BDA-enabled marketing capabilities and marketing performance

- A moderated mediation model

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Abstract. Currently, big data analytics (BDA) has become an important resource for enhancing marketing capabilities and performance, which brings new development opportunities for the development of BDA-enabled marketing capabilities (BDAMC). However, there is a lack of exploration of the role of BDAMC and marketing performance (MP) in the current academic community. The results found that: BDAMC has an indirect effect on MP; BDAMC has a significant positive impact on decision making (DM); DM plays a fully mediating role between BDAMC and MP; and the firm's analytical culture (AC) plays a moderating role in the relationship between BDAMC and DM and MP. Exploring the consequential factors and boundary conditions of BDAMC provides insights and reference values for firms to implement BDA and develop BDA marketing management.

Keywords: BDA-enabled marketing capabilities; big data analytics; decision-making; analytic culture; marketing performance.

1 Introduction

Considered the process of analyzing large and dispersed datasets using advanced technologies to derive meaningful insights, big data analytics (BDA) is a hands-on activity that enhances marketing and customer management in multiple ways [1]. In the context of BDA and increasingly competitive markets, more and more firms are developing BDA-enabled marketing capabilities (BDAMC) to create greater business value [2-4]. BDAMC not only helps to improve the efficiency of their marketing decisions to increase sales and attract new customers but also enhances the flexibility of the organization's innovation activities to enable product/service innovation [5], presenting a new development opportunity to achieve high levels of market performance (MP) [6]. However, there is a shortage of research on BDAMC in the existing literature, and in particular, how it affects MP has become an urgent issue that needs to be explored.

According to dynamic capabilities theory, BDAMC can positively influence the quality of firms' decisions in turbulent and complex environments [7]. For data-driven businesses, BDA enables real-time assimilation and precise analysis to form sound

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market judgments and organizational decisions, bringing value to the business in both financial and non-financial terms by developing new products or services. High levels of MP and outcome effectiveness cannot be achieved without correct organizational decision-making (DM) [8], and thus DM is an important pathway through which BDAMC has an impact on MP. Moreover, a data-driven analytical culture (AC) is a necessary intangible resource for organizations willing to make the best use of BDA, which plays an important role in achieving high performance. AC may be an important contributing factor in influencing the market for BDAMC, DM, and performance [9]. However, the existing literature on the above perspectives still has not provided adequate theoretical explanations. Therefore, this study constructs a model through knowledge related to dynamic capabilities theory and explores the following two questions: (1) Does BDAMC influence MP through DM? (2) How does AC affect the relationship between them? These questions are explored to provide insights and reference values for companies to implement BDA strategies and develop BDA marketing management.

2 Conceptual Framework and Hypotheses Development

Dynamic capabilities often support the alignment of marketing and technological capabilities with market conditions [2]. As emphasized by Teece [10], if firms want to identify and shape new opportunities in technologies and the market, they must possess a marketing capability, in particular, a BDA-enabled marketing capability [3], which can probably leverage BDA to help the organization understand customer needs and latent demand, market segments to target, and opportunities related to the integration of products/services. BDAMC is a dynamic capability that transforms data into valuable insights and intelligence through big data management, technical infrastructure, and talent capabilities to improve marketing, product/service development, and other core business functions. Therefore, firms building a dynamic BDAMC can increase market flexibility and agility, bringing positive benefits to their business decisions and MP [11].

2.1 BDAMC and MP

The rapid development and wide application of BDA have opened up tremendous new opportunities for innovation and marketing. BDAMC refers to the abilities of organizations to leverage big data technologies and analytics to mine valuable insights from massive amounts of data and apply them to their marketing activities [3, 12]. These capabilities help firms to effectively sense and predict future customer needs through the collection, collation, and analysis of data for marketing management and customer relationship management.

On the one hand, BDAMC helps to solve various business problems, enhance market awareness, and improve customer relationships [5]. The customer and market insights gained from BDA can effectively improve customer satisfaction and loyalty, enhance business operation efficiency, improve service customer and supplier satisfaction, and

create niche markets, thus creating new avenues of development and helping enterprises achieve higher MP. On the other hand, BDAMC can facilitate companies achieve product/service innovation and improve market acumen. Market acumen is an important MP indicator, and BDA (e.g., purchase preferences) can make customer behavior transparent, help firms to achieve customer personalization and customized service process improvement, and create opportunities for product /service development and innovation opportunities. Thus, the hypothesis is formulated:

H1: There is a direct positive effect of BDAMC on MP.

2.2 The Mediating Role of DM

Having BDA resources in the organization not only puts decision-makers in a fully perceptive decision-making environment, but also BDA tools can provide decision-makers with efficient means and supporting technologies [13]. In other words, BDAMC helps decision makers to allocate resources efficiently and to transfer and process information resources correctly, which in turn significantly reduces the risks and uncertainties arising from market turbulence. BDAMC empowers decision-makers with problem-solving capabilities and decision-useful data, information, and knowledge at the individual and organizational levels. Decision-makers make timely, informed, and appropriate DM measures and programmed choices based on a continuous understanding of their dynamic environment and information about customer needs, enhancing the effectiveness and quality of their decisions.

Decision quality in the strategic decision-making process is one of the most important determinants of performance [14]. BDAMC can facilitate effective DM in organizations. Information and knowledge gained through BDA can facilitate business process optimization, a deeper understanding of the business environment, customer relationship maintenance, and competitors' hidden behaviors, which in turn can enhance the effectiveness and efficiency of data-driven DM [7]. When firms are faced with investment opportunities, data and analytics will help organizations to quickly and accurately understand changes in the external market environment and improve the ability to process internal information resources. On the contrary, the organization that does not use BDA, has a weaker marketing capability, the relevant departments are inefficient in DM, and even its MP does not get the expected results. Thus, the hypothesis is proposed:

H2: DM has a mediating role in the relationship between BDAMC and MP.

2.3 The Moderating Role of AC

AC refers to the organizational culture that supports data analytics [15], which reflects a pattern of values, mindsets, and beliefs that have developed within the organization to support data analytics [9]. Existing literature identifies organizational culture as a key factor contributing to firm performance. AC plays an important role in marketing and performance research, and it is an important enabler for firms to use BDA-driven marketing to gain a competitive advantage [15].

In organizations that make full use of BDA, AC is a necessary intangible resource that facilitates organizations to analyze and generate valuable insights about their customers and creates favorable conditions for efficient DM [2, 9]. AC promotes knowledge transfer, trust, and collaboration among team members, which in turn accelerates DM, reduces the focus on extraneous processes for efficient management, and consequently, improves the decision-making efficiency and outcomes of DM teams. Thus, the hypothesis is formulated:

H3: AC moderates the relationship between BDAMC and DM.

2.4 The Moderated Mediation Effect

Existing literature suggests that cultural factors are important moderating variables of BDA-related capabilities affecting MP [15, 16]. AC is closely related to quality data and reporting, and the mindset that supports data analysis influences the behavioral norms of analysts, analytical processes, and control procedures handling techniques. These cultures promote efficient and effective decision-making in organizations, which in turn helps firms achieve higher MP. Thus, the hypothesis is formulated:

H4: AC plays a moderating role in the relationship between BDAMC, DM, and MP.

Therefore, the research model is presented in Figure 1.

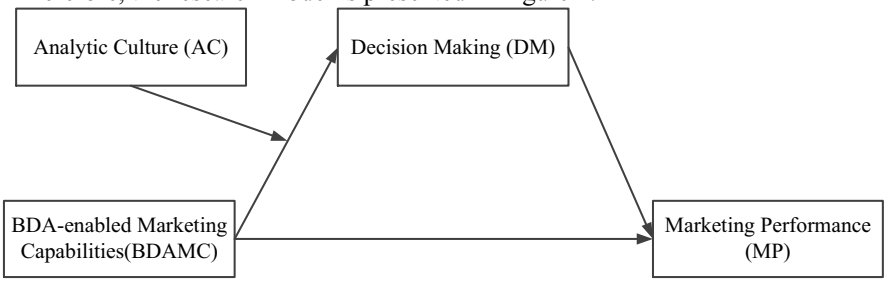

Fig. 1. Research model

3 Measures

3.1 Data Collection

This study takes the middle and senior managers of enterprises adopting big data analytics as the survey object, which mainly includes enterprises in two categories: manufacturing (automobile, etc.) and service industry (investment and finance and software service, etc.). 120 questionnaires were distributed in March 2024 through the MBA/EMBA classes and familiar enterprises around us to effectively recover 73 pre-survey samples, and after revision, the formal questionnaire was distributed. The formal research period lasts from April to July 2024. Collection channels are collected in a diversified way. Firstly, in cooperation with a big data research company, combining online platforms and offline survey methods, invitations to participate in the survey are issued nationwide to enterprises eligible for the survey, and about 500 invitations are

issued on the platform, and 178 valid questionnaires are recovered after screening eligible samples. Secondly, about 150 questionnaires were distributed through MBA/EMBA classes, and 62 effective questionnaires were recovered, with an effective recovery rate of 29.7%. Finally, the questionnaires were distributed through the channels of acquaintances, market supervision familiar government staff, and friends and relatives, about 70 questionnaires were distributed and 27 valid questionnaires were recovered. Therefore, this study finally received a total of 267 companies with valid samples.

Specific sample: enterprise size, 82 (30.7%) with less than 100 employees, 29 (10.9%) with 100-200 employees, 29 (10.9%) with 201-500 employees, 90 (33.7%) with 501-1,000 employees, and 37 (13.8%) with more than 1,000 employees; enterprise age, 50 (18.7%) with less than 5 years, 5-10 years 49 (18.4%), 11-15 years 45 (16.9%), 15-20 years 46 (17.2%), more than 20 years 77 (28.8%); enterprise type, automobile manufacturing 10 (3.7%), pharmaceutical manufacturing 47 (17.6%), computer and communication electronics manufacturing 41 (15.4%), durable goods and consumer goods and machinery manufacturing 12 (4.5%), Transportation 24 (9.0%), Warehousing and Postal Services 5 (1.9%), Wholesale and Retail 27 (10.1%), Finance 48 (18.0%), Real Estate, Leasing, and Business Services 37 (13.9%), Scientific Research, Technical Services, and Geological Surveying 6 (2.2%), Residential and Other Services 6 (2.2%), and 4 (1.5%) for others.

3.2 Variable Measurement

A well-established scale that is widely recognized and fits the research scenario was chosen for this study. The questionnaires were further revised and improved to form official questionnaires based on the feedback from the pre-survey, and all the questionnaires were adopted on a seven-point Likert scale. (1) *BDAMC*: Adopting the research scales of Hossain *et al.* and Manis and Madhavaram [3, 12]. BDAMC was classified into BDA-enabled sensing, adaptive, resilience, learning, responsiveness, etc., the questionnaire consists of 9 items. (2) *DM*: Adopting the research scales of Shamim *et al*. [7]. DM includes both decision-making efficiency and effectiveness, the questionnaire consists of 6 items. (3) *MP*: Adopting the research scales of Mikalef *et al*. [11] , the questionnaire consists of 7 items. (4) *AC*: Adopting the research scales of Germann *et al*. [9], which was used with 3 items. (5) *Control variables*: Firm size, firm age, and firm type were selected as control variables in this study.

4 Results

4.1 Descriptive Analysis

The reliability of a measurement questionnaire refers to the consistency or stability of the results, which is generally measured by Cronbach's α coefficient or α. In this study, the reliability of the questionnaire was examined using SPSS 18.0, and Cronbach's α coefficient and CR for each variable were greater than the recommended value of 0.7, and the AVE was greater than the recommended value of 0.5, thus the questionnaire

had good reliability. The mean, standard deviation, and correlation matrix of each variable are shown in Table 1. BDAMC was positively correlated with MP (r=0.131, p<0.05). BDAMC was positively correlated with DM (r=0.274, p<0.01). DM was positively correlated with MP (r=0.326, p<0.01). AC was positively correlated with MP (r=0.169. p<0.01). The above results provide preliminary support for the hypothesis testing.

Table 1. Descriptive statistics and correlational results of major variables.

Variables	M	SD	α	CR	AVE	1	2	3	4
BDAMC	4.619	0.768	0.887	0.9087	0.5261	-			
DM	4.261	0.784	0.831	0.8824	0.5585	0.274**	-		
AC	5.119	0.911	0.797	0.8811	0.712	0.106	-0.039	-	
MP	4.384	0.825	0.890	0.9155	0.6079	0.131*	0.326**	0.169**	-

Note. α=Cronbach's α, CR=Composite Reliability, AVE= Average Variance Extracted.

* p<0.05, ** p<0.01.

To ensure that the models could be successfully matched to each other as well as that the fitted models had discriminant validity, validation analyses were conducted using Mplus 8.3 on the four variables BDAMC, DM, AC, and MP (see Table 2). This was done by combining the variables two by two and then comparing the metrics of each model. The results showed that the data fit of the four-factor model was better than that of the other models (χ^2/df = 2.021; TLI = 0.908; CFI = 0.922; RMSEA = 0.062), which indicates that the model of the present study has good discriminant validity.

Table 2. Confirmatory factor analysis results(N=267).

Model	χ^2/df	CFI	TLI	RMSEA	SRMR
Four-factor model (BDAMC; DM; AC; MP)	2.021	0.922	0.908	0.062	0.073
Three-factor model (BDAMC; DM; AC+MP)	3.056	0.842	0.815	0.088	0.088
Two-factor model (BDAMC; DM+AC+MP)	4.987	0.683	0.642	0.122	0.115
Single-factor model (BDAMC+DM+AC+MP)	7.617	0.467	0.406	0.157	0.169

4.2 Common Method Bias Test

To prevent the results of the study from being adversely affected by the presence of severe homoscedasticity bias, this study, therefore, assessed the magnitude of homoscedasticity bias using Harman's single-factor test, which has been adopted by most scholars to test for common method bias. The results showed that a total of four variables were analyzed, while the eigenvalue of the first factor analyzed was 6.163, which explained only 24.654% of the variance, which was less than half of the total

variance explained, 65.061%, indicating that the problem of common method bias was not serious.

4.3 Model Hypothesis Testing

This study belongs to the moderated mediation model and it is recommended to use the test coefficient product to determine the direct and indirect moderated effects, and then further test the moderated mediation effects using the Bootstrap method. To avoid cumbersome validation steps, this study conducted structural model tests with the help of Mplus8.3. Table 3 and Figure 2 demonstrate the structural model results. The results showed that all control variables had no significant effect on MP, and the effect of BDAMC on MP was not significant (β= 0.074, $p > 0.05$), thus H1 was not supported.

In this study mediation effect test was calculated using the Bootstrapping method to calculate the indirect effect through the reset sampling method. The results showed that none of the control variables were significant for the dependent variable except for the path coefficient of Firm size on DM which was significant (β=-0.069, $p<0.05$). The path coefficient of the direct effect of BDAMC on DM was significant (β=0.296, $p<0.001$), the path coefficient of DM on MP was significant (β=0.347, $p<0.001$), and the indirect path effect value of BDAMC affecting MP through DM was 0.103 ($p<0.001$) with a 95% bias-corrected confidence interval [0.031, 0.192], suggesting that DM had a fully mediating role between BDAMC and MP, thus H2 was supported.

Table 3. The structure model results.

Path in the structure model	coefficients	SE	T-value	Outcomes
Firm size → MP	0.058	0.036	1.627	
Firm age → MP	0.009	0.034	0.256	
Firm type → MP	-0.001	0.013	-0.090	
BDAMC → MP	0.074	0.067	1.103	H1 Not Supported
DM → MP	0.347***	0.065	5.369	
BDAMC → DM→ MP	0.103***	0.041	3.509	H2 Supported
BDAMC → DM	0.296***	0.064	4.604	
AC → DM	-0.017	0.053	-0.318	
BDAMC × AC → DM	0.159***	0.044	3.620	H3 Supported
Conditional indirect effect	Indirect effect	Boot SE	Boot CI	
AC				
-1 SD (-0.911)	0.053	0.036	[-0.010,0.132]	
+1 SD (+0.911)	0.153	0.060	[0.047,0.277]	H4 Supported
Index of moderated mediation	0.055	0.030	[0.002,0.118]	

*$p<0.05$, ***$p<0.001$

In this study, the moderating role of AC between BDAMC and DM was tested. The results showed that the interaction term of BDAMC with AC had a significant positive effect on DM (β=0.159, p<0.001), thus H3 was supported. To observe this moderating effect more intuitively, this study conducted a simple slope analysis using the PROCESS procedure in SPSS (see Figure 3). When the AC is lower than 1 standard deviation, the regression slope of BDAMC versus DM is 0.151, p<0.05, 95% bias-corrected confidence interval [0.020, 0.283]; while when the AC level is higher than 1 standard deviation, the regression slope of BDAMC versus DM is 0.440, p<0.001, 95% bias-corrected confidence interval [0.276, 0.605]. It indicates that the higher the AC is, the more significant the effect BDAMC can have on DM.

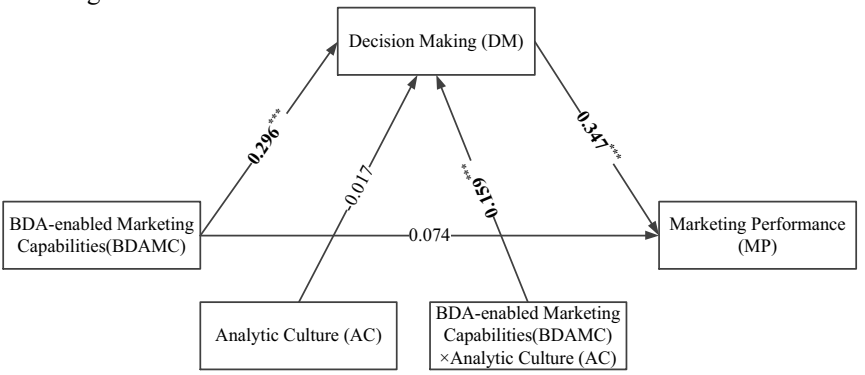

Fig. 2. The structure model results.

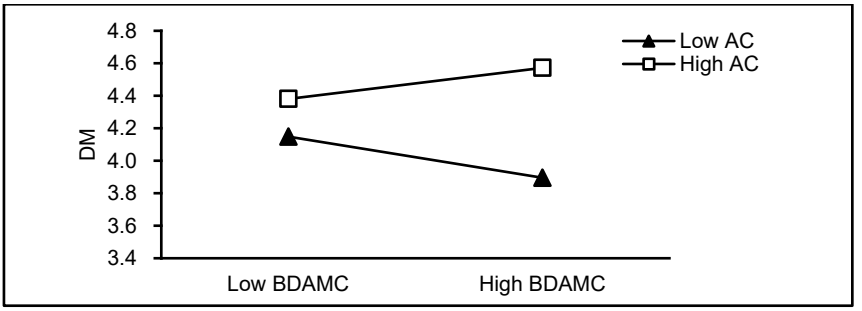

Fig. 3. The moderating effect of AC on the BDAMC-DM relationship.

4.4 The Moderated Mediation Test

As shown in Table 3, when DM was the mediating variable, the indirect effect value of the model at High AC was 0.153, and the 95% corrected deviation confidence interval was [0.002,0.118], which implies that the High AC time-continuous effect was significant. However, the indirect effect value of the model at Low AC was 0.053 with a 95% corrected bias confidence interval of [-0.010,0.132], which implies that the Low AC temporal indirect effect was not significant. It is worth noting that the difference between the indirect effects at the high and low levels is significant, i.e., the index of

moderated mediation effect value is 0.055, and the 95% corrected deviation confidence interval is [0.002,0.118], which means that the moderated mediation model is tested, thus H4 is supported.

4.5 Robustness Test

In this study, each variable was standardized and the results were tested for robustness by Hierarchical Linear Model (HLM) as shown in Table 4. In model 5, despite the significant effect of BDAMC on MP, however, the regression model *F-value* did not reach significance, thus, H1 was not supported. In model 6, DM acted as a full mediator between BDAMC and MP, thus, H2 was supported. In model 3, the interaction term between BDAMC and AC significantly affects DM, thus, H3 was also supported. In summary, the results of the robustness test did not change significantly from the above analyses, indicating that this study has a high degree of robustness.

Table 4. Robustness test results.

Variable	DM			MP		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variable						
Firm size	-0.194**	-0.152*	-0.132*	0.028	0.054	-0.083
Firm age	0.054	0.069	0.071	0.029	0.038	-0.074
Firm type	0.111	0.079	0.081	0.141	0.021	-0.046
Independent variable						
BDAMC		**0.231*****	**0.290*****		**0.145***	0.069
Mediator variable						
DM						**0.330*****
Moderator variable						
AC			-0.020			
BDAMC×AC			**0.214*****			
R^2	0.057	0.106	0.149	0.030	0.022	0.119
Adj-R^2	0.047	0.093	0.130	-0.009	0.007	0.102
F	5.328	7.793	7.608	0.237	1.472	7.067

5 Conclusion and Implications

5.1 Conclusion

This study constructs a theoretical model of BDAMC, DM, and MP based on dynamic capabilities theory. The results showed that BDAMC has an indirect effect on MP. There is a direct positive effect of BDAMC on MP, and DM plays a fully mediating role between BDAMC and MP. AC moderates the relationship between BDAMC and DM. Further, AC plays a moderating role in the relationship between BDAMC, DM,

and MP. This study investigates 267 firms applying BDA, provides in-depth analyses of theoretical models through Structural Equation Modelling (SEM), and expands the relevant literature in the field of BDA and marketing.

5.2 Theoretical Contributions

Firstly, constructing a firm's BDAMC will indirectly affect its MP. Existing literature suggests that BDA can provide generative critical digital technology resources that enable innovation by pooling, integrating, and deploying resources [5]. Firms using BDA achieve high operational efficiency and revenue growth over their competitors [17]. Large enterprises, often have the in-house capabilities to select, install, configure, and maintain complex IT systems, and thus building BDAMC can improve the ability to be market-aware and agile in its response, which in turn improves the demand forecasting, supply chain planning, sales support, and operational efficiency and speed, facilitating product/service process improvement and the delivery of new customer experiences and services [5], creating favorable conditions for achieving high market performance.

Secondly, DM is an important pathway for BDAMC to influence MP. It was found that DM plays a fully mediating role between BDAMC and MP, which is consistent with the existing literature on the role of indirect influence of BDA-related capabilities on market performance [11]. The use of BDA by firms can effectively improve marketing capabilities, obtain useful and effective market insights, and then the decision-making team analyses and makes decisions based on these useful market insights about the competitive environment, market changes, and customer needs, responding to market changes promptly to improve product quality and market share, which in turn improves market performance.

Finally, AC plays a moderating role in the relationship between BDAMC, DM, and MP. Research has shown that a data-driven culture can influence decision-making at all levels. This implies that the higher the level of an organization's AC, the more significant the positive impact of BDAMC on DM, which in turn promotes higher MP. This finding is consistent with related literature that emphasizes that the fit between management practices and organizational culture positively impacts performance [2]. Data-driven firms need to develop an organizational culture, which means that firms not only focus on the quality of data but also pay attention to fostering an atmosphere and behavioral patterns of analytical collaboration, openness, and support for data analysis, to promote BDA-enabled marketing effectiveness and usability [3].

5.3 Managerial Implications

The findings of this study also have important implications for management practices. Firstly, exploring the implications of BDA-enabled marketing capabilities in marketing management has significant practical value. For large firms, the positive attitude of senior management towards data analytics is the main driver for the development of BDA in the firm. Therefore, the management should be clear about the use of BDA in marketing management for strategic deployment and resource alignment actions. In addition, firms building BDAMC can help them maintain customer relationships,

facilitate the production of personalized products, and improve the efficiency of the marketing mix, and firms should create good foundations and conditions for the realization of BDA.

Secondly, our findings emphasize the enabling role of a data-driven analytics culture. Gaining a high level of decision quality requires not only the development of BDAMC but also an analytics culture where insights extracted from data are valued and acted upon. Managers should not just invest in BDA infrastructure and technology to develop marketing capabilities but also pay attention to the development of an organizational culture that supports data analytics in the firm. Firms can facilitate the development of an analytics culture in their organization through targeted workshops, technical staff, and related training.

5.4 Limitations and Further Research

This study still has certain limitations. Based on the limitation of research resources, only firm size, firm age, and firm type are selected as control variables in this study. Future research can select factors such as technological volatility and market orientation as control variables to enhance the accuracy of the conclusions. In addition, future research could incorporate case qualitative analyses to enrich further BDA-enabled marketing capabilities research.

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