Business Analytics Governance, External Uncertainty, and Firm Performance

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Abstract: Constantly evolving business environment and technological innovations, such as business analytics and artificial intelligence, press firms to rethink their information technology governance approaches in order to secure business value extracted from these technologies. Business analytics governance comprises several key mechanisms, among which is business analytics organizing, which guides the firm's business analytics activities, related decision-making authority, and location of business analytics function within the organization. The pros and cons of different approaches to business analytics organizing have been discussed in the existing business analytics literature, but there is only scant empirical evidence on how they help firms extract business value of their business analytics capability investments. Further, current literature posits that the level of uncertainty of the external business environment has a strong influence over which information technology governance approach a firm adopts, but the links between the external uncertainty, business analytics organizing, and firm performance are unestablished. Our study seeks to contribute to the contemporary business analytics literature by developing and testing a research model that comprises a firm's business analytics capability, firm's operational performance, and the moderating impact of business analytics organizing and uncertainty of the firm's external environment. In more detail, we propose that business analytics capability is positively associated with the firm's operational performance, and that business analytics organizing, ranging from centralized to decentralized, moderates this relationship. That is, centralized business analytics organizing characterized by concentrated expertise and standardization of analytics services helps firms achieve operational efficiency gains, while more de-centralized organizing approach burdened with a lack of control and possible agency issues weakens the association. Further, we also propose that the uncertainty of the external environment further moderates the other moderation effect, i.e., the centralized business analytics organizing approach works better in low uncertainty environments, while a decentralized organizing approach characterized by wider spread business analytics expertise and agile decision-making outperforms the centralized organizing approach in more uncertain circumstances. Our paired-response survey data collected from Finnish firms provide support for our hypotheses.

Keywords: Business analytics capability, Business analytics governance, Business analytics organizing, External uncertainty, Operational performance, Survey

1. Introduction

Firms seek to reap business benefits from their investments in information technology (IT) and information systems (IS) by building and strengthening their IS capabilities, such as business analytics capability (BAC), which is defined as the effective mobilization, deployment, and use of business analytics (BA) resources and the alignment of BA planning with the firm's strategy for improved firm performance (e.g., Gupta and George, 2016; Kristoffersen et al, 2021). To leverage BAC in business value creation necessitates firms to identify and deploy supporting organizational mechanisms for BAC, such as strategic IT flexibility (Mishra et al, 2019) and a suitable fit between the organization and its BA systems (Rialti et al, 2019), and BA governance (Fadler and Legner, 2021).

BA governance sets guidelines on how BA is used in firms, having implications for the business value a firm can reap from its BA investments (Baijens et al, 2022; Grossman and Siegel, 2014). BA governance literature is grounded in more established literature on IT governance (Weill and Ross, 2005), which has primarily focused on IT artifacts in general (De Haes and Van Grembergen, 2009) or the specific contents of these artifacts, such as data and information (Tallon et al., 2013). BA governance, however, differs from earlier IT governance concepts by placing greater emphasis on the transformation of IT artifact content (Baijens et al, 2022), for instance, to enable the use of data in a firm's business processes. Therefore, to efficiently transform a firm's data assets into, e.g., enhanced decision-making and business value, a firm needs to establish a BA governance, including its structural, process, and relational mechanisms (Baijens et al, 2022; De Haes and Van Grembergen, 2009; Tallon et al, 2013; Wu et al, 2015). Among the key structural mechanisms, a firm must choose and deploy a BA organizing model that defines the decision-making authority and the location of the analytics function in a firm (Grossman and Siegel, 2014). BA organizing can vary from centralized, hybrid, to decentralized approaches, with each of them involving potential advantages and disadvantages (e.g., Baijens et al, 2022; Fadler and Legner, 2021). However, BA governance literature is nascent in terms of empirical evidence on the impact of different ways of BA organizing on BA business value, with most of the works just lamenting the lack of contributions (Gröger, 2018; Grover et al, 2018) or offering conceptual foundations (Baijens et al, 2022). Further, IT governance literature suggests that the uncertainty of the external environment influences a firm's preferred IT governance model (Xue et al, 2011). However, there is a lack of understanding of how such externally driven decisions translate as IT business value, and even less empirical evidence on the optimal way of organizing BA in different degrees of external uncertainty. Therefore, the objective of this study is to improve the understanding of the relationship between BAC and firm's operational performance by examining the moderating roles of BA organizing and the uncertainty of the external environment. To meet this objective, we seek to answer the following research questions:

RQ1:Does BAC support a firm's operational performance?:

RQ2: Does BA organizing affect BAC's association with the firm's operational performance?

RQ3: Does the degree of uncertainty of the external environment impact the business value of different BA organizing models?

We propose that BAC is positively associated with a firm's operative performance, as it provides, e.g., data-driven insights for quicker and better-informed decisions (Lepenioti et al, 2020). Also, we propose that the BA organizing moderates the relationship between BAC and operational performance. That is, the more centralized the BA organizing model is, the more effectively it supports its operational performance through the economics of scale, stability, and standardized BA activities (Schüritz et al, 2017). On the contrary, a decentralized BA organizing model suffers from agency issues, such as a lack of control (Baijens et al, 2022), weakening the positive association between BAC and operative performance. We also propose that the external uncertainty, including dynamism, heterogeneity, and hostility (Newkirk and Lederer, 2006) further curvilinearly moderates the moderating effect of BA organizing, so that a centralized and stable organizing model provides operational business value mainly in stable conditions (i.e., low uncertainty environments), while highly uncertain conditions require more agile decentralized BA organizing model, where BA experts work in the business units. Our pair-matched data collected from BA experts and business unit directors/managers of 89 Finnish companies provide support for these propositions.

2. Research Model and Hypotheses

2.1 Business Analytics Capability and Firm's Operational Performance

Drawing from the resource-based view of the firm (RBV), BAC is often portrayed as a higher-order construct comprising of firm-specific combinations of various BA-related resources. These BA resources, including tangible (data, technology, time, funding, staffing), human (technical and managerial skills), and intangible (data-driven culture), are therefore in the focal point of BAC business value creation (e.g., Wamba et al, 2017; Mikalef et al, 2020a). Previous literature has provided evidence on the positive association between BAC and various tenets of firm performance (e.g., Wamba et al, 2017; Khan et al, 2024; Kristoffersen et al, 2021), including operational performance (Gupta and George, 2016) and sustainable performance (Tetteh et al, 2024). Therefore, we propose the following hypothesis:

H1: Business analytics capability is positively associated with the firm's operational performance

2.2 Business Analytics Governance and Firm's Operational Performance

IT governance facilitates the alignment of the firm's business objectives and the use of its IT resources by establishing governance mechanisms that enable business and IT stakeholders to fulfill their responsibilities, which ensures and sustains business value through the effective use of IT (De Haes et al, 2020). However, rapidly developing digital technologies, such as BA and artificial intelligence (AI) have challenged firms and scholars to revisit the structural, process, and relational mechanisms of IT governance (Enholm et al, 2021; Papagiannidis et al, 2023), as these new technologies are more concerned with the transformation and utilization of the contents of IT artifacts, such as data and information (Bajens et al, 2022). One of the most impactful structural mechanisms is the firm's BA organizing model, which defines the decision-making authority over analytics resources and the location of the analytics function in a firm (Table 1, see Grossman and Siegel, 2014). In a centralized organizing model, all data analytics activities, such as decision-making and problem prioritization, are concentrated within a single unit (Grossman and Siegel, 2014). In contrast, a decentralized organizing model distributes these activities across multiple units, while a hybrid structure combines elements of both, with some activities coordinated from a central unit while others are distributed across various units (Baijens et al, 2022).

For supporting the firm's operational performance, the centralized BA organizing is the most viable option, as it improves the firm's ability to leverage its BA to deal with its operational-level (e.g., daily and routine-like) tasks more efficiently through coordination and consolidation of activities, and by minimizing duplication (Baijens et al, 2022; Schüritz et al, 2017). Conversely, more decentralized BA organizing models might hinder the positive association between BAC and operational performance, as reuse of analytics resources is restricted to local levels and cannot be leveraged organization-wide (Grossman and Siegel, 2014; cf. Holmström and Milgrom, 1990). Therefore, we propose the following hypothesis:

H2: BA organization decentralization negatively moderates the relationship between BAC and the firm's operational performance

2.3 Business Analytics Governance and Environmental Uncertainty

A firm's IT governance structure reflects not only its strategic business needs but also the degree of A firm's IT governance structure reflects not only its strategic business needs but also the degree of uncertainty of a firm's external environment (Xue et al, 2011). The advantages of a centralized structure are more evident in firms operating in stable environments characterized by low dynamism, homogeneity, and reduced hostility. In such conditions, the centralized IT unit can effectively understand the needs of various business units and optimize resource allocation at an organizational level (Xue et al, 2011). Additionally, procuring IT infrastructure at the firm level offers greater bargaining power with IT vendors compared to procurement at the business unit level (Turban et al, 2006). Consequently, the economies of scale achieved through centralization contribute to improved operational performance in stable environments.

However, when uncertainty increases from low to higher levels, the benefits of decentralization become more evident. This is because the dynamism of the environment, the unique needs regarding new business opportunities, or suddenly arising threats are likely to be more effectively responded by individual business units through, e.g., direct communication with end users (Schüritz et al, 2017). Changes in the external environment may cause conflicts between business units managers' preferences and the firm's long-term goals, causing agency issue (Shpilberg et al, 2007), but the effective utilization of new business opportunities and neutralizing threats is more desirable in such situation than the stability provided by the centralized structure (Schüritz et al, 2017). Based on these, we propose the following hypotheses:

H3: Uncertainty of the external environment positively moderates the moderating effect of business analytics organizing in the relationship between BAC and the firm's operational performance

Table 1: Constructs and definitions

Construct	Definition	Sources
Business analytics capability	The ability of a firm to effectively mobilize, deploy, and utilize BA resources and align BA planning with its strategy to improve its performance.	Gupta and George, 2016; Kristoffersen et al, 2021; Wamba et al, 2017
Business analytics organizing	BA organizing defines the decision-making authority over analytics resources and the location of analytics function in a firm.	Grossman and Siegel, 2014
Uncertainty of the external environment (UNC)	UNC is characterized by the degrees of dynamism, heterogeneity, and hostility, impacting how firm can accurately and reliably predict the market dynamics.	Mikalef et al, 2020b; Newkirk and Lederer, 2006
Operational performance	The degree to which a firm has superior performance relative to its competition in areas of productivity, profit rate, return on investment, and sales revenue.	Gupta and George, 2016

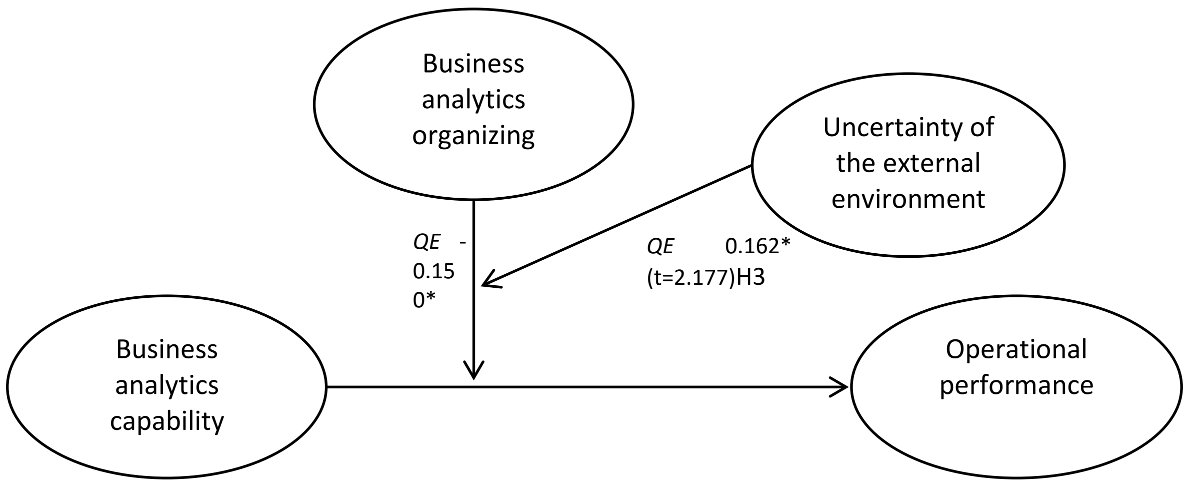

Figure 1: Research model

3. Empirical Study

3.1 Survey, Administration, and Data

The constructs and survey items selected for this study are consistent with the previously published and empirically validated latent variables (Table 2). The only exceptions are "Business managers' analytics skills", "Data-driven decision-making", and "BA governance", that were added as new constructs to better reflect the evolving nature of the firm's BAC. All constructs and respective survey items were operationalized on a 7-point Likert scale, which is a standard practice in large-scale empirical research where no standard or objective measures exist.

To test the research model, we collected data from medium to large-size Finnish firms (more than 100 employees) familiar with BA use. Data was collected in October-December 2023, resulting in 236 individual responses. After establishing a paired response dataset by combining the firm-level responses from 1) BA experts and 2) business managers, we attained the final dataset consisting of 89 valid responses (i.e., 178 individual responses from 89 firms), with responses were received nearly from all industries. Measured by the number of employees, the middle-sized firms with 100–249 employees (47.2%) and large firms with 250 or more employees (52.8%) were nearly equally represented. By the firm turnover (measured in 2022), firms with 20+ million-euro annual turnover constituted most of the sample (66.3%).

3.2 Measurements

To avoid common method bias and collect reliable data for the key constructs of this study, two different surveys were developed for two different respondent profiles. The survey for the respondent profile 1 comprised BAC and BA organizing measurements and it was targeted at senior managers in the BA unit or IT department, while the survey for the respondent profile 2 consisted of business environment and firm performance measurements and it was targeted at senior business directors and managers.

The survey scales for BAC (Gupta and George, 2016; Kristoffersen et al, 2021; Mikalef et al, 2017; Wamba et al, 2017), uncertainty of the external environment (Mikalef et al, 2020a; Newkirk and Lederer, 2006), and operational performance (Gupta and George, 2026) were mostly adopted from the existing literature. In addition, we developed two new scales for business manager's analytics skills and for BA resources taking inspiration from seminal BAC studies (e.g., Gupta and George, 2016; Kristoffersen et al, 2021). First, on the basis on analytics personnel's managerial skills measurement scale (Gupta and George, 2016), we developed a scale for business manager's analytics skills, adding a sub-dimension that incorporates the business managers' important role in leveraging BA in firms (e.g., Orjatsalo et al, 2025). Second, the data-driven culture measurement scale (Gupta and George, 2016; Kristoffersen et al, 2021) was split into data-driven decision-making and data-driven culture, as they measure fundamentally different sub-dimensions of BAC, i.e., to what degree firms make decisions based on data (e.g., Brynjolfsson and McElheran, 2016), and the organizational culture and attitudes related to the use of data in various firm's value creation activities (Gupta and George, 2016).

Further, based on earlier BA governance literature (Grossman and Siegel, 2014), we operationalized BA organizing centralization/decentralisation on a 4-point scale, ranging from (1) centralized to (4) decentralized BA organizing, with two items for different hybrid BA organizing approaches in the middle.

Control variables (continuous) of this study include firm age measured as the number of years since the establishment of the firm and firm size measured as the number of employees.

Table 2: Latent constructs and sub-dimensions

Third-order	Type	Second-order	Type	First-order	Type
Business analytics capability	Formative	Tangible resources	Formative	Data (DATA)	Reflective
				Technology (TECH)	Reflective
				Basic resources (BASIC)	Reflective
		Human skills	Formative	Technical skills (BAAS)	Reflective
				Analytics personnel's managerial skills (BAMS)	Reflective
				Business managers' analytics skills (MBAS)	Reflective
		Intangible resources	Formative	Data-driven decision-making (DDD)	Reflective
				Data-driven culture (DDC)	Reflective
		Uncertainty of the external environment (UNC)	Formative	Dynamism (DYN)	Reflective
				Heterogeneity (HET)	Reflective
				Hostility (HOS)	Reflective
				Operational performance	Reflective

4. Analysis

Data was analyzed with SmartPLS 4 (Ringle et al., 2024) to assess the measurement and structural models of the study. PLS-SEM is a commonly employed quantitative research method across various realms, including IT governance and BA (e.g., Riemer et al., 2020; Mikalef et al., 2020a), especially when studies predict constructs for structural models and estimate various relationships among them (Henseler et al., 2017). Moreover, PLS-SEM is preferred over covariance-based SEM in studies that use simultaneously formative and reflective constructs in higher-order model specification, and those that aim at theorizing instead of testing a validated theory (Akter et al, 2017).

4.1 Measurement Model

First, we established the validity and reliability of the used reflective and formative constructs as measures of BAC. For reflective constructs, we started by examining the outer loadings, leading to us confirming that most of the values exceeded the recommended threshold of 0.7 (Hair et al, 2017). The outer loadings for BAMS2 (0.63), BAMS4 (0.68), DDD2 (0.69), DDD4 (0.67), and DDC4 (0.69), were slightly below the recommended threshold of 0.7, but these items were decided to be retained due to their theoretically strong contribution to their respective first-order constructs. Regarding dynamism, heterogeneity, and hostility (the sub-dimensions of the uncertainty of the external environment), we found low outer loadings for DYN1, DYN2, and HOS 1-5, leading us to retain only dynamism and heterogeneity for further analysis. Further, all items measuring operational performance exhibited strong outer loadings (0.76-0.88) on its related construct.

Second, we assessed the reliability, convergent validity, and discriminant validity of the first-order reflective constructs (Table 3). Composite Reliability (CR) values were examined, with all exceeding the 0.70 threshold (Hair et al, 2024). Average Variance Extracted (AVE) values for the reflective constructs were above 0.5, establishing their convergent validity (Hair et al, 2021). Three tests were employed to assess the discriminant validity: 1) ensuring that the square root of each construct's AVE exceeded its highest correlation with any other construct (Fornell and Larcker, 1981), 2) confirming that each indicator's outer loading was higher than its cross-loadings with other reflective constructs (Farrell, 2010), and 3) using the heterotrait-monotrait ratio (HTMT) as recommended by MacKenzie et al (2011). The outcomes of these tests indicate that our first-order reflective constructs are robust indicators of their respective higher-order constructs.

Table 3: Assessment of reliability, convergent and discriminant validity of reflective constructs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) BAAS	0.830										
(2) BAMS	0.644	0.733									
(3) BASIC	0.496	0.574	0.891								
(4) BMAS	0.513	0.675	0.440	0.772							
(5) DATA	0.473	0.577	0.402	0.516	0.756						
(6) DDC	0.633	0.626	0.464	0.623	0.589	0.756					
(7) DDD	0.443	0.472	0.326	0.617	0.419	0.633	0.708				
(8) DYN	-0.170	-0.072	0.126	-0.220	-0.093	-0.146	-0.197	0.848			
(9) HET	0.054	-0.082	-0.105	0.030	-0.007	-0.025	-0.107	-0.156	0.802		
(10) OP	0.206	0.096	0.171	0.068	0.146	0.223	0.120	-0.232	0.232	0.815	
(11) TECH	0.585	0.435	0.434	0.301	0.289	0.573	0.283	0.009	0.069	0.260	0.777
CR	0.87	0.89	0.92	0.90	0.80	0.84	0.80	0.84	0.84	0.89	0.90
AVE	0.69	0.54	0.79	0.60	0.57	0.57	0.50	0.72	0.64	0.67	0.60

Third, we began evaluating the formative constructs by examining their indicator weights, confirming that all weights were positive and statistically significant. We then calculated Edwards' (2001) adequacy coefficient (R^2_a) to assess the validity of the sub-dimensions of the formative constructs, finding that all R^2_a values exceeded them minimum threshold of 0.50 (MacKenzie et al, 2011), which indicates that most of the variance in the indicators is shared with their respective formative constructs (Edwards, 2001). We then assessed the degree of multicollinearity among the formative construct indicators by assessing the Variance Inflation Factor (VIF) values, which are acceptable at levels below 5 (Hair et al, 2017). The VIF values for all of our formative constructs were under 3.3, indicating low multicollinearity (Cenfetelli and Bassellier, 2009).

Table 4: Formative higher-order construct validation

Construct	Measures	Weight	Significance	VIF	R^2_a
Tangible resources	Data	0.46	$p < 0.001$	1.216	0.58
	Technology	0.43	$p < 0.001$	1.256	
	Basic	0.43	$p < 0.001$	1.373	
Human skills	Technical skills	0.40	$p < 0.001$	1.741	0.74
	Analytics personnel's managerial skills	0.39	$p < 0.001$	2.356	
	Business managers' analytics skills	0.37	$p < 0.001$	1.873	
Intangible resources	Data-driven decision-making	0.44	$p < 0.001$	1.669	0.80
	Data-driven culture	0.66	$p < 0.001$	1.669	
BAC	Tangible	0.39	$p < 0.001$	2.623	0.82
	Human	0.35	$p < 0.001$	3.230	
	Intangible	0.37	$p < 0.001$	2.503	
UNC	Dynamism	0.66	$p < 0.001$	1.025	0.58
	Heterogeneity	0.66	$p < 0.001$	1.025	

Considering results attained for construct validity, reliability, and discriminant validity, all formative and reflective indicators of this study showed strong psychometric qualities.

4.2 Structural Model

A bootstrap analysis with 10,000 resamples was conducted to assess the structural model, including the explained variance of endogenous variables (R^2), the standardized path coefficients (β), effect size of the predictor variables (f^2), and the significance estimates (t-statistics). Two of our three hypotheses were empirically supported, with the structural model explaining 26.0% of variance in operational performance (R^2 =

0.260), and representing moderate predictive power (Hair et al, 2021). Regarding *f²*, referring to an exogenous construct's contribution to an endogenous latent variable, all direct values were above the threshold of 0.15, portraying moderate effect sizes. The impact of all control variables was nonsignificant.

The direct effect of BAC on operational performance was positive and statistically significant (β = 0.256, T = 2.955, p < 0.01). This indicates that higher BAC is associated with better operational performance, suggesting that enhancing a firm's BAC directly improves its operational performance. Therefore, our first hypothesis is supported (Table 5). The moderation effect of BAC*BA organizing was negative and highly significant (β = -0.282, T = 3.223, p < 0.001), confirming our second hypothesis and hinting that the centralized BA organizing model is more likely to support operational performance than the hybrid or decentralized approaches. The three-way interaction term BAC*BA organizing*UNC was statistically non-significant (β = 0.163, T = 1.219, p = 0.111). This implies that uncertainty of the external environment does not significantly alter the moderating effect of BA organizing on the BAC-operational performance relationship in a linear sense.

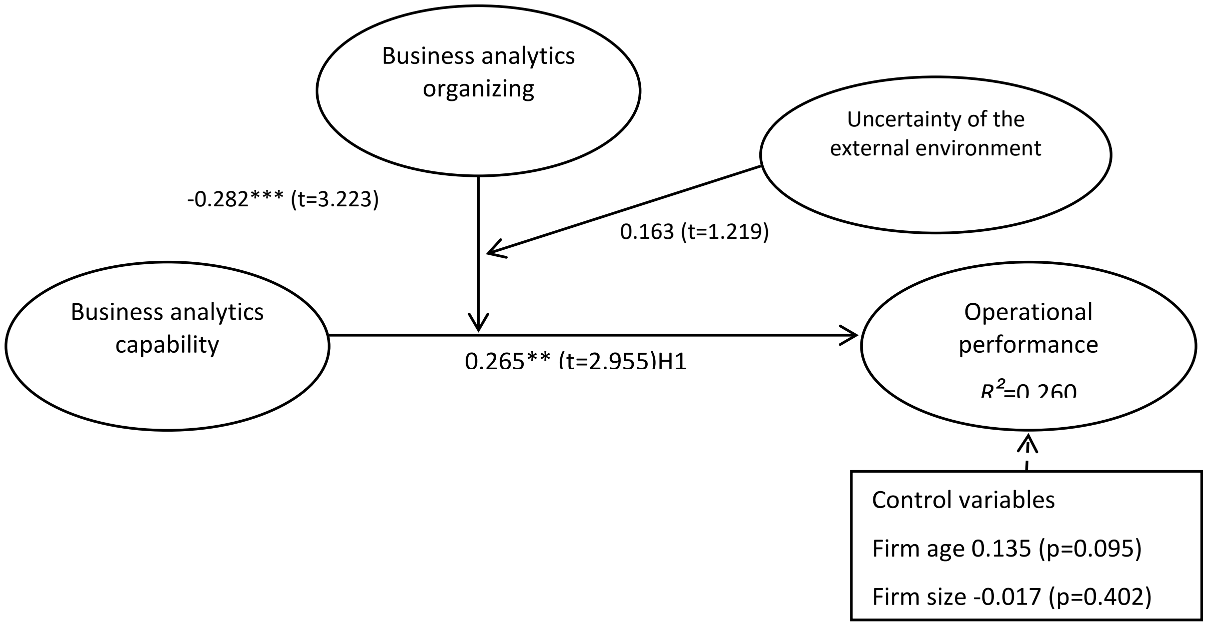

Figure 2: Results and estimated relationships of the structural model

Table 5: Summary of hypotheses and results of linear and nonlinear effects

Structural path	Effect	t-value[a]	Bias corrected 95% confidence interval	Conclusion
BAC -> Operational performance	0.265	2.955**	[0.110-0.403]	H1 supported
BAC*BA organizing -> Operational performance	- 0.282	3.223***	[-0.433- -0.148]	H2 supported (partial moderation)
BAC*BA organizing*UNC -> Operational performance	0.163	1.219	[-0.097-0.341]	H3 rejected
Quadratic effect (BAC*BA organizing) -> Operational performance	- 0.150	2.310**	[-0.247- -0.036]	Post-hoc test (partial nonlinear moderation)
Quadratic effect (BAC*BA organizing*UNC) -> Operational performance	0.162	2.177*	[0.017-0.272]	Post-hoc test (full nonlinear moderation)

[a] * significant at p < 0.05; ** significant at p < 0.01; *** significant at p < 0.001 (one-tailed test).

4.2.1 Post-hoc test for nonlinear effects

To extract more nuanced information about the role of our two moderating variables, we conducted a post-hoc test for their nonlinear, quadratic effects. The quadratic term for BAC*BA organizing was negative and statistically significant (β = -0.150, T = 2.310, p < 0.05), indicating a nonlinear moderating effect and suggesting that the impact of BA organizing on the BAC-operational performance relationship changes at different degrees of centralization/decentralization. Specifically, the negative coefficient hints that when BA organizing is highly decentralized, the weakening effect on the BAC-operational performance relationship becomes more pronounced. This additional finding further bolsters the hypothesized moderating role of BA organizing. The quadratic three-way interaction term for BAC*BA organizing*UNC was also positive and statistically significant ($\beta = 0.162$, $T = 2.177$, $p < 0.05$), suggesting that at higher levels of external uncertainty, the moderating effect of BA organizing on the BAC-operational performance relationship becomes less negative or even positive, hinting at the suitability of more decentralized BA organizing approaches in higher levels of environmental uncertainty.

5. Discussion

This study aimed at improving the understanding of the intra- and extra-organizational conditions under which firms may reap business value on their BAC investments. Specifically, we were interested in exploring the effects that BA organizing and the uncertainty of the firm's external environment may have on the association between BAC and the firm's operational performance. Based on our empirical survey data collected from Finnish firms, we found that both BA organizing and external uncertainty have significant roles in BAC business value creation, but their interplay might be more complex than expected, including both linear and nonlinear effects.

First, in line with past BAC literature (e.g., Khan et al, 2024; Wamba et al, 2017), our findings suggest that variance in a firm's BAC is directly related to variance in firm performance. More specifically, as we hypothesized based on earlier literature (Gupta & George, 2016), in the higher the level of a firm's BAC, the better its operational performance. A firm that has invested heavily in BAC is likely to improve its operational performance by, for instance, enabling quicker and better decision-making (Lepenioti et al, 2020). For instance, a retail company using BA to manage inventory can reduce stockouts and overstock situations, leading to improved productivity, sales and profit rate.

Second, the extant literature on BA governance has been mostly conceptual by nature (Baijens et al, 2022)

and/or bemoaned the lack of empirical evidence regarding the business value implications of different BA governance approaches (Gröger, 2018; Grover et al, 2018). The findings of this study contribute to BA governance by addressing and empirically confirming the impact of the degree of BA organizing centralization/decentralization in terms of reaping operational performance gains from the firm's BAC. In more detail, the attained negative moderation coefficient suggests that a centralized BA organizing approach, characterized by standardization of services, consolidation of activities, and duplication minimization (Schüritz et al, 2017) has a positive impact on the relationship between BAC and operational performance, while this positive impact decreases when BA organizing becomes more decentralized. Further, our post-hoc test for the nonlinear effect bolstered this finding, indicating that the more decentralized the firm's BA organizing approach is, the stronger the weakening effect becomes. This could mean that beyond a certain point, decentralized BA organizing might add complexity without corresponding benefits, potentially leading to, e.g., local, business unit-level optimization that does not serve the entire firm (Grossman and Siegel, 2014). Addressing such problem, past literature has suggested that the lack of control and potential agency issues may be the main disadvantages of the decentralized approach (Holmström and Milgrom, 1990; Xue et al, 2011). However, more research should be done specifically in the BA and BAC context to better understand the optimal fit between the degree of BA organizing de-centralization and different facets of firm performance.

Third, the existing literature has addressed the role of environmental uncertainty in effective IT governance (Turban et al, 2006; Xue et al, 2011) but has not provided sound empirical evidence on its business value implications. The results of our study showed non-significant linear moderation effect, but the post-hoc test for nonlinear moderation affirmed that the negative impact of a decentralized BA governance on the BAC-operative performance relationship might be mitigated or even reversed in highly uncertain conditions. For instance, during a period of rapid market changes, a decentralized BA organizing model might provide the necessary agility and framework to adapt quickly, navigate the uncertainty more effectively, thus enhancing the positive impact of BAC on operational performance. Or, as stated in earlier research, a centralized structure may simply lack insight into urgent data analytics needs across firm (Schüritz et al, 2017). We emphasize that even though the nonlinear impact was not hypothesized in this study, the finding is valuable starting point to better understand the interplay between these intra- and extra-organizational factors in BAC value creation.

6. Conclusion

In this study, we explored the moderating effects of BA organizing and the uncertainty of the firm's external environment on the association between BAC and operational performance. Our findings provide novel insights on BAC business value creation mechanisms, emphasizing the importance of addressing both internal and external factors and underlining the criticality to match the impact of the uncertainty of the external environment with a suitable BA organizing approach. Our study found that a centralized structure supports firm's efforts to leverage its BAC for operational performance gains in low to moderately uncertain conditions, while a decentralized approach seems to suit highly uncertain environments. That said, more research should be done to address this phenomenon to confirm these findings.

Ethics Declaration: Ethics approval was not required.

AI Declaration: AI tools were not used in the creation of this paper.

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