.ivens@uni-bamberg.de

Daniel Hein
_University of Bamberg_, daniel.hein@uni-bamberg.de

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Completed Research Paper

Steffen Wölfl
University of Bamberg
Marketing Intelligence
Feldkirchenstraße 21
96052 Bamberg, Germany
steffen.woelfl@uni-bamberg.de

Alexander Leischnig
Queen Mary University of London
School of Business and Management
Mile End Road, London E1 4NS, UK
a.leischnig@qmul.ac.uk

Björn S. Ivens
University of Bamberg
Marketing
Feldkirchenstraße 21
96052 Bamberg, Germany
bjoern.ivens@uni-bamberg.de

Daniel Hein
University of Bamberg
Marketing
Feldkirchenstraße 21
96052 Bamberg, Germany
daniel.hein@uni-bamberg.de

Abstract

Based on organizational information processing theory, this paper develops and tests a research model to deepen the understanding about the conditions under which the use of data analytics contributes to innovation performance. This paper suggests that firm innovativeness, as an organization cultural concept, should moderate the relationship between data analytics use and innovation performance. The results of a moderation analysis based on data from cross-sectional survey support this account. The findings indicate a significant inversely U-shaped effect of innovativeness on the relationship between data analytics use and innovation performance. The effect of data analytics use on innovation performance is strongest under medium levels of innovativeness but comparatively weaker when firms have a low or a high level of innovativeness. These insights contribute to the IS literature by clarifying the important role of firm cultural factors in shaping information needs and deployment of information processing capabilities.

Keywords: Analytics, innovativeness, innovation performance, nonlinear moderation
Introduction

Innovation is one of the key drivers of competitive advantage and firm performance (Mansury and Love 2008). As a recent study by the Boston Consulting Group (2017) indicates, several of the most innovative firms worldwide are also leaders in data analytics. Data analytics refers to “the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions” (Davenport and Harris 2007, p. 7). Data analytics can offer valuable insights into hidden patterns and structures, unforeseen relationships or other valuable information (Duan and Cao 2015) and, as such, support decision makers in firms by providing relevant information and knowledge for managerial action. Capitalizing on data analytics, however, seems to be harder than it looks at first sight. For example, business experts estimate the share of failed big data projects to be higher than 50 percent (e.g., Bertolucci 2015; Marr 2015). In addition, a survey with 2,037 business executives, managers, and analysts from organizations located around the world indicates that one half of the respondents tends to agree that analytics is helping their organizations to innovate, while the other half are rather undecided or tend to disagree (Kiron et al. 2014a). A potential explanation for these figures is that data analytics per se does not make firms more innovative.

To unfold performance-enhancing effects, data analytics should be part of a value creation process, which implies the need for alignment with other organizational factors in a synergistic manner (e.g., Kohli and Grover 2008). Academic research on data analytics lends support for this account and indicates that data analytics use can have significant positive effects on firms’ performance outcomes (e.g., Brynjolfsson et al. 2011; Germann et al. 2013). However, it indicates also that these effects are contingent on a variety of factors residing within and beyond organizational boundaries (e.g., Akter et al. 2016; Ghasemaghaei et al. 2016). Recent calls for research thus emphasize the need to further illuminate how data analytics lead to value and to deepen the understanding about how, why, and when data analytics contribute to organizational performance (Sharma et al. 2014).

The purpose of our study is to take a step in this direction and examine the interplay among data analytics, innovativeness, and innovation performance. Based on an organizational information processing perspective (Daft and Lengel 1986; Galbraith 1974), we investigate how firm innovativeness impacts the effect of data analytics on innovation performance in an attempt to better understand the conditions under which data analytics fit into organizational innovation. Analyzing data from a sample of 161 firms operating in a wide range of industries, we demonstrate that firm innovativeness influences the effect of data analytics on innovation performance in a nonlinear way. We show that the association between data analytics and innovation performance is strongest under medium levels of innovativeness but comparatively weaker when firms have a low or a high level of innovativeness. Our study adds to the existing body of work on the performance implications of data analytics by proposing and demonstrating a novel inverse U-shaped moderation effect that characterizes the interplay between data analytics and innovativeness for achieving innovation performance. Our research thus delineates the conditions under which data analytics complement organizational innovation, which contributes to ongoing discussions on the role of analytics for innovation purposes (e.g., Anand et al. 2016; Duan and Cao 2015; Kiron et al. 2014b).

Theory and Hypotheses

Theoretical Basis

The primary theoretical lens of our inquiry is that of information processing theory (Daft and Lengel 1986; Galbraith 1974) which holds that one of the central tasks for organizations is to manage two information contingencies: uncertainty and equivocality. Uncertainty refers to the absence of information and expresses in “the difference between the amount of information required to perform the task and the amount of information already possessed by the organization” (Galbraith 1973, p. 5). Uncertainty stems from environmental complexity and increases in situations in which organizations face frequent environmental changes due to, for example, environmental turbulence. In contrast, equivocality refers to ambiguity due to multiple and conflicting interpretations and expresses in “confusion and a lack of understanding” (Daft and Lengel 1986, p. 556). Equivocality thus stems from different meaning attached
to data due to, for example, alternative processes of translating events into common understanding (Daft and Weick 1984).

According to the organizational information processing view, organizations may reduce uncertainty by collecting new data or by developing buffers to reduce uncertainty effects. For equivocality reduction, however, firms need to develop answers and clarity, which involves sense making and which not necessarily involves the collection of additional data (Daft and Lengel 1986). For high organizational performance, the amount of information processing should thus be matched with the forces of uncertainty and equivocality, which involves establishing fit between information needs and information processing capabilities.

In this research, we use the information processing view of the organization as the theoretical basis for our research model (Figure 1). The model depicts the three focal concepts under investigation—data analytics, innovativeness, and innovation performance—and proposes two main and a (nonlinear) moderation effect. From an organizational information processing perspective, the value of data analytics for achieving innovation performance should be high when its deployment matches the requirements of the organizational innovation landscape, that is, when it fits with innovativeness. To examine this effect, we employ the “interaction approach” as suggested by (Drazin and Van de Ven 1985).

**Hypothesis Development**

Our first hypothesis pertains to the direct effect of data analytics on firms’ innovation performance, defined as the effectiveness of firms in developing novel offerings relative to competitors (Verhees and Meulenberg 2004). Studies in a broad range of disciplines have examined the role and nature of data analytics, critical antecedents and consequences for individuals and organizations, as well as areas of application (e.g., Chen et al. 2012 and the papers in this Special Issue). The cumulative findings of these studies suggest that data analytics can help an organization to develop a better understanding of its business and environment, and “leverage opportunities presented by the abundant data and domain-specific analytics” (Chen et al. 2012, pp. 1168). Increased digitization and advanced technologies provide a vast amount of data in different formats and from a variety of sources (Sharma et al. 2014), thus offering a rich basis to obtain insights for managerial action. At the same time, various analytic tools and methods such as descriptive, predictive, and prescriptive analytics enable organizations to detect patterns and describe the status quo, forecast future events, and make informed decisions, for example, in terms of efficient resource allocation within and across organizational functions (Sivarajah et al. 2017).
Prior work shows that the use of data analytics improves firms’ process capabilities (Wamba et al. 2017) and ultimately transforms into several favorable effects including increased profitability and productivity (e.g., Anand et al. 2016; Brynjolfsson et al. 2011; Chen et al. 2015; Teo et al. 2016; Wamba et al. 2017; Wu and Hitt 2015) and higher market performance (Akter et al. 2016; Chen et al. 2015; Germann et al. 2013, Wamba et al. 2017). With focus on innovation, studies indicate that the use of data analytics contributes to managers’ innovative idea set (Roberts et al. 2016) and improves the novelty and meaningfulness of new product developments (Duan and Cao 2015). Deployment of data analytics increases the ability of firms to obtain relevant information about key market actors (Erevelles et al. 2016), thus reducing the uncertainty typically associated with innovation. The use of data analytics can provide vision for customer needs, competitor actions, and potentially relevant sources of technology and knowhow (e.g., R&D partners) and, as such, satisfy essential information needs for the development of new products and services. Hence, our first hypothesis reads as follows:

**H1:** Use of data analytics has a positive effect on innovation performance.

Our second hypothesis relates to the relationship between innovativeness and innovation performance. Innovativeness is defined as a firm’s receptivity and openness to new ideas as part of a firm’s culture (Hurley and Hult 1998). High innovativeness expresses in a strong inclination to adopt new perspectives and an organizational orientation toward experiencing and developing new things. Studies show that innovativeness encourages entrepreneurial thinking, the absorption of new ideas, openness to external stimuli, risk-taking, and creativity (Deshpandé et al. 1993; Koberg and Chusmir 1987). In firms with a high innovativeness, employees and managers alike believe in the relevance of new and innovative offerings to generate competitive advantages and constantly strive for innovation (de Brentani and Kleinschmidt 2004). In such firms, performance measures focus on market opportunities and new directions for growth, and employees do not have to worry punishment when projects fail (Deshpandé et al. 1993). In addition, a high willingness to take risks stimulates investments in new product and services development ahead of competition. Firms that heavily invest in new ideas are in a better position to translate their innovative ideas quickly in marketable products and services and are thus at the cutting edge of technology as well as first-to-market with their new developments. Thus, our second hypothesis reads:

**H2:** Innovativeness has a positive effect on innovation performance.

The third hypothesis of our research framework refers to the effect of innovativeness on the relationship between data analytics and innovation performance. We propose that the association between data analytics deployment and innovation performance should be strongest when firms have a medium level of innovativeness and comparatively weaker when innovativeness is low or high. When innovativeness is low, receptivity and openness for novel information decrease and it is more likely that insights obtained through data analytics are ignored or even discarded. The use of data analytics may then produce ‘data cemeteries’, that is, huge quantities of unused (or unwanted) information, which reflects a situation of misfit from an information processing perspective. When innovativeness is high, receptivity and openness to new information increase. The use of data analytics may then help address information needs and reduce innovation-related uncertainty. However, such a data-driven and fact-based approach may interfere with creative thinking and may create undesired mental boundaries that limit the scope of possible options due to data-driven rigidity. Innovative processes rely heavily on tacit knowledge, gut feeling, and other types of information that are less accessible through structured information processing (Nonaka and von Krogh 2009). In firms with a high innovativeness, the use of data analytics may then be perceived as a competitive internal force. In summary, low innovativeness characterized by a low outside-orientation as well as high innovativeness characterized by a high need for freedom of ideas and unconditional creativity are assumed to decrease the impact of the use of data analytics on innovation performance. The positive impact of the use of data analytics on innovation performance should thus be strongest at a medium level of innovativeness. More formally, our third hypothesis reads as follows:

**H3:** Innovativeness moderates the effect of data analytics use on innovation performance such way that the effect is strongest under medium levels of innovativeness and comparatively weaker when innovativeness is low or high.
Research Design

Data Collection and Sample Characteristics

To test the hypothesized relationships, we conducted a survey as part of a major research project. The sampling frame consisted of firms identified through a proprietary database and involved key informants with expert knowledge about firms’ business approaches (i.e., CEOs, marketing and sales directors, and managers). The firms covered various industries such as manufacturing, professional services, retail, or consumer goods to ensure sufficient variation and inferences across different industries.

Data for this study were collected in a multi-wave survey (mail survey; email reminder; telephone reminder). Key informants received the questionnaire together with a cover letter that invited them to participate in the survey. The cover letter informed the key informants that there are no correct or wrong answers and that all data are collected anonymously (Podsakoff et al. 2003). After this initial mail survey, we sent a reminder via e-mail, including a link to the questionnaire in online format to allow the key informants to participate online. Finally, we phoned a random sample of the key informants who did not participate in the study so far.

In total, we received 161 valid responses. The average firm in the sample has 50 to 300 employees and a sales volume between 5 million and 50 million Euro. Approximately 64 percent of the firms operate mainly in business markets. 21 percent of the respondents have a top management position, 48 percent have a senior-level management position, 19 percent have a mid-level management, and 12 percent have other positions within the firm. Respondents’ average organizational tenure is 12.2 years (SD = 9.1) and the mean age is 45.3 (SD = 10.2).

Construct Measures, Measurement Validation, and Tests for Potential Biases

We used a standardized questionnaire as the data collection instrument, using multiple-item scales from prior studies to capture the constructs of interest in this study. We measured use of data analytics with four items based on Germann et al. (2013) and Roberts and Grover (2012). To capture firms’ innovativeness, we used three items based on a study by Hurley and Hult (1998). For innovation performance, we employed the scale developed by Oke (2007). The items for all questions were presented on 7-point Likert-type agreement scales anchored in 1 for “strongly disagree” to 7 for “strongly agree”. Besides the substantive constructs, we captured also control variables. We measured firm size based on archival data about firms’ number of employees. In addition, we captured whether firms pursue a differentiation strategy (Verhoef and Leeflang 2009). Firm size and differentiation strategy have been identified as relevant common underlying reasons for potential correlations (e.g, Malladi and Krishnan 2013). Table 1 below details the measurement instruments for each of the constructs and provides information on reliability and validity criteria and Table 2 provides information on discriminant validity.

We established the measurement models of the multiple-item constructs using confirmatory factor analysis (CFA) and by assessing global fit indices and criteria for the internal structure of the model (e.g., Bagozzi and Yi 1988; Bagozzi et al. 1991). To assess the overall model fit, we used multiple indices including the comparative fit index (CFI), the Tucker–Lewis index (TLI), and the root mean square error of approximation (RMSEA). The results showed that the measurement model has an acceptable overall model fit (χ² = 82.61; df = 51; χ²/df = 1.62; CFI = 0.97; TLI = 0.96; RMSEA = 0.06). We assessed local validity and reliability criteria of the construct measures by calculating additional parameters. The results of these analyses showed that Cronbach’s alpha ranges between 0.77 and 0.90. These values exceed the commonly accepted threshold of 0.7 (Nunnally 1978). Furthermore, the results showed that composite reliability (CR) ranges between 0.78 and 0.91 and that average variance extracted (AVE) ranges between 0.54 and 0.71, thus exceeding the thresholds of 0.6 and 0.5, respectively (Bagozzi and Yi 1988). We examined discriminant validity following the procedure as suggested by Fornell and Larcker (1981). Comparison of the AVE of each construct with the squared correlation between any pair of constructs indicates discriminant validity (Table 2). The highest squared inter-construct correlation was 0.33 and thus falls below the AVEs obtained by the CFA. In summary, the results of the measurement model validation procedure indicated that the model fits the empirical data well.
### Table 1. Information on Construct Measures

<table>
<thead>
<tr>
<th>Use of Data Analytics (α = 0.90, CR = 0.91, AVE = 0.71)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7-point Likert-type agreement scale ranging from 1 = “completely disagree” to 7 = “completely agree”</td>
</tr>
<tr>
<td>To what extent do you agree or disagree with the following statements?</td>
</tr>
<tr>
<td>– We master many different quantitative analysis tools and techniques.</td>
</tr>
<tr>
<td>– We have different applications for simulations and what-if analyses.</td>
</tr>
<tr>
<td>– We use different applications that offer decision-making tools (such as optimization, scenario analysis, etc.).</td>
</tr>
<tr>
<td>– We employ appropriate marketing analysis tools for different decision problems.</td>
</tr>
</tbody>
</table>

### Innovativeness (α = 0.77, CR = 0.78, AVE = 0.54)

7-point Likert-type agreement scale ranging from 1 = “completely disagree” to 7 = “completely agree”
To what extent do you agree or disagree with the following statements?
- Technical innovation, based on research results, is readily accepted.
- Management actively seeks innovative ideas.
- Innovation is readily accepted in program/project management.

### Innovation Performance (α = 0.90, CR = 0.90, AVE = 0.66)

7-point Likert-type agreement scale ranging from 1 = “completely disagree” to 7 = “completely agree”
Our business unit is ...
- at the leading edge of innovation.
- perceived by customers to be more innovative than our competitors.
- better than our competitors at developing products and services to meet customer needs.
- more effective than our competitors at taking existing ideas and making them into something better.
- one of the first to market with innovative new products and services.

**Notes:** α = Cronbach’s α; CR = composite reliability; AVE = average variance extracted

### Table 2. Discriminant Validity

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovativeness</td>
<td>0.54</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Use of Data Analytics</td>
<td>0.02</td>
<td>0.71</td>
<td></td>
</tr>
<tr>
<td>Innovation Performance</td>
<td>0.33</td>
<td>0.07</td>
<td>0.66</td>
</tr>
</tbody>
</table>

**Note:** AVE on the diagonal and squared correlations between constructs below.

We performed additional tests to control for potential biases. We tested for nonresponse bias (Armstrong and Overton 1977) using two tests. First, we compared archival data on structural parameters (i.e., sales volume and number of employees) for responding and nonresponding firms. The results of this test revealed no significant differences (all p > 0.05). Next, we compared the responses of early and late respondents for the focal constructs. The results of a series of t-tests revealed no significant differences (all p > 0.05). Based on these results, nonresponse bias does not constitute an issue in our study.

Besides nonresponse bias, we controlled for potential common method bias (Podsakoff et al. 2003; Podsakoff and Organ 1986). Harman’s single factor test based on exploratory factor analysis indicates that no first factor explained the majority of the variance in the variables. Additionally, a χ²-difference test based on CFA (Malhotra et al. 2006) revealed that the single-factor model fits the data significantly worse than the hypothesized multi-factor model in which all items loaded on their respective factors (Δχ² = 451.56, Δdf = 3, p < 0.001). Based on these results, common method bias does not constitute an issue in our study.
Hypothesis Testing

To test the hypotheses, we used ordinary least squares (OLS) regression based on the procedure recommended by Jaccard (2003). First, we computed average scores for the multi-item constructs. Next, we mean-centered the interacting variables (i.e., use of data analytics and innovativeness). We then calculated the square of the moderator variable (i.e., innovativeness). Finally, we constructed linear and squared product terms and specified the following regression equation to test the proposed effects:

\[
\text{Innovation Performance} = b_0 + b_1 \text{Data Analytics} + b_2 \text{Innovation Culture} + b_3 \text{Data Analytics} \times \text{Innovation Culture} + b_4 \text{Innovation Culture squared} + b_5 \text{Data Analytics} \times \text{Innovation Culture squared} + b_6 \text{Firm Size} + b_7 \text{Differentiation Strategy} + e
\]

A significant coefficient for the squared moderator product term (i.e., \(b_5\)) indicates the presence of a quadratic moderation effect (Hayes 2015; Jaccard 2003). A positive sign of this coefficient would indicate a U-shaped moderation effect, whereas a negative sign would indicate an inversely U-shaped moderation effect, as it is hypothesized here. A negative coefficient of the squared moderator product term implies that the effect of data analytics use on innovation performance is strongest for a medium level of innovativeness and that the effect is comparatively weaker for low and high levels of innovativeness.

Table 3 displays the results of the regression analysis. According to the results, use of data analytics has a significant positive direct effect on innovation performance (\(\beta = 0.32; p < 0.01\)), which supports H1. In addition, innovativeness has a significant positive effect on innovation performance (\(\beta = 0.48; p < 0.01\)). Thus, H2 is supported as well. Regarding H3, the results indicate a significant negative effect of the squared moderator product term on the relationship between data analytics use and innovation performance (\(\beta = -0.18; p < 0.05\)), which provides empirical support for an inversely U-shaped effect. The effect of data analytics use on innovation performance is strongest under a medium level of innovativeness and it is comparatively weaker for low or high levels of innovativeness, which supports H3.

We conducted additional analyses to probe the nonlinear moderation effect, using the PROCESS tool for SPSS (model 2; Hayes 2013) and following the recommendations by Hayes (2015). Specifically, we conducted a floodlight analysis to identify regions of significance of the moderation effect. Figure 2 shows the results of this analysis and displays the effect size as well as 95 percent confidence intervals (CI) of the effect of data analytics use on innovation performance depending on varying levels of innovativeness. The vertical axis of the graph shows values of the regression coefficient for the association between data analytics use and innovation performance and the horizontal axis shows values of the moderator variable (innovativeness). The positive effect of data analytics use on innovation performance is strongest and significant at a medium high level of innovativeness and it is comparatively weaker and insignificant at low or high levels of innovativeness, thus lending additional support for the anticipated inversely U-shaped moderation effect.

<table>
<thead>
<tr>
<th></th>
<th>b</th>
<th>(\beta)</th>
<th>S.E.</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>4.34</td>
<td>0.18</td>
<td>24.43</td>
<td></td>
</tr>
<tr>
<td>Data Analytics</td>
<td>0.29**</td>
<td>0.32</td>
<td>0.08</td>
<td>3.50</td>
</tr>
<tr>
<td>Innovativeness</td>
<td>0.49**</td>
<td>0.48</td>
<td>0.08</td>
<td>6.56</td>
</tr>
<tr>
<td>Innovativeness squared</td>
<td>0.01</td>
<td>0.01</td>
<td>0.05</td>
<td>0.15</td>
</tr>
<tr>
<td>Data Analytics × Innovativeness</td>
<td>-0.02</td>
<td>-0.03</td>
<td>0.06</td>
<td>-0.38</td>
</tr>
<tr>
<td>Data Analytics × Innovativeness squared</td>
<td>-0.09*</td>
<td>-0.18</td>
<td>0.04</td>
<td>-2.03</td>
</tr>
<tr>
<td>Firm Size</td>
<td>-0.00</td>
<td>-0.01</td>
<td>0.00</td>
<td>-0.09</td>
</tr>
<tr>
<td>Differentiation Strategy</td>
<td>0.15</td>
<td>0.05</td>
<td>0.19</td>
<td>0.79</td>
</tr>
</tbody>
</table>

Table 3. Results of the Model Estimation

Note: \(b/\beta = \) un/standardized coefficient; S.E. = standard error; ** \(p \leq 0.01\); * \(p \leq 0.05\).
Digitization has led to an enormous increase in data availability, and firms in many industries have recognized the potential of using data for operational and strategic decision making (Wu and Hitt 2015). While analysis of data from enterprise information systems can enhance operational efficiency (e.g., Aral et al. 2012), analysis of data from market actors and market developments helps firms draw detailed pictures about key stakeholders and the business environment (e.g., Wu and Brynjolfsson 2014). Despite these benefits, business experts report that the majority of big data projects do not achieve intended goals, and many experts tend to disagree that data analytics provide impetus for innovation (e.g., Bertolucci 2015; Kiron et al. 2014a). Therefore, following recent calls for research to further examine how data analytics lead to value (Sharma et al. 2014), we conducted an empirical study to better understand how data analytics relate to firms’ innovation performance.

The findings of our study reveal support for all hypothesized effects. We find that data analytics and innovativeness improve innovation performance. These results correspond to those of prior research (e.g., Anand et al. 2016; Duan and Cao 2015; de Brentani 2001). Above and beyond, we demonstrate that innovativeness moderates the effect of data analytics on innovation performance in a nonlinear way. The effect of the use of data analytics on innovation performance is strongest at a medium level of innovativeness and it is comparatively weaker at low and high levels of innovativeness. The results of our research thus offer an explanation for why many innovation-related data projects fail. Low and high levels of innovativeness can backfire when it comes to seizing opportunities with data analytics. They can produce misfit between information needs and information processing capabilities which—based on the information processing view of the organization (Galbraith 1973; Daft and Lengel 1986)—lowers performance. The results of our study demonstrate this effect for data analytics and organizational innovation.

This knowledge makes several contributions to the literature. We add to ongoing discussions about the performance implications of data analytics by proposing and demonstrating a framework including a novel inversely U-shaped moderation effect that explains when data analytics unfold its innovation performance-enhancing effect. Our findings show that data analytics use does matter to innovation performance and advance extant knowledge by pointing to relevant contingencies and situations of misfit. As such, our study explains boundary conditions for the use of data analytics in the context of organizational innovation. It shows that aspects of organizational culture (innovativeness) can interfere with information processing capability deployment (data analytics use) and lead to tensions that hinder
the effective transformation of capability leveraging in performance outcomes (innovation performance). The results suggest that employees in firms have to “buy in” to transform data analytics and the insights provided by its use into innovation performance. In addition, the findings of our study contribute to organizational information processing theory. IS research has uncovered a wide range of factors that affect the information needs of organizations to be matched with information processing capabilities. Factors that shape the information needs of firms encompass aspects related to technology (Anandarajan and Arinze 1998; Trkman et al. 2010), strategy (Fairbank et al. 2006; Rogers and Bamford 2002), human resources (Francalanci and Galal 1998), organizational structure (Gattiker and Goodhue 2005), task characteristics (Kim and Umanath 1992), and product characteristics (Premkumar et al. 2005). Our research adds to this body of work by pointing to firm innovativeness as an organization cultural concept associated with organizational information processing. Furthermore, the nonlinear effect identified in our study underlines the need to further illuminate organizational information processing and the concept of fit in a more nuanced way, for example, by considering asymmetric effects. These insights provide several directions for further research.

While our research has shown how innovativeness as one firm-internal contingency factor affects the relationship between data analytics and innovation performance, more research is still needed to better understand how and when organizational information processing capabilities unfold performance-enhancing effects. For instance, a research question that derives from the findings of our study concerns the value that intra-organisational units attach to information processing capabilities, such as data analytics, and the factors that affect this perception. Unless internal units perceive information processing capabilities, their development, and their deployment as useful, an effective integration with other organizational factors and, in turn, leveraging for value creation will hardly be achieved. A further avenue for future work pertains to the choice of contingency factors that may interfere with the effective use of information processing capabilities to produce performance gains. Here, future studies might extend to factors that lie beyond the boundaries of an organization. For example, prior work indicates that an enhanced understanding of digital ecodynamics, which refer to the “confluence among environmental turbulence, dynamic capabilities, and IT systems,” constitutes an important frontier in IS research (El Sawy et al. 2010, p. 835). Thus, future work should consider not only internal contingency factors but also external factors that reside within the business environment to improve the understanding about how and when data analytics works together with other internal as well as external factors to build performance-enhancing amalgams.

The findings of our study have also implication for business practice. The message that the findings of our study suggests to managers is manifold. First, investments into data analytics (e.g., for recruitment of analysts, installation of advanced technology, and exploitation of analytic tools, methods, and techniques) can pay off in terms of higher innovation performance. In addition, innovativeness contributes to innovation performance as well, and firms are good advised to encourage innovativeness to realize overall innovation objectives. However, to achieve a maximum performance-enhancing effect, firms must be aware that the use of data analytics should match the requirements of the organizational innovation landscape, especially the level of firm innovativeness. Hence, effectively capitalizing on data analytics requires consideration of intra-organizational mindsets and cultures, which implies the need for a firm to develop comprehensive understanding of potential sensitivities within functions.

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