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Realizing Value from Business Analytics Platforms: The Effects of Managerial Search and Agility of Resource Allocation Processes

Research-in-Progress

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Abstract

Few organizations have been able to realize value from their investments in business analytics. This could be due to an inadequate understanding of the pattern of investments required to realize value from business analytics. Specifically, we propose that business analytics requires an upfront investment of infrastructure capital to build a mature platform, followed by multiple investments of innovation capital to create value through competitive actions informed by analytics-enabled insights. Drawing on dynamic capabilities and digital options literatures, we develop a model in which the effect of investments in maturity of the business analytics platform on organizational value is moderated by the agility of the process allocating resources for innovation, and by the efforts expended by line managers to search and select the insights. The model is tested on data collected from a survey of line managers. The findings support the proposed model. Implications and plans for future research are discussed.

Keywords: Business Value, Business Analytics, IT Investment Patterns, Managerial Search, Resource Allocation Agility

Introduction

Firms are making increasing investments in big data and business analytics platforms in order to capture value that investments in those technologies promise (For comprehensive review, see Chen et al. (2012)).[1] For instance, General Electric invested more than $2 billion dollars in big data software and analytics centers to manage and optimize its asset managements and operations (Davenport 2013), Walmart invested $10.16 billion and Bank of America invested $5.33 billion in 2014 on information technology (IT) and analytics platforms (Gartner 2015; InformationWeek 2015). Global spending on big data and analytics platforms is projected to reach $143.3 billion by the end of 2016 (ComputerWeekly 2013).

A key capability that analytics platforms offer to managers is the ability to search through and analyze vast amounts of data in order to identify valuable insights that can then be employed to create value through interventions designed to improve performance. In that respect, business analytics platforms are akin to options generators (Sambamurthy et al. 2003). A key feature of such platforms is that value is created through a two-stage investment process (Anand et al. 2016). *The first stage*, akin to buying a real option, is the investment in creating the infrastructure of the analytics technologies and the associated capabilities. As is typical of infrastructure investments, this stage of the investment does not by itself create value. Rather, value is created in *the second stage* of investments, akin to exercising real options, which involve a large number of innovative actions that exploit the insights generated by managers' exploiting the infrastructure capabilities (Anand et al. 2016).

The literature on the business value of information technology (BVIT) has identified a number of factors that contribute to creating value from organizational investments in IT. Some of those factors include IT infrastructure capability, IT personnel capability, IT management capability, and IT-business strategy alignments (Anand and Fosso Wamba 2013; Anand et al. 2013a; Bharadwaj 2000; Coltman et al. 2015; Kohli and Grover 2008; Tallon and Pinsonneault 2011). However, the implicit model of investment assumed in that literature is a *one-stage investment* in the technology followed by various individual and organizational changes to encourage effective use and appropriation of the capabilities of the technology (Aral and Weill 2007; Kohli 2007; Melville et al. 2004). In contrast, investments in business analytics follow a different pattern: a significant upfront investment in the infrastructure followed by smaller investments in multiple innovations over a long period of time (Anand et al. 2016).

The objective of this paper is to extend the literature on the business value of IT by identifying managerial and organizations factors that contribute to value creation from investments in business analytics platforms. In particular, drawing on the dynamic capabilities and the digital options literature (Helfat et al. 2007; Sambamurthy et al. 2003; Teece 2009), we extend prior BVIT literature by understanding the roles of key organizational factors and managerial actions that contributes to value creation from investments in business analytics platforms. In particular, this paper focuses on two key factors that are particularly salient for this context, *managerial search processes* and the *organizational processes for allocating resources* to innovations that exploit insights discovered through the use of analytics capabilities. The research model developed here is tested on data collected from a survey of line managers. As hypothesized, our analysis finds that the effort spent by line managers on search and select activities as well as the agility of organizational resource allocation processes moderate the effects of investments in analytics platform on organizational value creation. The findings have important implications for managers as prior research finds that organizations are finding it difficult to convert their investments in business analytics into business value (Marchand et al. 2013).

The rest of the paper is organized as follows. Drawing on the above-cited theoretical perspectives, we develop our research model and hypotheses. Next, we describe the instrument development process, data collection protocol adopted, data sources, and data analyses and validation techniques employed. This is followed the results, discussion and implications, future research and conclusion.

[1] For simplicity and consistent with Chen et al. (2012), we use business analytics as a unified term that comprises latest analytics technologies such as big data analytics, web analytics, text analytics, network analytics and mobile and sensor-based analytics.

Business Analytics and Value Creation

Modern day business analytics systems trace their roots to decision support systems and business intelligence of previous decades, going as far back as the 1970s where decision support systems were employed to support decision-making (Watson 2014). A common theme underpinning those informate technologies are the applications, technologies and processes of gathering, storing, accessing and analyzing data for more informed decision-making. Some key defining characteristics of business analytics systems include the high volumes, velocity and variety of data that are now available to managers for performing complex analyses, for learning and making faster and superior decisions, often using descriptive, predictive and prescriptive capabilities embedded within analytics platforms, and 'speed to insights' and 'pervasive use' (Wixom et al. 2013).

While the promise of realizing value from investments in business analytics platforms has motivated organizational investments in developing mature analytics platforms, anecdotal evidence suggests that success in capturing value has been limited (Schrage 2014a; Schrage 2014b). Marchand et al. (2013) argue that one-reason organizations may be failing to realize value from business analytics is that they are employing the same strategies that succeeded in realizing value from other IT investments, such as transaction processing systems or enterprise systems. For instance, implementation and adoption of automate IT systems such as Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) relies on one time infrastructure capital to build and deploy the technology on time, to plan, to specifications and within budget, followed by effective management of the implementation process.

A key difference between business analytics systems and other technologies lies in the pattern of investments needed to create value from those technologies (Anand et al. 2016). While both need infrastructure capital to develop the technologies and the associated organizational skills to use them effectively, business analytics systems also need a continuous flow of innovation capital to exploit the insights obtained by managers through the use of the business analytics capabilities (Anand et al. 2016). Unlike other technologies, business analytics systems do not directly contribute to performance and value creation. Rather, they contribute indirectly through informed actions by managers (Sharma et al. 2014).

The BVIT literature has a rich tradition of theorizing the relationship between IT capabilities, IT assets and organizational performance (Anand and Fosso Wamba 2013; Anand et al. 2013a; Kohli 2007; Kohli and Grover 2008). A key argument in that literature is that competitive actions mediate the relationship between IT investments and performance. Sambamurthy et al. (2003) argue that IT investments create digital options that can be exploited through competitive actions, such as innovations in products, services and channels. Similarly, Piccoli and Ives (2005) argue that IT-dependent competitive moves are key to the creation and appropriation of economic value and delivering high levels of firm performance. Extending that literature, this paper argues that understanding the strategic role that managers and managerial actions play in developing, implementing and successfully exercising *competitive actions* will advance our understanding of how organizations can realize value from investments in business analytics. Those are important factors due to the uncertainty that is inherent in investments in real options: while infrastructure investment can be planned, the specific options that will require the expenditure of innovation capital cannot be predicted *ex-ante*. The leveraging of emerging options into specific IT-enabled competitive actions is the result of managerial entrepreneurial actions, not of *ex-ante* planning.

The real options nature of investments in business analytics suggests a need to include the role of mangers in understanding value realization from those investments. This paper draws upon and extends the literature on dynamic capabilities to explain value realization from business analytics. The dynamic capabilities literature takes a process-oriented approach to highlight the strategic role of managers in creating value through "orchestrating complementary and co-specialized assets, inventing and implementing new business models, and making astute investment choices in situations of uncertainty and ambiguity" (Helfat el al. 2007 p. 25). Specifically, it identifies the key roles of managerial search and select processes, and asset orchestration processes in creating value from IT resources (Anand et al. 2013b; Helfat et al. 2007; Sharma et al. 2010; Sirmon et al. 2011). Search and select processes include designing new business models, identifying new opportunities, selecting configurations of co-specialized assets, selecting investments and courses of action to invest in, and selecting organizational, governance

and incentive structures (Helfat et al. 2007). Asset orchestration processes involve putting search and select decisions into effect by implementing new combinations and co-alignment of assets (Teece 2009).

The role of managerial search and select processes: In the context of business analytics use, managerial search and select, i.e. the effort spent by managers in acquiring and analyzing information to generate and discover insights are the key actions and capabilities enabled by business analytics platforms. For example, Kohli's (2007) case study of United Parcel Service (UPS) highlights the critical role of the investments in informate capabilities to identify and exploit value creating opportunities. Sustained IT investments provided UPS with highly integrated data flows that enabled UPS's managers to employ business analytics to identify opportunities. It also highlights the role that managerial entrepreneurship played in exploiting the capabilities of the platform and undertaking value creating actions (Sharma et al. 2010). For instance, UPS's managers could estimate the costs and profitability of individual routes, which then became the basis for subsequent investments in competitive actions to improve performance. Similar patterns are reflected in other cases described in the literature, for instance, Guess (Wixom et al. 2013), Norfolk Southern (Wixom et al. 2011) and StyleSeek (Kiron et al. 2014). Managerial search is an expression of entrepreneurial alertness, as managers employ analytics platforms to explore markets, environments and identify opportunities for continual innovations. The outcomes of search are insights that underpin investments in competitive actions (Sambamurthy et al. 2003).

H1: The value realized by organizations from business analytics is a function of the search and select efforts expended by managers to acquire and exploit insights.

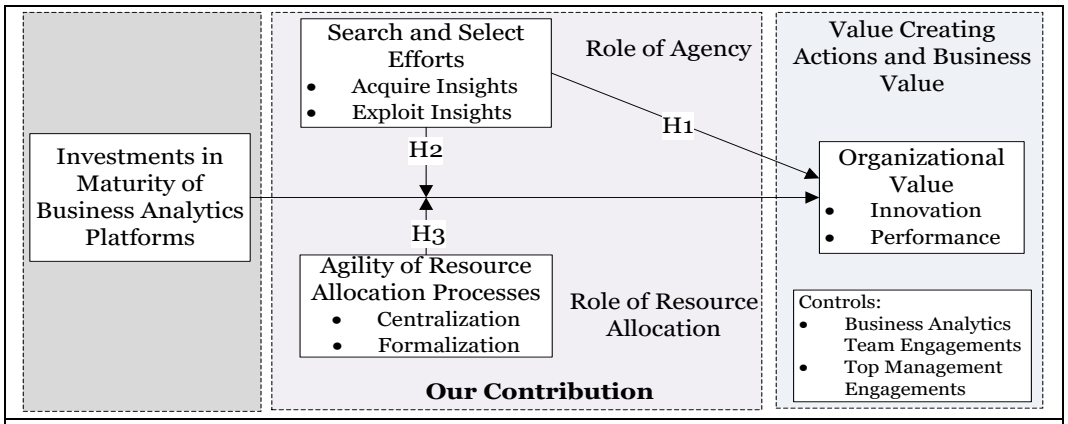

Figure 1. Research Model

The role of the analytics platform: While managerial use of business analytics to discover insights for competitive actions is important, the quality of the insights and competitive actions emerging from managerial search are a function not only of the search efforts expended by managers (H1), but also of the maturity of the analytics platform. For instance, descriptive analytics platforms enable reporting, online analytical processing (OLAP), dashboards and data visualizations, which are employed primarily to monitor and report on predefined metrics and performance indicators. In contrast, more mature analytics platforms offering descriptive and predictive analytics capabilities offer managers the ability to discover valuable insights into what happened and project what might happen under different scenarios. For instance, managers can employ the capabilities of the more mature platforms to use real time data, time series analyses, advanced statistical analytics and data mining techniques to continuously develop insights, validate assumptions and test hypotheses (Anand et al. 2016; Pigni et al. 2016). As highly mature analytics platforms are likely to provide more complex and valuable insights (Davenport 2006; IBM 2013), organizations are making increased investments towards enhancing their maturity of analytics platforms to increase the quality and range of insights that managers can generate. However, while more mature platforms offer the potential for more valuable insights, the actual realization of that potential will depend on the efforts expended by managers to exploit those capabilities that organizations has invested on. Increasing the maturity of the analytics platforms is less likely to add value unless managers' employ and use the platforms to search for new insights and exercise those insights. Therefore, we propose that creating value from investments in analytics platforms is contingent on the search and select efforts expended by managers.

H2: The search and select effort expended by managers to acquire and exploit insights moderates the effect of the maturity of the analytics platform on the value realized by organizations from business analytics.

The role of resource allocation processes: Insights and options generated through managerial search and select processes need innovation capital to exploit those insights through competitive actions (Sambamurthy et al. 2003; Sharma et al. 2014; Sharma and Shanks 2011). Those include, e.g. commitments of resources, including time, personnel and capital. We argue that the extent to which managers can expeditiously obtain innovation capital to resource competitive actions has an important bearing on value creation. Organizations typically employ various formal and informal processes, and governance mechanisms for allocating innovation capital. An important factor that has a bearing on the extent to which managers can undertake competitive actions is the agility of the resource allocation process (Anand et al. 2016; Damanpour 1991; Jansen et al. 2006; Zmud 1982).

The discretion to allocate resources for innovation is often distributed within organizations and often varies across hierarchical levels. Decisions pertaining to the allocation of innovation capital are often centralized and formalized, e.g. through capital budgeting processes and strategy formulation processes (Cardinal 2001; Noda and Bower 1996). In centralized resource allocations, senior management exert a high degree of control over discretionary resources (Damanpour 1991). Centralized structures often narrow communication, limit opportunities to broker resources between managers and senior management, and reduce the likelihood of resources being allocated in time to convert insights into value creating actions. Similarly, formalized structures reflect the extent to which managers need to follow formal rules, procedures, instructions to communicate with senior management (Khandwalla 1977). Formalized protocols hamper experimentation and ad hoc problem solving efforts, which are important ingredients for competitive actions (Benner and Tushman 2003). High levels of centralization and formalization reflect less agile resource allocation processes that are likely to have a negative impact on innovation and organizational performance. In contrast, low levels of centralization and formalization reflect a high agility resource allocation process that is likely to have a positive impact on innovation and organizational performance.

In the context of business analytics, generating and acquiring insights involves managers making extensive and sophisticated use of the business analytics infrastructure. Agile resource allocation processes have a bearing on the extent to which managers can exploit business analytics platform and influence innovation and organizational performance. Less centralized and less formalized resource allocation process can encourage more entrepreneurial activities. Prior research shows that high agility environments are nurtured by organizations to promote innovation. In contrast, low agility resource allocation processes discourage managerial entrepreneurship and innovation (Jansen et al. 2006).

H3: The agility of the resource allocation process moderates the effect of the maturity of the analytics platform on the value realized by organizations from business analytics.

Methods

Instrument Development, Data Collection and Validation

Our conceptual model was developed based on an in-depth literature review and iteratively refined based on 10 field interviews and several informal discussions with practitioners. Following the guidelines from prior research (Coltman et al. 2008; MacKenzie et al. 2011), we developed and validated a survey instrument to test our proposed theory. To improve the validity and reliability of our instrument, we adopted several guidelines. Each construct was conceptually defined prior to identifying items to operationalize the construct. For constructs, *investments in maturity of business analytics platforms, agility of resource allocation processes, top management engagements* and *organizational value*, we adapted items validated in prior research to fit the business analytics context. We developed items for new constructs, *search and select efforts of managers* and *business analytics team engagement*. All items were written as single idea statements. The instruments were further refined using a focus group interview with three academics with expertise in this research subject and also in measurement theory. Three IT managers were also consulted to assess content validity, to identify items that may be ambiguous or unfamiliar to practitioners and refined them following their suggestion. The initial instrument was pre-

tested with separate interviews with four additional IT managers. We pilot tested the instrument in two separate web-based surveys to examine the instrument (e.g., clarity, length, structure) using two different presentation samples to analyze the feasibility of the web based survey for any potential technical glitches (e.g., spams filters, mail server filtering) and methodological concerns (e.g., anonymity issues). The pilot tests also provided an initial assessment of the measurement properties of the scales. To reduce the effect of *common method bias* (Sharma et al. 2009), where possible, we employed open-ended numerical scales and *behavioral* measures *(e.g. how many meetings, how many projects, how much money was spent etc.*) Archival measures of financial performance were employed to test the validity of the self-report *organizational value* construct for organizations where the stock ticker was provided by respondents.

Survey Instruments

Organizational value (OV): Organization value is operationalized to reflect two key aspects: *innovation performance* and *organizational performance*. We employed items from He and Wong (2004), Jansen et al. (2006) and Jansen et al.'s (2008) scales to measure *explorative* and *exploitative innovation*. Items to measure organizational performance came from previously validated self-report measures from Kearns and Sabherwal (2007), and Lee and Choi (2003). The self-report measure of organizational performance was validated against available objective financial measures (Net Income) obtained from publicly available financial statements. The results indicated a strong correlation *(r=.78*, $p \leq 0.05$*)* between Net Income and the self-report measures, suggesting a high degree of validity for the self-report measure of organizational performance.

Investments in maturity of business analytics platforms (MAPS): We employed the existing scale developed by Cosic et al (2012; 2015) to measure the maturity of the analytics platform. Their scale measures reflect maturity across four key aspects: *data management capability, system integration capability, reporting and visualization capability,* and *predictive discovery capability*. Each capability is measured on a four-point scale ranging from 1=non-existent to 4=optimized, indicating a fully enhanced analytics capability. Their scales are consistent with other conceptualization of maturity of business analytics in the practitioner literature (Davenport 2006; IBM 2013).

Agility of resource allocation processes (ARAP): We measured agility of the resource allocation processes to reflect two key aspects: *level of centralization* and *level of formalization*. These reflect how easily managers can obtain resources to convert insights into competitive actions. Previously validated items that reflect *level of centralization* came from Kearns and Sabherwal (2007), Lee and Choi (2003) and Jansen et al (2006), while items that reflect *level of formalization* came from Lee and Choi (2003) and Jansen et al (2006). The items were modified to fit business analytics context.

Search and select efforts of managers (MESS): Past research has primarily conceptualized search at the organizational level, not at the managerial level (Li et al. 2013; Sirmon et al. 2011). Our literature review identified two key aspects to measure the efforts of managerial search and select: *efforts to acquire business analytics insights* and *efforts to exploit business analytics insights*. We measured these concepts in terms of the actual behaviors of managers, *e.g. the extent to which managers spent time on those activities and committed actual resources (time, personal and financial)*. This is a new construct and the instrument to measure this construct was developed in this study.

We also employed two constructs as control variables for testing our hypotheses as those constructs have been argued in prior research to contribute to creating value from business analytics. We developed a new scale for *business analytics team engagement (BATE) i.e. the extent to which the business analytics team engaged with and supported line managers*. The items developed for this construct reflects two key aspects, the *extent of training provided to line managers* and the *extent of engagements of the analytics team with line managers*. Existing scales were employed to measure *top management engagement (TME)*. Items in this construct reflect *resource support, vision support, support for change* and *monitor support* (Bhatt and Stump 2001; Kearns and Lederer 2003; Sharma et al. 2005; Thong et al. 1996). Both constructs are employed as control variables in the analysis.

Sample and Data Collection

Since the primary users of business analytics capabilities in organizations are line managers, the targets of this study were managers and senior managers in various line management functions, such as general

management, human resources, marketing and finance (Table 1). The target respondents came from a wide range of industries and roles from banking and finance, government, information and communications technologies, utilities, hospitals and medical, manufacturing and retail, public services and transportation in Australia and New Zealand. We specifically excluded managers from IT functions and analytics competence centers. Respondents came from contact lists maintained by a leading analytics vendor and included clients as well as non-clients of the vendor. Job titles of respondents were examined to ensure that the responses came from line managers. We administered the survey jointly with our industry partner vendor. We received usable responses from 72 respondents. Stock tickers from 22 available respondents' companies were used to collect archival performance data.

Table 1: Sample Demographics

Industry	*Approx. %*	*Respondent Titles*	*Approx. %*
Banking and Finance	23	Managers	45
Government	15	Directors	17
ICT	14	Senior Managers	9
Utilities	8	Coordinators and Leads	6
Healthcare	7	Consultant	2
Manufacturing / Retail	6	Others	21
Public Services	3		
Transportation	1		
Others	23		
Respondent Experience Years	*Approx. %*	*Budget Spent on BA Projects (last 6 months)*	*Approx. %*
<2.5	25	0-30,000	50
2.5-5	17	30,001-60,000	11.1
6-10	26	60,001-150,000	4.2
11-15	6	150,001-600,000	11.1
16-20	1.5	600,001-1 Million	5.5
>20	6	>1 Million	9.7
Not Available	18.5	Not Available	8.3

Analyses

The data was checked for robustness against validity threats arising from linearity, heteroscedasticity, autocorrelation, multicollinearity, outliers and influential observations. Results from outlier analysis detected one data point with a residual greater than |2|, which was excluded from further analyses. The reliabilities of the scales were well above acceptable values. Table 2 shows the correlations and descriptive statistics.

Table 2: Correlations and Descriptive Analysis (n = 71)

	MAPS	MESS	ARAP	OV	TME	BATE	*Cronbach Alpha*	*Min*	*Max*	*Mean*	*SD*
MAPS	1						.85	4	20	10.90	3.15
MESS	.137	1					.86	4	24	12.25	5.17
ARAP	.149	-.064	1				.85	6	30	19.23	4.99
OV	.381**	.527***	.068	1			.93	6	30	19.65	6.07
TME	.389**	.504***	.121	.568***	1		.90	9	40	26.63	7.52
BATE	.600***	.383**	-.014	.635***	.569***	1	.90	7	28	17.72	5.42

P-values: *<.05 **<.01 ***<.001,

We employed linear least square regression models to test the hypotheses. All the predictor variables were centered for moderation analysis in order to avoid multicollinearity issues. H1 and H2 predict that the corresponding regression coefficients will be positive and significant. H3 predicts that the regression coefficient will be negative and significant, as we have theorized higher agility in resource allocation is analogous to low centralizations and low formalizations.

Results

H1, *The value realized by organizations from business analytics is a function of the search and select efforts expended by managers to acquire and exploit insights*, is supported (Table 3, Model 1: β = .28, p <.01).

H2, *The search and select effort expended by managers to acquire and exploit insights moderates the effect of the maturity of the analytics platform on the value realized by organizations from business analytics*, is supported (Table 3, Model 4: β =.095, p <.05).

H3, *The agility of the resource allocation process moderates the effect of the maturity of the analytics platform on the value realized by organizations from business analytics*, is supported (Table 3, Model 4: β = -.164, p <.05).

Table 3. Results from Linear Regression Analysis (DV is Organizational Value, n = 71)

	Model 1	Model 2	Model 3	Model 4	Hypotheses Supported
	Standardized Coefficient	Standardized Coefficient	Standardized Coefficient	Standardized Coefficient	
Direct Eff.					
MAPS	.011	.008	.006	-.006	
MESS	.280**	.274**	.243*	.267**	H1 Supported
ARAP	.069	.085	.000	.035	
Interactions					
MAPS*MESS		.103*		.095*	H2 Supported
MAPS*ARAP			-.186*	-.164*	H3 Supported
Control					
TME	.173	.163	.190	.179	
BATE	.424***	.435***	.405***	.381**	
R^2	.52	.54	.61	.56	

P-values: *<.05 **<.01 ***<.001, MAPS: investments in maturity of the analytics platforms, MESS: *search and select efforts of managers*, i.e. efforts to acquire and exploit insights, ARAP: agility of the resource allocation process, **Control Variables:** BATE: business analytics team's training and engagements, TME: top management engagement. **Note:** The interaction effect between MAPS*ARAP is negative as the items that measured ARAP construct was reverse coded i.e. high formalizations and high centralizations reflected less ARAP and vice versa.

Discussion and Implications

The above analysis supports the proposed model, with all three hypotheses being supported. The findings support our theory that the effect of investments in maturity of the analytics platform on organizational value are moderated by both efforts expended by managers on search and select, and agility of the resource allocation process.

The proper interpretation of the interaction effects is aided by a review of the interaction plots (Figure 2). Figure 2A plots the interaction effects of maturity of the analytics platform with managerial search & select effort on organizational value. Figure 2A shows that the intercept as well as the slope under high search & select effort condition are higher than under the low condition. This implies that the marginal returns from investment in maturity of the platform increase with search & select effort.

Figure 2B plots the interaction effects of maturity of the analytics platform with agility of the resource allocation processes on organizational value. The plot in Figure 2B shows that the marginal returns from investments in maturity of the analytics platforms are higher under a high agility resource allocation process (i.e., less formalized and less centralized). Of note is the observation that the regression lines for the low and high agility resource allocation processes intersect at around the mean value of the maturity of the analytics platform. Organizational value is higher under the low agility condition than under the high agility condition when maturity is below the mean. Our interpretation of the pattern of interaction effects is that under low maturity, an agile resource allocation process results in lower organization value as organizations are likely to be making inefficient allocations of innovation capital. However, when

maturity of the platform is above average, organizations are advised to progressively make their resource allocation process more agile in order to capture high marginal returns from their investments in the maturity of the analytics platform. This insight is an important contribution to practice.

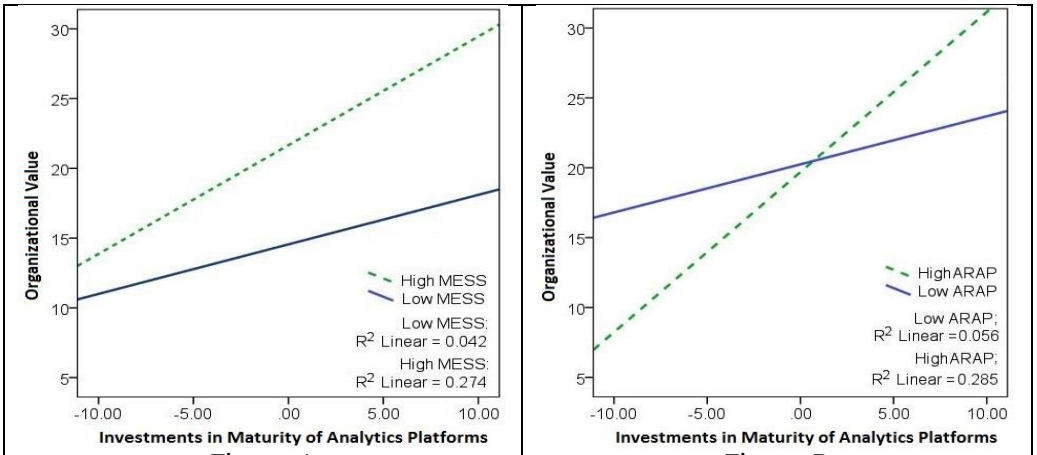

Figure 2A | Figure 2B

Figure 2. Interaction Effects of MESS and ARAP on Organizational Value

This study makes theoretical contribution to BVIT research in two ways. Prior research in BVIT has theorized that *'competitive actions'* mediate the relationship between IT investments, IT capabilities and organizational value. Drawing on the dynamic capabilities and digital options literatures, this study extends that notion by identifying two key factors that have important bearings on the extent to which organizations can create value from business analytics. One key factor is that the extent of *managerial search and select processes* focused on discovering insights using analytics platforms, and the other is the *agility with which managers can acquire innovation capital to resource competitive actions*. In identifying the roles of these factors, this research extends the existing theorization in BVIT by incorporating an understanding of the roles of managerial actions that underpin competitive actions and resource allocation processes. Further, the implicit model of investments assumed in BVIT literature is a one-stage investment in the technology followed by various individual and organizational changes to encourage effective use and appropriation of IT capabilities. This study argues that in the context of business analytics, traditional one stage investment pattern is unlikely to work and extends prior models to account for second stage investments in multiple innovation capital. This study provides empirical evidence to support the two-stage investment sequence for creating value in the context of business analytics. By highlighting the two-stage investment pattern and identifying a unique set of interventions that organizations can undertake to create value, in particular, the role of agility of the resource allocation processes and managerial search efforts are important practical implications arising from this study.

Future Research and Conclusion

This paper has presented initial findings from a larger study investigating the role of business analytics platforms in creating organizational value. The next stage of this research will focus on extending the theoretical model to include the effects of the competence of the business analytics and the level of top management engagements. Further work will also focus on employing structural equation models to test a more comprehensive theoretical model. For the next stage, we will also be collecting data from organizations in US and Canada.

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