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The Missing Link Between Analytics Readiness and Service Firm Performance

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ABSTRACT

Although the importance of analytics is a veritable mantra in today's business environment, little academic research has been devoted to understanding the degree to which firms are ready to incorporate an analytics strategy into their business model and *how* and *when* analytics readiness (AR) translates into firm performance. Three studies address this void. In Study 1, we conduct interviews with MBA students from the United States to assess the AR construct. In Study 2, we develop and validate an AR scale using data from Turkish service firms. In Study 3, we test how and when AR translates into firm performance using data from South Korean service firms. The results contribute to the analytics literature in the following ways: First, AR is a higher-order construct comprised of five lower-order dimensions: cultural readiness, leadership commitment, strategic alignment, structural readiness, and talent capacity. Second, an exploratory (exploitative) market learning strategy amplifies (mitigates) the effect of AR on relative emphasis on data- (vs. instinct-) driven decision making. We discuss theoretical and managerial implications along with limitations and directions for further research.

Keywords: Analytics readiness, Analytics, Data-driven decision making, Exploratory learning, Exploitative learning

At first glance, it may be difficult to identify any commonalities across service firms such as Netflix, UPS, Capital One, Amazon, and Caesars Entertainment, as these firms compete in very different industries. However, a closer examination reveals that they are all leading firms in their industries with respect to leveraging analytics as a source of differentiation and competitive advantage. Service firms are proactively leading the “analytics mandate” by providing a new path to value creation for customers and driving revenue by changing and uprooting traditional business models (Kiron et al., 2014). Although these firms have mainly used analytics to target individual customers, we increasingly observe firms such as Salesforce.com and SAS leverage the power of analytics for competitive advantage. The goal of this paper is to obtain a deeper understanding of *how* and *when* service firms can use analytics to improve firm performance.

Analytics is strategically important for service firms as they help firms achieve the following three objectives: personalization, prioritization, and cost minimization. Take the example of Riiid, an educational technology firm that provides personalized learning experiences to users who need to take standardized tests by harnessing the power of analytics and artificial intelligence. Riiid offers adaptive learning by tailoring a different learning path for every user based on the pattern of questions answered. UPS’s ORION (On-Road Integrated Optimization and Navigation) project also stands out in terms of how analytics has contributed to cost minimization. ORION is widely considered the largest commercial analytics endeavor to date, which has taken more than a decade to develop. It is a logistical analytics marvel that produces different routes every day for drivers based on weather, traffic, and pickup and drop-off locations that can vary on a daily basis, saving the company hundreds of millions of dollars (Davenport & Harris, 2017).

While many firms may be analytically ready by having leadership support, an analytics culture, and state-of-the-art technology, they may not be able to cash in on performance metrics such as sales growth. Firms such as UPS and Riiid are exceptions rather than the norm. We posit that (1) there is a critical missing link between analytics readiness (hereinafter, AR) and firm performance that needs to be established for firms to reap the reward of being analytically ready and (2) certain conditions may amplify or mitigate the role of this missing link. Strategic research in analytics has been dominated by consultants rather than academics. Thus, our paper takes a more rigorous approach to integrate analytics research from the practitioner and academic points of view.

To this end, we address the following three research questions. First, what does AR imply for service firms? In other words, if a service firm is analytically ready, what does this entail? Second, is AR sufficient to drive firm performance, or is there a critical missing link that ensures higher firm performance through AR? Third, what are the boundary conditions for when AR pays off? Do certain strategies facilitate versus hinder AR's effectiveness?

Although there are studies on consumer technology readiness (Prodanova et al., 2018; Tuan, 2021; Yen, 2005), no scale measuring AR has been developed or validated from a rigorous scientific perspective. Despite many attempts, especially on the practitioner side, no comprehensive scale exists that meets robust psychometric properties. Our paper fills this gap by developing and validating an AR scale.

Although it is widely believed that firms that are strong in AR outperform those that are not, the process through which this occurs has not been validated from a scholarly perspective. We define AR as the extent to which firms are prepared, in many different respects (e.g., leadership, culture, talent), to use data, statistical analysis, and predictive and prescriptive modeling to make strategic decisions (Davenport & Harris, 2017). Although it may be assumed that firms that are strong in AR can leverage and unleash the power of data, from an empirical perspective, the extant literature has yet to unambiguously establish how and when such firms outperform those that are weaker in AR (Germann et al., 2013). Understanding the relationship between AR and performance and the process by which the former influences the latter will shed light on *how* AR contributes to higher firm performance (e.g., sales growth). Practically speaking, the monetization of analytics (e.g., increased revenue and cost savings, as in the UPS and Riiid examples) and understanding how this process unfolds is critical to establishing analytics as the next frontier for sustainable competitive advantage.

Furthermore, we lack knowledge on *when* AR pays off. Does a firm always benefit from AR, or are there boundary conditions in determining when AR is more or less effective? Is the return on AR greater for firms that pursue certain strategies than others? Although one may expect a universal relationship between AR and firm performance, this paper provides theoretical and empirical evidence to suggest otherwise. There is dearth of knowledge on the contingency conditions under which AR leads to different levels of firm performance. Therefore, this paper examines when AR yields more or less performance results.

Against this backdrop, we contribute to the burgeoning analytics literature in three ways by drawing on the input-process-output (IPO) framework as the overarching theoretical net (Hackman, 1987; McGrath, 1984). First, building on and extending prior work in the literature (e.g., Germann et al., 2013), we develop and validate a construct we call "analytics readiness," or AR, which captures the degree to which firms are prepared to use data to make strategic decisions. We conceptualize this construct as a multidimensional, higher-order construct comprising five lower-order dimensions: cultural readiness, leadership commitment, strategic alignment, structural readiness, and talent capacity.

Second, we develop a model that explicates the process by which AR affects firm performance. We posit and empirically show that AR is insufficient for firms to experience improved performance. We hypothesize that a relative emphasis on data-driven decision making (hereinafter, DDDM), defined as the ratio of a firm's decision processes that are data-driven versus instinct-driven, plays a critical mediating role between AR and firm performance. That is, unless firms practice a relative emphasis on DDDM, AR alone will not result in enhanced firm performance. Although prior studies have examined analytics use and deployment (e.g., Chen et al., 2015; Germann et al., 2013), no study has formally tested the trade-off between data versus intuition in decision making as the conduit between AR and firm performance.

Third, we explicate the conditions under which the impact of AR on relative emphasis on DDDM is amplified versus attenuated. We delineate the boundary conditions that must be considered to avoid the erroneous belief that analytics is an all-purpose panacea in the digital economy. We posit that different market learning strategies—namely, exploration, which is more conducive to experimentation, and exploitation, which is more inclined to continue building on proven approaches (March, 1991)—will shape how much decision making is data-driven from AR as opposed to instinct-driven. This is the first study to investigate the two market learning strategies in the analytics context for service firms, and we subsequently argue and show that the two market learning strategies play different moderating roles in the relationship between AR and relative emphasis on DDDM.

The remainder of this paper proceeds as follows: In the next section, we discuss the IPO framework, the core constructs of the model, and the hypotheses. We then report the results from three studies. In Study 1, we conduct interviews with MBA students from the United States to assess the AR construct. In Study 2, we develop and validate the AR scale using data from Turkish service firms. In Study 3, we test the conceptual model using data from South Korean service firms in diverse industries. We conclude with a discussion of the theoretical and managerial implications of our findings as well as directions for future studies.

THEORETICAL FRAMEWORK AND CONSTRUCTS

The Input-Process-Output (IPO) Framework

Our overarching theoretical approach draws from the IPO framework (Hackman, 1987; McGrath, 1984), from which we develop our conceptual model (see Figure 1). The central tenet of this framework is that outcomes are driven by inputs and that processes are the "black box" that transforms inputs into outcomes. Inputs can be individual or organizational factors, such as leadership characteristics or organizational design and structure (Hülsheger et al., 2009). In contrast, processes are transformational in nature because they enable (transform) inputs to help achieve desired outcomes. Examples of processes include communication, coordination, collaboration, and knowledge sharing (Hülsheger et al., 2009). Outcomes are results, and performance is one of the most widely studied outcome variables (Bommer et al., 1995).

The IPO framework is relevant and adequately explains our conceptual model because the constructs in the model map onto the three elements of the IPO framework, and the framework explicates the mediating role that process plays in linking input to outcome. The central tenet of the IPO framework asserts that input is too distal to have a direct effect on outcome and that process plays a critical mediating role by channeling the impact of input on outcome. Our conceptual model, shown in Figure 1, reflects the mediating effect of relative emphasis on DDDM as a nexus between AR and sales growth.

[Insert Figure 1 here]

There has been growing criticism of the traditional IPO framework and calls for more research to examine contingency effects (Ilgen et al., 2005). To this end, our conceptual model builds on advancements made to the traditional IPO framework by asserting that AR (input) interacts with market learning strategy (input) to influence relative emphasis on DDDM (process). As we explain subsequently, our core argument is that AR does not universally affect relative emphasis on DDDM to the same extent but differs depending on the type of learning strategy (i.e., exploration or exploitation) a firm deploys.

Constructs

Analytics Readiness (AR). We define AR as the degree to which firms are prepared to use data to guide their strategic decision making. We posit that AR is an input in our model because AR is the factor that is being fed into the system—that is, it is being used by an organization to produce desirable outcomes. With the proliferation of big data, firms have at their fingertips an abundance of data for developing strategies (Agarwal & Dhar, 2014; Chen et al., 2015). Different firms will be in different stages of AR—some may be more advanced, while others may still be in their infancy. The Five Stages of Analytical Competition summarize firms as follows (Davenport & Harris, 2017): analytical competitors (Stage 5), analytical firms (Stage 4), analytical aspirations (Stage 3), localized analytics (Stage 2), and analytically impaired (Stage 1). Frameworks such as the DELTA (*D*ata, *E*nterprise, *L*eadership, *T*argets, and *A*nalysts) model have been proposed to inform firms about what they need to accomplish to become more analytically competent. Having high-quality, unique data, integrating analytics into an organization-wide effort as opposed to operating in siloes, having leadership commitment and investment, using analytics to focus on and support specific capabilities and functions, and securing competent human resources (analysts) through hiring and training can all help firms become more analytically ready (Davenport & Harris, 2017).

Although prior research in this area has been progressive and illuminating, it has fallen short by not considering AR as a multifaceted concept. The AR construct needs to cast a wide net and avoid a narrow conceptualization as the mere possession of analytical skill sets (e.g., human capital). As with many transformations, it is not merely technology per se but the culture, leadership, and structure and systems that need to be in place for a pervasive change to occur.

Research in big data and analytics suggests that although technology can be a factor, the more challenging element of change management lies in managerial issues such as culture and leadership. For example, McAfee and Brynjolfsson (2012, p. 7) acknowledge that "the technical challenges of using big data are very real. But the managerial challenges are even greater." We find widespread agreement that organizational and managerial issues can be stumbling blocks for many organizations. Chen et al. (2015, p. 32) acknowledge this, concluding that "having a technical requirement in place for BDA (Big Data Analytics) is only part of the picture. BDA championship by top management is essential to bridging the organizational and environmental factors into actionable usage of BDA." Furthermore, according to a NewVantage Partners survey of large U.S. firms, 95% of the firms reported cultural, organizational, and process challenges as the biggest obstacles to analytics adoption, while only 5% cited technology as the problem (Smith et al., 2019).

Although the marketing analytics, information systems, and decision sciences literatures have contributed to this stream of research, they fall short in that no study provides a comprehensive view of AR (see Table 1). For example, in the decision sciences literature, Ghasemaghaei (2019) examines data analytics competency, and Ghasemaghaei and Calic (2019) investigate big data utilization. However, they only provide a fragmented and piecemeal approach to AR that lacks a holistic perspective. This deficiency is clearly evident in the practitioner literature as well (see Table 2). Thus, based on a thorough review of the analytics, information systems, and decision sciences literatures, we posit that AR is a multidimensional construct made up of five lower-order dimensions: cultural readiness, leadership commitment, strategic alignment, structural readiness, and talent capacity.

[Insert Tables 1 and 2 here]

Cultural Readiness. A data-driven culture is defined as "the extent to which organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data" (Gupta & George, 2016, p. 5). Culture can be a catalyst or a culprit with respect to AR (Smith et al., 2019). The importance of culture cannot be overstated. As Díaz et al. (2018, p.1) state, "organizational culture can accelerate the application of analytics, amplify its power, and steer firms away from risky outcomes." Therefore, our AR construct includes cultural readiness as a dimension by underscoring that data should be treated as a core asset, that analytics has changed how business is conducted, and that analytics has caused a power shift within the organization.

Leadership Commitment. The role of leadership is clearly documented in the extant literature. Drawing on upper echelons theory (Hambrick & Mason, 1984), top management team advocacy for analytics had a profound impact on the deployment of analytics (Germann et al., 2013). Leadership commitment can come in different ways, such as through structural commitment (e.g., investment in technology and training) and/or relational commitment (e.g., best practice communication) (Tabesh et al., 2019). We posit that AR is a top-down rather than a bottom-up process and that without the commitment and engagement of senior management (e.g., the chief executive officer [CEO], the top management team), tangible results are not possible (Gupta & George, 2016). Without support and push from top management, analytics will not be properly disseminated and embraced as a strategic priority at the enterprise level and most likely will remain a departmental exercise (Chen et al., 2015).

Strategic Alignment. By strategic alignment, we refer to the need for analytics strategy and overall business strategy to complement each other. That is, analytics strategy and overall business strategy should reinforce each other (Ladley & Redman, 2020; McAfee & Brynjolfsson, 2012). The significance of strategic alignment has been empirically supported in the analytics literature, which shows that analytics capability–business strategy alignment positively moderates the relationship between big data analytics capabilities and firm performance (Akter et al., 2016). Alignment between information systems strategy and business strategy also has a positive effect on overall business performance, but only for prospectors and analyzers (Sabherwal & Chan, 2001). Therefore, analytics strategy and business strategy need to be compatible, in sync, and mutually reinforcing.

Structural Readiness. By analytics structure, we refer to systems and policies that enable better customer service and experiences through enhanced data accessibility (i.e., data democratization) and the seamless sharing and flow of data across departments and functions. Analytics control, connectivity, and coordination are elements that support an effective analytics infrastructure (Akter et al. 2016). Having the appropriate analytics structure ensures that customer-facing employees have the right data at the right time to enhance customer experiences, generate more sales, and improve profitability. The importance of organizational structure in realizing the potential of a firm's strategy has been a long-researched area in marketing (e.g., Olson et al., 2005; Vorhies & Morgan, 2003). More recently, Moorman and Day (2016) have asserted that structure, an element of configuration, is a critical component in organizing for marketing excellence. Analytics structure is the "data highway" that allows data to flow and be shared in every corner of the organization where it is needed.

Talent Capacity. Finally, to "walk the talk," an organization must have the human resources (e.g., data scientists, analysts) to actually execute an analytics strategy. That is, firms need the appropriate skills and competencies to carry out the complex tasks associated with analytics. Without the necessary talent, analytics will never see the light of day. The strategic significance of human talent that will allow an organization to be analytically ready cannot be overstated (e.g., Akter et al. 2016; Germann et al., 2013; McAfee & Brynjolfsson, 2012). As an illustration, data analysts at Netflix used visualization and demand analytics tools to better understand consumer behavior and preferences, contributing to the success of the "House of Cards" show in the United States (Ramaswamy, 2013).

Market Learning Strategy. Along with AR, a firm's market learning strategy is an input in our model because a market learning strategy can be conceived of as a driver or impetus that firms can leverage to deliver desirable outcomes. The organizational learning literature distinguishes two types of learning: exploratory and exploitative (Levinthal & March, 1993; March 1991).

Exploratory learning occurs when there is "pursuit of new knowledge" (Levinthal & March, 1993, p. 105) and is depicted by "search, variation, risk taking, experimentation, play, flexibility, discovery, and innovation" (March, 1991, p. 71). Exploratory learning focuses on the search for innovative and creative solutions, the pursuit of opportunities that may entail risk but are ultimately compensated with high returns, and a departure from existing and well-established routines to experimentation with novel procedures. To achieve superior firm performance (e.g., sales growth), exploration underscores searching for new opportunities and cultivating new competencies through disruptive activities that entail risk taking, experimentation, flexibility, discovery, and innovation.

In contrast, exploitative learning refers to “the use and development of things already known” (Levinthal & March, 1993, p. 105) and is characterized by “refinement, choice, production, efficiency, selection, implementation, and execution” (March, 1991, p. 71).Thus, exploitative learning is defined as learning that involves refinement, renewal, and reconfiguration of existing knowledge to improve efficiency and productivity (March, 1991). Exploitation, with its focus on consistency and stability, is chiefly concerned with investing in existing technologies, routines, and competencies. Consequently, exploitation attempts to optimize and exploit such learning in current services and customer and supplier relationships (March, 1991). Exploitative learning relies on less risky (safer), more established, and proven processes and methods, thus leading to more predictable and stable outcomes. As March (1991, p. 85) succinctly states, the essence of exploitation is “the refinement and extension of existing competencies, technologies, and paradigms.”

Relative Emphasis on DDDM. We define relative emphasis on DDDM as the ratio of a firm’s decision process that is data-driven versus instinct-driven. In our model, relative emphasis on DDDM is a process because this construct is the conduit that channels the input to the outcome. Our position is that a hallmark of an analytics firm is that decision making and resource allocation investments are driven primarily by insights gleaned from data rather than based on experience, instinct, intuition, or “gut feeling.” There is growing consensus that data culture is decision culture. This perspective is exemplified by the following statement: “The fundamental objective in collecting, analyzing, and deploying data is to make better decisions" (Díaz et al. 2018, p. 2).

Our central thesis is that being analytically ready is insufficient to realize higher firm performance unless decision makers actually make decisions based on data rather than simply intuition and instinct. Being prepared is one thing; actually using what has been prepared is another. Unless the latter happens, preparation is fruitless. Although prior studies have used constructs such as deployment of analytics (Germann et al., 2013) and big data analytics use (Chen et al., 2015), which indicate decision making based on data, few studies, if any, have explicitly captured the degree to which firms use data-driven *versus* intuition-driven decision making. We argue that this is an important point of departure from previous studies and helps us understand the trade-offs that decision makers have to make between data and intuition.

Mapping Constructs to the IPO Framework

We explain how the constructs in our conceptual model map onto the IPO framework. We posit that the model's constructs correspond to three organizational competencies that explain firm performance: input-based competencies, transformational (process) competencies, and output-based competencies (Lado et al., 1992; Lado & Wilson, 1994). These three competencies are also consistent with the Sources of Advantage-Positional Advantage-Performance Outcome framework advocated by Day and Wensley (1998).

Input-based competencies represent sources of advantage (Day & Wensley, 1998) such as tangible or intangible resources, skills, and knowledge that are fed into the system and result in desirable outcomes (Lado & Wilson, 1994). An example of an input-based competency is human asset specificity, or the unique knowledge, skills, and abilities pertaining to a firm's human resources (e.g., salespeople, engineers, analysts). In our model, we advance that AR and market learning (exploration and exploitation) are input-based competencies.

Transformational competencies are the "organizational capabilities required to advantageously convert inputs into outputs" (Lado et al., 1992, p. 85). Transformational competencies are the conduit through which input-based competencies are converted into desirable outcomes (e.g., superior firm performance). Positional advantages (e.g., superior customer value, lower relative costs), market-sensing capabilities, and customer relationship management are examples of transformational competencies (Day & Wensley, 1998). We submit that relative emphasis on DDDM is a transformational competency that channels AR's impact on firm performance.

Finally, output-based competencies are outcomes that result from inputs and their transformation. Brand or corporate image, reputation, customer satisfaction, and customer loyalty are examples of intangible output-based competencies, while market share, sales and other financial metrics, and innovative products are tangible output-based competencies (Day & Wensley, 1988). In our model, sales growth is an output-based competency.

HYPOTHESES DEVELOPMENT

The Mediating Effect of Relative Emphasis on DDDM

Decision making is about choosing between alternatives and involves trade-offs. This happens after carefully considering choices from a set of several options, mapping the likely consequences of choices, and finally choosing the best course of action to take. Prior literature in analytics has not examined decision making when trade-offs need to be considered (Ghasemaghaei, 2019). Our research captures the trade-off in decision making between data and intuition. Leonard et al. (1999) argue that the quality of decision making affects the quality of the decision outcome, which in turn affects firm performance. In the analytics context, it is increasingly argued that data-driven decisions are "safer" and mitigate risks, especially with decisions that involve uncertainty and novelty because facts drive decisions rather instincts that are more subjective and biased (McAfee & Brynjolfsson, 2012).

We argue that both types of decision making (data- and instinct-driven) play an important role in channeling the impact of AR on firm performance. That is, we seek to move beyond the more obvious relationship between relative emphasis on DDDM and performance (i.e., more DDDM is better and has a more positive impact on firm performance) to quantifying a ratio of data- versus instinct-driven decision making and studying its role in the relationship between AR and firm performance. Nevertheless, AR alone cannot guarantee a successful impact on firm performance. That is, unless AR is channeled through relative emphasis on DDDM, firm performance will not benefit from AR.

Even if a firm is analytically ready, if decisions are made based on patterns and relationships that are observed and internalized, AR's impact on firm performance may be limited (McAfee & Brynjolfsson, 2012). For example, if employees favor decision-making rules that have been institutionalized over time (e.g., "we've always done it this way," "everybody does it this way," "that's just the way things are done around here"), firm performance will not benefit from AR (Oliver, 1997).

Kiron and Shockley (2011) argue that firms with strong analytics capabilities have more than just the relevant expertise; they have processes in place that encourage new ideas that challenge current decision-making practices. We posit that such processes affect the choice of data- versus intuition-based decision making and that this crucial piece serves as the conduit through which AR affects firm performance. Therefore, we hypothesize that a relative emphasis on DDDM versus instinct-driven decision making mediates the impact of AR on firm performance. That is, a firm can be analytically ready, but unless employees actually use data rather than instincts to make decisions, firm performance is unlikely to benefit from AR. As one of the interviewees indicated, "*In my opinion, it is not enough to have information, but you need to understand it and use it to make better decisions*." Formally, we hypothesize the following:

H1: *AR has an indirect positive effect on firm performance that is mediated by a relative emphasis on DDDM over instinct-driven decision making.*

The Moderating Effect of Market Learning Strategy

We focus on the two market learning strategies, exploration and exploitation, in our model and argue that the type of market learning strategy will either strengthen or weaken AR's impact on relative emphasis on DDDM. Our interaction hypotheses respond to calls in the extant literature to expand the traditional IPO framework via more research on contingency relationships in the IPO model (Ilgen et al., 2005). Accordingly, we hypothesize that AR interacts with the two market learning strategies to influence relative emphasis on DDDM. These hypotheses provide important insights for firms seeking to understand the conditions under which data will be used more than instinct as a result of being analytically ready. We assert that although a firm may be analytically ready, the degree to which decision making relies on data versus instinct is contingent on the firm's learning strategy.

The Moderating Role of Exploratory Learning. To navigate uncharted territories in which outcomes are less certain and stable, firms need to be more dependent on data than on instinct or experience (e.g., Kane & Alavi, 2007). Because exploratory learning involves risk and experimentation, both of which lead to greater uncertainty, data become instrumental in mitigating ambiguity and provide a clearer path to expected outcomes (Ghasemaghaei & Calic, 2019). For exploratory learning that involves novel and unproven approaches to problem solving, relying on data for decision making will be less biased and risky than using intuition. Exploratory learning is forward looking and future oriented as it involves searching for market information where a market may not even be currently developed (March, 1991). Thus, the utility of experience, which has traditionally been a resource, will play less of a role. Furthermore, because outcomes associated with exploratory learning can be more distal and fluctuating, data can play an important role in providing greater predictability (March, 1991).

Therefore, with its emphasis on data, exploratory learning will unleash the competency of firms that are analytically ready to put more relative emphasis on DDDM. That is, we submit that two inputs—AR and exploratory learning—reinforce each other and have a positive interaction effect on relative emphasis on DDDM. Exploratory learning will bring out the importance of data from analytically ready firms and increase relative emphasis on DDDM. Consequently, we expect the impact of AR on relative emphasis on DDDM to be amplified. In line with the preceding arguments, we hypothesize the following:

H2: *The effect of AR on relative emphasis on DDDM over instinct-driven decision making is strengthened as exploratory market learning increases.*

The Moderating Role of Exploitative Learning. Because exploitative learning relies on proven techniques and well-established routines that leverage existing knowledge, analytically ready firms will be less inclined to rely on data than on past experience and instinct when making decisions (e.g., Kane & Alavi, 2007). That is, even for firms that are analytically ready, there is less motivation and incentive to use data to make decisions because under exploitative learning, which focuses on the renewal and reconfiguration of prior knowledge, decision making that utilizes past experience and instinct may suffice (Ghasemaghaei & Calic, 2019). Despite being analytically ready, firms that pursue an exploitative learning strategy may engage in less relative emphasis on DDDM because such a learning strategy does not rely on data to provide greater accuracy, predictability, certainty, and stability. When executing strategies that involve similar routines and patterns that are well established, the strategic importance of data is expected to diminish, and analytically ready firms will not fully capitalize on their readiness for DDDM. Furthermore, exploitative learning is present and past oriented because its focus is on existing market needs and leveraging what is already known and has already been tried (Levinthal & March, 1993; March, 1991). Thus, the emphasis on data is likely to be lower, and more focus will be on using experience and instinct to guide and direct decision making.

Therefore, we advance that the two inputs (i.e., AR and exploitative learning) are incompatible such that exploitative learning mitigates the significance of data in analytically ready firms, leading to less relative emphasis on DDDM. We hypothesize the following:

H3: *The effect of AR on relative emphasis on DDDM over instinct-driven decision making is weakened as exploitative market learning increases.*

STUDY 1: QUALITATIVE INTERVIEWS

To further develop the AR construct, we conducted electronic interviews via email to tap into the multidimensional nature of the AR construct. We received responses from 23 MBA students with average work experience of 7.7 years. These respondents had worked in various service industries, such as financial services, logistics, transportation, retailing, and information technology. We asked the students to list all the factors they believed firms would need to qualify as analytically ready. The results, which we report next, provide strong support for the five lower-order dimensions that fall under AR.

Cultural Readiness

As we discussed previously, in the literature, one of the most significant factors affecting AR is the dimension of culture. This was strongly confirmed by our interviewees, who viewed culture as the "glue" that integrates people under a common goal and that leadership plays a significant role as the "engine" in developing and supporting an analytics culture. As one interviewee put it, "*For a firm to be analytically ready the first and foremost is leadership support and firm culture alignment.*" As another commented, "*The firm managers should embrace core processes and appropriate culture to embrace insights produced by the analytic team to appropriately address arising issues*."

Leadership Commitment

Many interviewees highlighted that senior leadership support and commitment are critical if investments in analytics are to pay off. As one respondent stated, "*[AR] has to come from the top, from the CEO through the executive leadership down to every employee. The CEO has to be passionate, engaging and frankly sell the entire organization on 'Why'. Every single employee needs to clearly understand the 'Why' and see a clearly defined future that incorporates analytics*."

Strategic Alignment

Results from the interviews confirm that a firm's analytics strategy and its overall business strategy must go hand-in-hand and not proceed in parallel fashion. As one of the comments indicated, "*Firm[s] should not use analytics mainly for cost reduction purposes when the overall brand strategy is delivering a premium and exclusive customer experience or the other way around*."

Structural Readiness

Many interviewees stated that systems, structural designs, and incentives are critical to facilitate data accessibility for customer-facing employees and remove barriers for communication and knowledge sharing between data scientists and nonanalytics personnel. As one responded asserted, "*There needs to be policies and systems to help determine which data will and will not be shared and to promote regular cadence of sharing of data*." As another respondent stated, "*Adequate IT department with the right infrastructure and database/data warehouse because often data is stored in different systems that usually don't communicate well with one another. This makes it difficult to extract meaningful data efficiently to produce insightful analysis*."

Talent Capacity

Our interviews strongly support the significance and difficulty of hiring not only people with the technical skills but also those with the capability to communicate (e.g., through visualization) complex and technical material to others who do not have an analytics background. As one respondent asserted, "*Having the right team (data scientist, data analyst, data engineers) and learning platform for continuous skill development and the ability to communicate to the rest of the organization to make sure everyone understands the benefits of focusing on advance analytics is key*." This was further underscored by the following statement: "*Getting the right skillset in the analytics department capable of interacting with the data to tell a meaningful story, developing advanced statistical models like predictive modeling, and writing algorithms usually for machine learning*."

STUDY 2: SCALE DEVELOPMENT AND VALIDATION

Step 1: Scale Development

Despite the increasing number of studies on "analytics" in the literature, there is no comprehensive scale for measuring AR. The need for a comprehensive (multidimensional) scale arises from the findings of previous studies. For example, Germann et al. (2013) focus on the antecedents of marketing analytics, such as senior management advocacy, analytics culture, and marketing analytics skills. However, no study to date has explicitly measured readiness, per se. Thus, we developed a multidimensional AR scale to fill the gap in the literature. We followed Churchill's (1979) procedure to develop and validate the scales.

First, based on the interview results (Study 1) and literature review, we identified AR as a higher-order construct comprising (1) cultural readiness, (2) leadership commitment, (3) strategic alignment, (4) structural readiness, and (5) talent capacity (e.g., Germann et al., 2013). We performed a thorough review of conceptual studies in the field of analytics to generate the items. Accordingly, we created a list of 37 items. Second, we interviewed 34 senior managers of service firms in Turkey. The most important reason we conducted interviews with senior managers is that they direct the strategic activities of the firms and can therefore evaluate their structural and cultural characteristics better than other managers. Table 3 reports the sample characteristics. Managers evaluated the scale items in terms of content and face validity. On the basis of their feedback, we removed seven items, added three new items, and modified some items so that they can be generalized in a variety of contexts.

[Insert Table 3 here]

Step 2: Scale Validation

Context and Sample. Data for this study were collected in Turkey. Turkey is one of the world's 20 largest economies. The share of the service sector in the gross national product of the country is 60.7%. Transportation, financial services, tourism, and telecommunications all represent important subsectors within the service sector. In addition, the share of health care services in the service sector has been increasing in recent years (World Economic Outlook, 2020). In parallel with internationalization targets and increasing internal competition, service firms have started to use modern management and marketing techniques more intensively, and the tendency to make data-driven decisions has increased. This trend has made the applications of big data, artificial intelligence, and business/marketing analytics more attractive for firms (Microsoft & EY, 2018). For these reasons, the Turkish service sector offers an attractive research environment to test the validity and reliability of the scales we aim to develop. We selected 146 service firms to collect data using the convenience sampling technique. As in the qualitative research, participants were CEOs or senior executives because top-level managers can evaluate the cultural, strategic, structural, and human resources characteristics of the firms as a whole (see Table 3).

Measure Validation. We conducted confirmatory factor analysis (CFA) to assess the validity and reliability of the five dimensions of AR. The CFA indicated good fit to the data (χ^2 = 777.77, *df* = 485; Tucker–Lewis index [TLI] = .939; comparative fit index [CFI] = .944; root mean square error of approximation [RMSEA] = .065). All factor loadings are statistically significant (Table 4). As Table 5 reports, Cronbach's alpha and composite reliability coefficients are above .70. The average variance extracted (AVE) scores are greater than .50. Therefore, the scales demonstrate convergent validity. In addition, statistically significant factor weights and the high correlation between the first-order dimensions provide further evidence that AR can be operationalized as a higher-order construct.

[Insert Tables 4 and 5 here]

STUDY 3: MODEL TESTING

Sample and Data Collection

We collected data from firms that are officially registered in the enterprise resource planning system at the South Korean Productivity Center. When we started this study, 3739 private firms were registered in the system. Firms operated in industries such as machinery, automotive, chemicals, construction materials, pharmaceuticals, consumer goods, information technology, telecommunications, professional services, and financial services. For data collection purposes, we created a database containing contact information of all service firms (i.e., 700). We identified CEOs or senior executives as participants as they are key members of senior management and determine the strategic direction of firms. The participants received a package containing an introductory letter, the questionnaire, and a postage-paid envelope with a separately posted return address label. We attempted to increase the response rate by providing the participants with a report of the study's findings. After two follow-ups, we obtained 204 usable responses (response rate of 29%).

We tested nonresponse bias by dividing the final sample into two groups: early participants (i.e., after the first wave) and late participants (i.e., after follow-ups) (Armstrong & Overton, 1977). *T*-test results revealed that nonresponse bias was less likely because the model's core variables and firm demographics did not differ significantly between early and late participants. We checked key informant quality by asking participants to answer a single-item question (1 = "very limited information," and 7 = "very important information") (e.g., Atuahene-Gima, 2005). An average score of 6.52 indicated a high level of informant quality. In addition, because our participants are CEOs or senior executives, we were confident that they were knowledgeable of their firms' capabilities and actions. Table 3 reports sample characteristics.

Measures

We conducted the survey in Korean. We originally designed the survey in English and translated it into Korean using the translation and back-translation method (Brislin et al., 1973). While designing the survey, we took the necessary measures to eliminate response bias (Podsakoff et al., 2003). First, we informed participants that the scale items do not have right or wrong answers and that their responses would be held strictly confidential. Second, we randomized scale items to reduce priming effects and item-context-induced mood states. Third, we obtained responses about firm performance using different anchor labels to avoid common scale properties (Ostroff et al., 2002). We used the five-point Likert format (1 = "strongly disagree," and 5 = "strongly agree") for all scales except for firm performance.

Main Variables. We identified AR as a five-dimensional, higher-order construct. We measured cultural readiness with seven items, strategic alignment with three items, leadership commitment with five items, talent capacity with eight items, and structural readiness with ten items. We measured exploratory and exploitative learning with a five-item scale (Atuahene-Gima, 2003). We measured relative emphasis on DDDM as the ratio of DDDM to instinct-driven decision making. We asked participants to estimate the ratio of their firm's decision processes that are data-driven versus instinct-driven, such that the two add up to 100%. Because the data were not normally distributed, we took the natural logarithm of raw values prior to model estimation. Following previous studies (e.g., Homburg & Pflesser, 2000), we measured firm performance as sales growth. Participants evaluated their firm's average annual sales growth rate over the past 24 months relative to both their major competitor and the firm's objectives: (1) sales have declined, (2) 0% per year–4% per year, (3) 5% per year–9% per year, (4) 10% per year–14% per year, (5) 15% per year or more.

Control Variables. Including control variables in the model provides benefits such as maximizing the observed heterogeneity, being able to observe the explanatory power of the main variables when the control variables are in the equation, and minimizing omitted variables bias. However, there are also disadvantages of including control variables that do not have theoretical and, more importantly, statistical significance (insignificant correlation) with the model's dependent variables, such as decreasing the power of the model and unnecessarily decreasing the effect of the relationships between the main variables (Becker et al., 2016). Considering these issues, we included CEO background, market dynamism, and technological uncertainty when predicting relative emphasis on DDDM and firm type when predicting firm performance. We measured CEO background (1 = marketing, 2 = finance and accounting, 3 = operations, 4 = human resources, 5 = sales, 6 = research and development, 7 = analytics, 8 = information technology) and firm type (1 = business-to-business [B2B], 2 = business-to-consumer [B2C], 3 = both B2B and B2C) using dummy variables. We measured market dynamism with five items and technological uncertainty with four items (Jaworski & Kohli, 1993).

Measurement Model

The CFA revealed a good fit to the data (χ^2 = 2036.42, *df* = 1238; GFI = .891; TLI = .902; CFI = .908; RMSEA = .056). All factor loadings were statistically significant (Table 4). Cronbach's alpha, composite reliability, and AVE values were above their thresholds (Table 6). The AVE values were greater than the squared intercorrelations (i.e., the measurement error-adjusted intercorrelations) between two constructs (Voorhees et al., 2016). These findings support the convergent and discriminant validity of the constructs. Because there was a high level of correlation between the first-order dimensions (from .846 to .984), we created a composite AR construct by multiplying the mean scores of the five dimensions by their importance weights.

[Insert Table 6 here]

Analytic Approach

Model Estimation. The database consists of multiple firms operating in each sector. The nested nature of our data may require us to use multilevel modeling. First, the intraclass correlation coefficient (ICC1 = .083) and analysis of variance ($F(14,189) = 2.206$, $p < .01$) show that industry membership explained 8% of the variance in firm performance. According to LeBreton and Senter (2008), multilevel modeling should be used when the ICC(1) exceeds 0.05. Second, the Breusch-Pagan test reveals heteroskedasticity in our data, indicating that ordinary least squares–based standard errors may be misleading unless corrected (i.e., cluster-corrected robust standard error). Therefore, we estimated the model simultaneously using two-level path modeling. Because our goal was to estimate firm-level variability in performance, we used industry-level fixed effects for all coefficients and random effects for the intercept. Thus, we employed grand-mean-centering for all firm-level variables and created interaction effects by multiplying the relevant variables (Hofmann & Gavin, 1998). Using the R-mediation package, we calculated the indirect effects with the Monte Carlo approach.

Common Method Bias. We used the latent common factor technique to minimize the effect of method bias on model estimation. There was a statistically significant difference between the method model and the measurement model ($\Delta\chi^2 = 321.6$, $\Delta df = 52$, $p <. 01$), and the method factor explained 11% of the variance. Using the regression-based imputation method (Arbuckle, 2018), we calculated the estimated values of the method factor for each observation and included these values in the model as an additional control variable.

Endogeneity Bias. In estimating the model, we took into account the endogeneity of AR, exploration, and exploitation. Traditional techniques available to control for endogeneity bias require the presence of instrumental variables for each endogenous variable in question (i.e., strong correlation with the independent variable but not with the dependent variable). However, we could not find instrumental variables containing these attributes. Instead, we used the latent variable technique (Lewbel, 2012). With the help of the ivreg2h command in Stata (Baum & Schaffer, 2015), we used the data set to create instrumental variables. In this technique, because model identification is based on finding regressors that are unrelated to the product of heteroskedastic errors, we used the mean-centered form of the model's variables to generate instruments. The F-statistic for each of the first-stage equations was above the threshold of 9.08 (lowest F-value = 11.02), supporting the instruments' relevance. The Hansen's J-statistic (lowest p = .11) and the difference of two Sargan–Hansen statistics (all ps > .10) indicated that the null hypotheses could not be rejected, suggesting that the instruments are exogenous and uncorrelated with the error terms. Finally, the endogeneity of AR, exploration, and exploitation was supported, as the Durbin–Wu–Hausman tests rejected the null hypothesis.

Results

Table 7 presents the results. We estimated the proposed model in two steps (Preacher et al., 2010). First, we predicted direct effects (Model 1) to test H1. Second, we included interaction effects to Model 1 to test H2 and H3 (i.e., Model 2).

[Insert Table 7 here]

Main and Indirect Effects. Table 7 (Model 1) reports that AR is positively related to relative emphasis on DDDM (γ = .354, p < .01) and relative emphasis on DDDM is positively related to firm performance (γ = .363, p < .05). The indirect effect of AR on firm performance (γ = .114, p < .05; 95% bootstrap confidence interval [CI] [.020; .260]) is significant, whereas the direct effect of AR on firm performance is not. Thus, relative emphasis on DDDM serves as a full mediator in the relationship between AR and firm performance, in support of H1.

Interaction Effects. Table 7 (Model 2) reports that the interaction effect of exploratory learning and AR is positively related to relative emphasis on DDDM ($\gamma = .316$, $p < .01$). The AR–DDDM relationship is significant at high levels of exploratory learning ($\gamma = .600$, $p < .01$) but not at low levels of exploratory learning ($\gamma = .170$, *ns*), in support of H2. The interaction effect of AR and exploitative learning is negatively related to relative emphasis on DDDM ($\gamma = –.177$, $p < .05$). The effect of AR on relative emphasis on DDDM is stronger at lows level of exploitative learning ($\gamma = .506$, $p < .01$) than at high levels of exploitative learning ($\gamma = .264$, $p < .01$), in support of H3. Figures 2 and 3 display both interaction effects.

[Insert Figures 2 and 3 here]

Robustness Check and Additional Analyses

We assessed the robustness of our analysis. First, we tested the interaction effects of AR with exploration and exploitation by entering them into the model one at a time. The significance level of the interaction effects remained the same in each case. Second, we tested whether the three-way interaction of AR, exploitation, and exploitation had a direct effect on relative emphasis on DDDM and an indirect effect on firm performance. The results did not support such effects. Collectively, these results confirm the robustness of our original findings.

We conducted additional analyses to further explicate the moderating role of the two types of market learning. Accordingly, we performed a simultaneous simple slope test for both types of market learning. As Table 8 reports, the effect of AR on relative emphasis on DDDM is strongest when exploration is high and exploitation is low ($\gamma = .721$, $p < .01$). Similarly, the effect is also significant when exploration and exploitation are at high/high ($\gamma = .479$, $p < .01$)

and low/low ($\gamma = .291$, $p < .01$) levels. However, the effect is not significant when exploration is low and exploitation is high ($\gamma = .049$, *ns*).

[Insert Table 8 here]

We computed the indirect effect of AR on firm performance under the moderating role of the two market learning strategies (Table 9). The indirect effect of AR on firm performance is strengthened as exploratory market learning increases. The indirect effect of AR on firm performance is stronger at high levels of exploratory learning ($\gamma = .194$, $p < .05$) than at low levels of exploratory learning ($\gamma = .055$, *ns*). The indirect effect of AR on firm performance is weakened as exploitative market learning increases. The indirect effect of AR on firm performance is weaker at high levels of exploitative learning ($\gamma = .085$, $p < .05$) than at low levels of exploitative learning ($\gamma = .164$, $p < .05$). Furthermore, the indirect effect is strongest when exploration is high and exploitation is low ($\gamma = .233$, $p < .05$) but not significant when exploration is low and exploitation is high ($\gamma = .016$, *ns*). The indirect effect is positive and significant when exploration and exploitation are at high/high ($\gamma = .155$, $p < .05$) and low/low ($\gamma = .094$, $p < .05$) levels.

[Insert Table 9 here]

DISCUSSION

This article draws on the IPO framework, which mirrors three different organizational competencies—*input*-based competencies, transformational (*process*) competencies, and *output*-based competencies (Lado et al., 1992; Lado & Wilson, 1994) to explicate the mediation process between AR and firm performance and the boundary conditions of the AR–relative emphasis on DDDM relationship. Our results yield important theoretical and managerial contributions.

Theoretical Implications

From a theoretical perspective, we conceptualize and empirically examine the role of AR in driving firm performance for service firms and the process by which this occurs as well as the boundary conditions. Our first contribution is the creation of a higher-order AR construct at the firm level. In Study 2, we develop and validate the AR scale through a two-step process (Step 1: qualitative study; Step 2: a quantitative study) by building on the results of Study 1 (interviews). While some of the dimensions in our higher-order AR construct—namely, leadership commitment and cultural readiness—have been studied as antecedents to the deployment of analytics (Germann et al., 2013), we find that the correlations between these constructs are high, suggesting that these (and other) dimensions could make up the higher-order AR construct. Our final product is an AR construct comprised of five dimensions: cultural readiness, leadership commitment, strategic alignment, structural readiness, and talent capacity. By synthesizing the disjointed literature on what it means to be analytically ready at the firm level, our research provides a unified construct that encompasses many of the subdimensions that have been studied in a fragmented manner across different studies in marketing analytics, decision science, and information systems. As Tables 1 and 2 indicate, no studies in academic or practitioner outlets have incorporated all five dimensions of AR. The current research substantiates, qualitatively and quantitatively, the five dimensions of AR across three separate studies, supporting the robustness of the construct.

Second, our results support the well-known "data rich but information poor" conundrum that many firms face. We find that AR does not have a direct effect on firm performance but is fully mediated by relative emphasis on DDDM. Firm performance does not benefit from AR alone; employees must be willing to use analytics-based insights and to support decisions using analytics-based facts for AR to have any impact on sales growth. Although a large body of literature has supported the notion that being analytically ready is simply better for firm performance (Davenport & Harris, 2017), we investigate the process through which AR positively influences firm performance, shedding light on *how* AR affects firm performance. Simply put, AR may be too distal to have a direct effect on firm performance, and a more proximal construct that captures behavioral action stemming from AR is necessary for AR to affect firm performance. Our results suggest that resource allocations for better, smarter, and more technologically advanced analytics programs and capabilities need to be made with great prudence. Firms need to not only develop AR itself but also set up processes that are supportive of and conducive to using analytics-based decisions. Using data rather than experience or instinct to make decisions can be disruptive in many organizations and create discomfort, but DDDM is a critical process for AR to positively affect firm performance. As one of the interviewees keenly pointed out, "*Data analytics can be disruptive in different departments' traditional decision-making process. To effectively have buy-in from all departments the leadership needs to clearly articulate the future, the 'Why' and back it up through positive and cohesive reinforcement*."

An important and novel point of departure from the extant literature is the mediating construct of relative emphasis on DDDM. This construct captures firms' inclination to move away from experience- and instinct-driven decision making—such as "we've always done it this way," "everybody does it this way," or "that's just the way things are done around here"—and toward DDDM. We operationalized this construct as the ratio of a firm's decision process that is data-driven versus instinct-driven. While prior studies have included decision making based on data when measuring constructs such as deployment of analytics (Germann et al., 2013) and big data analytics use (Chen et al., 2015), no study to date has formally measured the trade-off between data-driven *versus* intuition-driven decision making. Thus, this construct captures whether employees on the ground are actually making decisions based on data rather than instinct in their daily operations, which is critical if AR is to improve firm performance.

Third, our findings support the assertion that the impact of AR on relative emphasis on DDDM is contingent on the type of market learning strategy used. Our results indicate that exploratory learning reinforces AR's effect on relative emphasis on DDDM, while exploitative learning dampens AR's impact. These results shed new light on the type of market learning strategy that an AR firm needs to pursue if it wants to achieve a relative emphasis on DDDM. Our study is among the first to examine return on AR within the context of exploratory and exploitative learning. Our findings provide a more nuanced understanding of when AR benefits firms. Also, they underscore the strategic significance of moving from a universal lens to a contingency lens to obtain more subtlety in analytics research. Post hoc analysis also reveals that the indirect effect of AR on firm performance through relative emphasis on DDDM is conditional. That is, we find that the indirect effect is maximized when exploratory learning is high and exploitative learning is low, while the same indirect effect is minimized when exploratory learning is low and exploitative learning is high. The underlying mechanism that explains the conditional indirect effect is that relative emphasis on DDDM increases (decreases) under the combination of high (low) exploratory learning and low (high) exploitative learning.

Managerial Implications

Our findings provide several implications for managers. One practical implication is that AR is insufficient for firms to realize sales growth. Although the practitioner community has extolled the virtues of analytics and affirmed the hype surrounding it, our results suggests that this is a necessary but insufficient condition if firms are to reap the benefits of AR. Being analytically ready is one thing; actually using data to drive decision making is another. Currently, analytics is being used to justify actions ex post and not to guide decision making proactively. Indeed, contrary to popular opinion, LaValle et al. (2011) find that getting access to good, clean data is not the greatest obstacle to extracting value from data. Rather, the major barrier is the general lack of understanding of how to use analytics in decision making. If decisions in the field and on the frontline are not made based on data but rather on experience and intuition, then AR alone will be deficient in delivering on performance promises. We contend that relative emphasis on DDDM is the linchpin for enabling AR to unleash its full potential.

Another important insight is that the role of relative emphasis on DDDM as a conduit between AR and firm performance is contingent on the type of market learning a firm deploys. Our results show that AR will have a greater effect on sales growth when a firm adopts an exploratory strategy because under exploration, AR results in more relative emphasis on DDDM. Exploratory learning involves novel and unexplored approaches to problem solving; therefore, relying on data will be less risky than decision making that uses intuition. The nature of exploratory learning complements a more data-driven (vs. instinct-driven) decision approach.

Conversely, AR will have a weaker effect on sales growth when a firm utilizes an exploitative strategy because under exploitative learning, AR results in less relative emphasis on DDDM. Because exploitative learning relies on proven techniques and well-established routines that leverage existing knowledge, analytically ready firms will be more inclined to rely on past experience and/or instinct when making decisions rather than on data. Therefore, the nature of exploitative learning will complement a more instinct-driven (vs. data-driven) decision approach.

Taken together, our findings underscore the significance of the choice of a market learning strategy if managers truly desire to maximize the return on AR. In short, an important managerial decision is to embrace a more exploratory (vs. exploitative) learning strategy to encourage more relative emphasis on DDDM, which in turn is the key mediator between AR and firm performance. Furthermore, we find that the indirect effect of AR on firm performance is maximized when exploration is high and exploitation is low and minimized when exploration is low and exploitation is high. These results provide firms with the ideal mix between exploration and exploitation, if they are to reap the rewards of their investments in analytics.

Some of the most successful firms are practicing what they preach. Walmart Labs, the big data analytics arm of Walmart, uses real-time data to make decisions about emerging and dynamically changing consumer preferences (Tabesh et al., 2019). One of the most well-known examples of a firm that has harnessed the power of analytics to thrive on DDDM is Netflix, which uses a movie recommendation engine called CineMatch. These firms are not only analytically ready but, more importantly, make decisions based on data rather than experience and instinct, creating a competitive advantage that has proved more sustainable.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study is not without its limitations, which in turn provide guidance and opportunities for further research. First, we have only one response from each firm. While the participants were all CEOs and senior managers and therefore the most knowledgeable about their firms, future studies could be designed with multiple participants. Second, the cross-sectional nature of the data does not permit us to rule out reverse causality. That is, firms that experience higher performance may invest more resources to become more analytically ready. Future work might employ a longitudinal design to enhance confidence that AR results in higher firm performance rather than the other way around. Next, using a subjective assessment of firm performance exposes us to common method bias. While we control for this statistically in our study, future studies could use objective firm performance to address common method bias. Researchers might also examine customer-related performance, such as customer satisfaction and customer experience, in addition to firm performance. Finally, other mediators could be considered. For example, AR could lead to different types of benefits, such as cost reduction and customer experience enhancement. It would be insightful to examine how the effect of AR on firm performance through cost reduction and customer experience enhancement varies depending on different market learning strategies or leadership types (e.g., transactional vs. transformational vs. empowering). We hope that our study on the role of AR and its impact on firm performance sparks other scholars to further investigate this theoretically and managerially important area.

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Table 1. Selected Academic Articles on Analytics

Selected academic articles on analytics	Create and validate an AR scale	Identify boundary conditions of AR (analytics/big data)	Impact of market learning strategies in the analytics context	Overarching theoretical framework
Germann et al. (2013)	N	Y	N	Y
Agarwal and Dhar (2014)	N	N	N	N
Chen et al. (2015)	N	Y	N	Y
Gupta and George (2016)	N	N	N	N
Ghasemaghaei (2019)	N	Y	N	Y
Ghasemaghaei and Calic (2019)	N	N	N	Y
Tabesh et al. (2019)	N	N	N	N
Current paper	**Y**	**Y**	**Y**	**Y**

Table 2: Selected Practitioner Articles on Analytics

Selected practitioner articles on analytics	Culture readiness	Leadership commitment	Strategic alignment	Structural readiness	Talent capacity	Create/validate a scale with all of these elements?
Kiron and Shockley (2011)	Y	Y	N	Y	Y	N
McAfee and Brynjolfsson (2012)	Y	Y	N	N	Y	N
Ramaswamy (2013)	N	Y	N	N	Y	N
Kiron et al. (2014)	Y	Y	Y	N	Y	N
Diaz et al. (2018)	Y	Y	N	Y	N	N
Smith et al. (2019)	Y	Y	N	Y	N	N
Ladley and Redman (2020)	N	Y	Y	Y	Y	N
Current paper	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**

Table 3. Sample Characteristics (Study 2 and Study 3)

	Study 2		
	Step 1: scale development (N = 34)	**Step 2: scale validation (N = 146)**	**Study 3 (N = 204)**
Sectoral distribution (%)			
Information technology services	18	37	12.3
Transportation	12	2.8	2.5
Healthcare	12	12	3.9
Professional services	24	12.3	11.8
Financial services	22	18.4	7.4
Hospitality	12	12	2.9
Real estate		4.1	1.0
Entertainment, media, and publishing		1.4	7.4
Logistics and distribution			12.7
Educational services			11.3
Telecommunications			10.8
Security and protection services			9.8
Energy supply services			1.0
Social services			1.0
Total	100.0	100.0	100.0
Firm size (% of full-time employees)			
Less than 100		12	23
101 and more		88	77
		100.0	100.0
Firm type (%)			
B2B			7.8
B2C			35.8
Both		66.4	56.4
Total	n.a.	100.0	100.0
CEO or senior manager's functional background (%)			
Information technology		43.8	10.3
Marketing		14.4	40.2
Operations		13	5.4
Finance/accounting		12.3	2.5
Sales		6.8	19.1
Research and development		2.1	13.2
Analytics		4.1	2.9
Human resources		3.4	6.4
Total	n.a.	100.0	100.0
CEO or senior manager's experience (as an average year)			
Industry	19.2	11.4	
Work	24.7	19.2	
Firm	9.7	5.4	
Total	100.0	100.0	n.a.

Note: n.a. = not available.

Table 4. Scales and Factor Loadings

Scales	Study 2	Study 3
Cultural readiness		
At our firm,… Data is treated as a core asset.	.775	.753
Our business supports a culture that asks the right kinds of analytic questions that solve business problems.	.714	.779
Data analysis outweighs management experience when addressing key business issues.	.765	.713
Organizational openness to new ideas and analytics approaches challenge current practices.	.774	.678
Analytics has changed the way we conduct business.	.801	.745
Analytics has caused a power shift in the organization.	.707	.670
Analytics is being applied to key business issues by the organization as a whole.	.686	.795
Strategic alignment		
At our firm,… Analytical insights guide future strategy.	.739	.772
Data strategy is aligned with business strategy.	.751	.686
There is an integration of information management and business analytics into strategy.	.738	.792
Leadership commitment		
At our firm,… Senior management is driving the organization to become more data-driven and analytical.	.738	.828
Senior Management plans investments in analytics technology, new talent and training.	.703	.808
Senior Management promotes analytics best practices.	.788	.861
Senior management is committed to seeing analytics succeed.	.793	.846
Senior management is committed to use analytics to transform how customers are served.	.772	.887
Talent capacity		
At our firm,… We are, as a whole, competent at analyzing information and disseminating data insights.	.747	.844
We have the appropriate analytical talent to make good use of analytics.	.764	.824
Individual managers feel adequately prepared to use the organization's data to address business issues.	.818	.765
Executives are effective at balancing analytics and intuition.	.765	.782
We are competent at capturing and cleaning data.	.754	.833
We are competent at aggregating/integrating data.	.672	.842
We are competent at visualizing data.	.743	.745
Analytics has changed the way we conduct business.	.643	.756
Structural readiness		
At our firm,… We strive to connect analytics teams with business teams so that they are on the same page.	.776	.737
Managers have all the data they need to make key business decisions.	.688	.798
Customer-facing employees have access to insights from data to help drive sales and productivity.	.682	.809
Access to useful data has improved during the past year.	.852	.845
Customer-facing employees have access to insights from data that can be used to improve customer experience.	.696	.781
We have systems and policies in place that allows us to use analytics to better serve customers.	.736	.800
Functional areas are planning to make investments in analytics technology in the next 12 months, and/or have already made investments in the past 12 months.	.676	.739
Data is shared across functional silos and/or business units.	.740	.790
There is collaborative use of data across firm lines.	.716	.800
Analytics has changed the way we share information across departments.	.577	.778
Exploratory learning		
Our firm… Collects market information that forces the firm to learn new things in our markets.		.810

Searches for novel and useful approaches to solving problems to market needs that may not be required at that time.		.788
Searches for market information and ideas with no identifiable market needs.		.757
Searches for market information involving experimentation and high risk.		.661
Searches for market information that takes the firm beyond its current market service experiences.		.793
Exploitative learning		
Our firm… Adheres to existing ideas and methods of solving market and service problems.		.711
Undertakes market search activities that we knew we could do well rather than those that may lead to mistakes.		.777
Emphasizes current methods and solutions to market problems that build on the firm's experience.		.774
Searches for market information and ideas that take the firm into its existing markets and areas of learning.		.790
Undertakes information search activities that tap into current experiences of the firm.		.740
Technological uncertainty		
The service technology has been changing rapidly.		.784
Technological changes provide big opportunities in the service category.		.857
A large number of new service ideas have been made possible through technological breakthroughs in this service category.		.774
There have been major technological developments in this service category.		.784
Market dynamism		
In our kind of business, customers' preferences change quite a bit over time.		.729
Our customers tend to look for new services all the time.		.718
Sometimes our customers are very price sensitive, but on other occasions, price is relatively unimportant.		.783
We are witnessing demand for our services from customers who never bought them before.		.737
New customers tend to have service-related needs that are different from those of existing customers.		.720

Note: All factor loadings are significant at $p < .01$.

Table 5. Descriptive Statistics, Correlations, and Reliabilities (Study 2)

Variables	1	2	3	4	5
1. Cultural readiness					
2. Structural alignment	.781				
3. Leadership commitment	.784	.741			
4. Talent capacity	.797	.773	.817		
5. Structural readiness	.862	.796	.769	.822	
Mean	3.97	3.98	3.96	4.05	4.00
SD	.64	.66	.75	.67	.62
Cronbach's alpha	.90	.78	.87	.91	.90
Composite reliability	.90	.79	.87	.91	.91
Average variance extracted	.56	.55	.58	.55	.51

Note: All correlations are significant at $p < .01$ (two-tailed test).

Table 6. Descriptive statistics, Intercorrelations, and Reliabilities (Study 3)

Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
1. Sales growth																
2. Relative emphasis on DDDM (ln)	.210**															
3. Analytics readiness	.213**	.497**														
4. Exploratory learning	.150*	.381**	.465**													
5. Exploitative learning	–.086	–.238**	–.113	–.037												
6. Firm type (B2C)	–.139*	.066	.048	.038	–.115											
7. Firm type (both B2B and B2C)	.126	–.055	–.027	–.016	.067	–.849**										
8. Technological uncertainty	.105	.206**	.375**	.445**	.031	.033	.010									
9. Market dynamism	.067	.251**	.383**	.447**	.121	.001	.038	.632**								
10. CEO background (marketing)	.100	–.183**	–.244**	–.081	.064	–.070	.076	–.073	–.109							
11. CEO background (operations)	–.005	.171*	.077	.051	–.022	–.042	.035	.049	.040	–.196**						
12. CEO background (human resources)	–.117	–.019	–.092	–.076	–.074	.140*	–.135	.070	.038	–.214**	–.062					
13. CEO background (sales)	.030	.017	.084	–.010	–.014	–.077	.126	–.076	.005	–.399**	–.116	–.127				
14. CEO background (RD)	–.016	.173*	.145*	.114	–.027	.010	–.065	.107	.164*	–.320**	–.093	–.102	–.190**			
15. CEO background (analytics)	–.063	–.114	–.033	.028	.048	–.009	.036	–.039	–.092	–.143*	–.042	–.045	–.085	–.068		
16. CEO background (IT)	–.024	.037	.148*	.045	–.019	.117	–.092	.031	.001	–.278**	–.081	–.088	–.165*	–.132	–.059	
Mean	—	.79	3.38	3.49	3.41	—	—	3.79	3.95	—	—	—	—	—	—	—
SD	—	.55	.68	.68	.69	—	—	.61	.69	—	—	—	—	—	—	—
Cronbach's alpha	—	—	.93	.87	.87	—	—	.88	.85	—	—	—	—	—	—	—
Composite reliability	—	—	.93	.87	.87	—	—	.88	.86	—	—	—	—	—	—	—
AVE	—	—	.78	.58	.58	—	—	.64	.54	—	—	—	—	—	—	—

Notes: ln = ln transformed, RD = Research and Development, IT = Information Technology
[a]Base category (B2B).
[b]Base category (finance and accounting).
*$p < .05$; **$p < .01$ (two-tailed test).

Table 7. Results (Study 3)

	Model 1				Model 2			
	Relative emphasis on DDDM (ln)		**Firm performance (sales growth)**		**Relative emphasis on DDDM (ln)**		**Firm performance (sales growth)**	
	γ	**SE**	**γ**	**SE**	**γ**	**SE**	**γ**	**SE**
Constant	–.144	.281	2.638**	.149	–.132	.280	2.638**	.149
Main effects								
Relative emphasis on DDDM (ln)			.363*	.150			.363*	.150
Analytics readiness	.354**	.077			.385**	.075		
Exploratory learning	.286**	.071			.262**	.071		
Exploitative learning	–.131**	.047			–.100*	.047		
Interaction effects								
AR × Exploratory learning					.316**	.107		
AR × Exploitative learning					–.177*	.090		
Control variables								
Firm type (B2C) [a]			–.250	.308	–.250	.308	-.250	.308
Firm type (both B2B and B2C)[a]			.061	.294	.061	.294	.061	.294
CEO background (marketing)[b]	–.027	.204			–.033	.200		
CEO background (operations)[b]	.344	.238			.318	.233		
CEO background (human resources)[b]	.045	.234			–.006	.229		
CEO background (Sales)[b]	–.035	.210			–.031	.206		
CEO background (research and development)[b]	.126	.217			.147	.212		
CEO background (analytics)[b]	–.269	.268			–.261	.264		
CEO background (information technology)[b]	–.035	.219			–.075	.215		
Market dynamism	.121	.071			.123	.070		
Technological uncertainty	–.023	.061			–.003	.060		
Common method bias correction	–.083	.062	.161	.116	–.114	.061	.161	.116
Endogeneity correction (exploratory learning)	–.085	.065	.116	.158	–.144*	.067	.116	.158
Endogeneity correction (exploitative learning)	–.029	.074	–.358*	.172	–.120	.078	-.358*	.172
Endogeneity correction (analytics readiness)	.212*	.089	.356	.206	.224	.090	.356	.206
Pseudo R^2 (within industry)	.174		.059		.199		.059	
Pseudo R^2 (between industry)	.566		.259		.344		.259	
Total R^2	.187		.079		.206		.079	
Log-likelihood (df)		–458.04 (14)				–.450.61 (16)		

Notes: ln = ln transformed, SE = robust standard error.
[a]Omitted category (B2B).
[b]Omitted category (finance and accounting).
*p < .05, **p < .01 (two-tailed test).

Table 8. Simple Slope Tests (Study 3)

Moderating variables		Effect		Confidence intervals
Exploration	**Exploitation**	γ	**SE**	**(LLCI, ULCI)**
Mean	Mean	.385*	.077	(.213, .520)
Low (–1SD)	Mean	.170	.102	(–.055, .357)
High (+1SD)	Mean	.600*	.114	(.381, .819)
Mean	Low (–1SD)	.506*	.106	(.285, .698)
Mean	High (+1SD)	.264*	.094	(.057, .427)
Low (–1SD)	Low (–1SD)	.291*	.114	(.038, .494)
Low (–1SD)	High (+1SD)	.049	.126	(–.228, .278)
High (+1SD)	Low (–1SD)	.721*	.145	(.446, .997)
High (+1SD)	High (+1SD)	.479*	.114	(.244, .689)

*$p < .01$ (two-tailed test).
Notes: Confidence intervals (LLCI = lower-level of confidence interval; ULCI = upper-level of confidence interval) at 95% appear in parentheses (1,000 bootstrap), SE = robust standard error.

Table 9. Analysis of Conditional Indirect Effects of Analytics Readiness on Sales Growth (Mediator = Relative Emphasis on DDDM) (Study 3)

Moderating variables		Indirect effect		Confidence intervals
Exploration	**Exploitation**	γ	**SE**	**(LLCI, ULCI)**
Mean	Mean	.114*	.063	(.020, .260)
Low (–1SD)	Mean	.055	.045	(–.001, .183)
High (+1SD)	Mean	.194*	.102	(.032, .425)
Mean	Low (–1SD)	.164*	.088	(.028, .370)
Mean	High (+1SD)	.085*	.053	(.008, .219)
Low (–1SD)	Low (–1SD)	.094*	.062	(.007, .263)
Low (–1SD)	High (+1SD)	.016	.045	(–.060, .127)
High (+1SD)	Low (–1SD)	.233*	.124	(.035, .514)
High (+1SD)	High (+1SD)	.155*	.085	(.027, .353)

*$p < .05$ (two-tailed test).
Notes: Confidence intervals (LLCI = lower-level of confidence interval; ULCI = upper-level of confidence interval) at 95% appear in parentheses (1,000 bootstrap), SE = robust standard error.

Figure 1. Conceptual Model

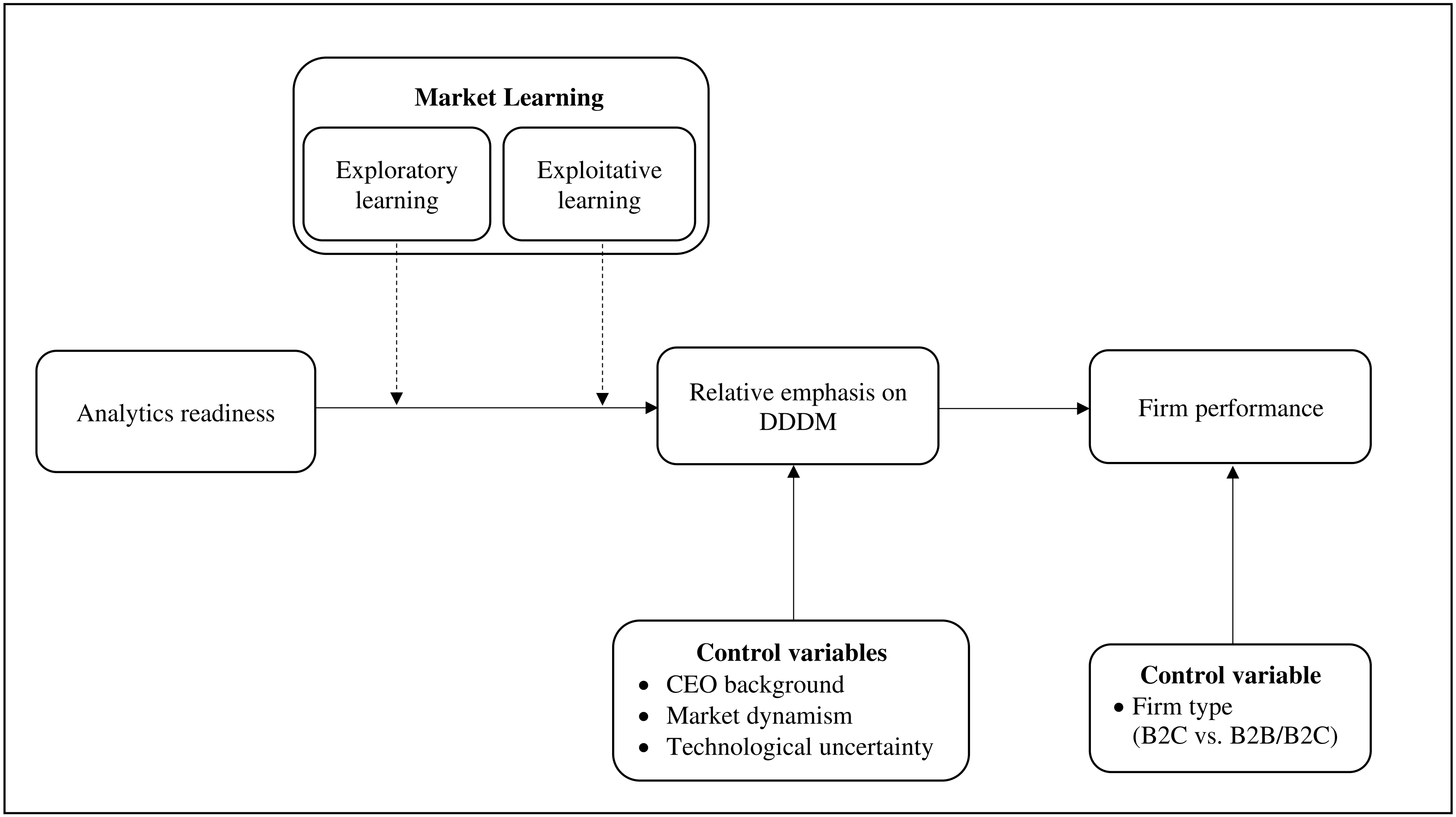

Figure 2. The Moderating Role of Exploration on the Relationship Between Analytics Readiness and Relative Emphasis on DDDM

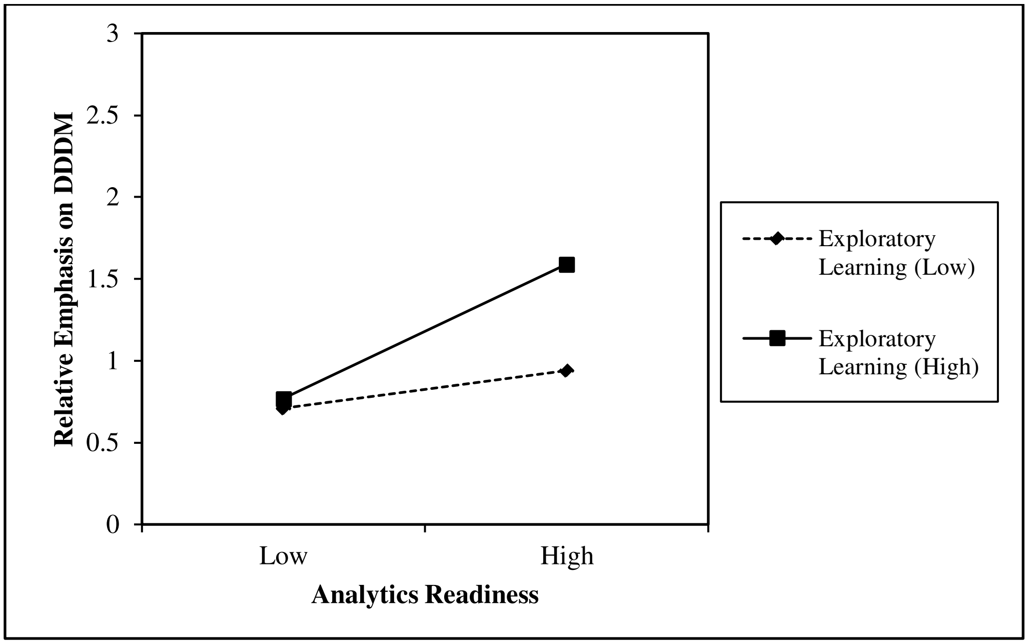

Figure 3. The Moderating Role of Exploitation on the Relationship Between Analytics Readiness and Relative Emphasis on DDDM