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Factors Impacting E-Commerce Performance via Big Data Analytics in Hangzhou

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Abstract

Purpose: This study investigates the factors influencing firm performance (FP) through big data analytics (BDA) in E-commerce companies. Specifically, it examines the effects of integration (INT), global sourcing (GS), competitive advantage (CA), business value (BVAL), and satisfaction (SAT) on FP, along with the effect of INT on GS and BVAL on SAT**. Research design, data and methodology:** Based on the resource-based view (RBV), dynamic capability view (DCV), and information systems (IS) success model, a quantitative approach was adopted. Data were collected from 500 employees across eight types of E-commerce companies in Hangzhou using stratified random sampling. Confirmatory factor analysis (CFA) and structural equation modeling (SEM) were used to test hypotheses and analyze relationships among variables. **Results:** BVAL has the strongest effect on SAT, INT significantly enhances GS, but its direct effect on FP is unsupported. GS, BVAL, CA, and SAT significantly impact FP. This study highlights the strategic value of BDA in driving performance outcomes. **Conclusions:** This offers actionable insights for E-commerce firms to strengthen integration, optimize sourcing, create business value, and enhance satisfaction. By focusing on these areas, businesses can better navigate the global digital marketplace, build sustainable competitive advantages, and improve overall firm performance.

Keywords: Big Data Analytics, Global Sourcing, Satisfaction, Business Value, Firm Performance

JEL Classification Code: D22, L81, L86, M15, O33

1. Introduction

Big data has emerged as a strategic driver of digital transformation, characterized by its large volume, high velocity, variety, and low value density (Khan et al., 2014). Its growing significance is evident across industries, fueled by advancements in cloud computing, artificial intelligence, and the increasing demand for data-driven decision-making. In the context of E-commerce, big data analytics (BDA) enables companies to better understand consumer behavior, enhance operational efficiency, and gain competitive advantage through timely insights and innovation (Bresciani et al., 2021). Prior research has highlighted the positive impact of BDA on firm performance, often mediated by factors such as global sourcing, integration, business value, and satisfaction (Razaghi & Shokouhyar, 2021; Wamba et al., 2018). However, despite growing scholarly attention, there is limited understanding of how these factors interact within a unified model—particularly in rapidly evolving digital ecosystems.

This study addresses that gap by exploring how integration, global sourcing, competitive advantage, business value, and satisfaction influence firm performance through BDA. The research focuses on Hangzhou, a major E-commerce and big data hub in China, where the digital economy is deeply integrated with industrial development. Hangzhou is home to leading technology companies like Alibaba and is ranked among the top big data cities in China. Its mature digital infrastructure, strong innovation capacity, and global E-commerce influence make it an ideal context for investigating the strategic role of BDA. Additionally, the presence of diverse E-commerce enterprises in the region

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provides a rich sample for examining differences across business types.

Despite the growing application of BDA in E-commerce, many companies still lack clarity on how to effectively align key analytics-driven capabilities—such as integration, sourcing strategies, and value creation—with performance outcomes. This research aims to fill that gap by identifying the most impactful BDA-related factors and their interrelationships. Specifically, the study has three objectives: (1) to determine which BDA-related factors significantly affect firm performance; (2) to examine the mediating role of integration on global sourcing and business value on satisfaction; and (3) to offer practical insights for E-commerce companies to optimize BDA implementation. By grounding the research in theoretical frameworks such as the Resource-Based View (RBV), the Dynamic Capability View (DCV), and the Information Systems Success Model, this study contributes to the literature on digital transformation and analytics strategy, while offering actionable recommendations for firms operating in highly competitive and data-rich environments.

2. Literature Review

2.1 Integration (INT)

Integration refers to the alignment of internal departments and external partners to enable smooth coordination across business functions. Early definitions emphasized internal consolidation (Kahn & Mentzer, 1996; Webster, 1966), while more recent research highlights cross-organizational collaboration as essential to supply chain efficiency (Flynn et al., 2010; Yu & Fang, 2023). Integration enhances the flow of information, products, and services, leading to improved responsiveness and reduced costs (Frohlich & Westbrook, 2001). However, findings on integration's direct impact on firm performance remain mixed. While some studies suggest minimal effect, others argue integration plays a vital role when combined with big data analytics capabilities (Wang et al., 2023). Particularly in E-commerce, where data-driven decision-making is critical, integration can support real-time collaboration and enhance supply chain agility.

Despite its importance, few studies have empirically explored integration's dual role in global sourcing and performance within digital markets. This study addresses that gap by examining how integration, supported by big data analytics, affects global sourcing strategies and firm performance in E-commerce companies. Based on the literature and gaps identified, the following hypotheses are proposed:

H1: Integration has a significant impact on global sourcing.

H3: Integration has a significant impact on firm performance

2.2 Global Sourcing (GS)

Global sourcing involves the strategic coordination of procurement across international borders to access cost advantages, skilled labor, and specialized technology (Jia et al., 2017). It is not limited to purchasing but includes upstream integration across design, production, and supplier networks (Cagliano et al., 2012). These strategies help firms improve efficiency and expand market reach. In recent years, global sourcing has evolved through digital tools. Big data analytics enhance supplier evaluation, risk forecasting, and sourcing optimization (Alkire et al., 2023; Razaghi & Shokouhyar, 2021). However, there is limited research on how global sourcing—enabled by analytics—translates into measurable performance outcomes, especially in data-intensive industries like E-commerce.

This study builds on existing work by focusing on how global sourcing contributes to firm performance in digitally advanced markets. It extends the conversation by exploring this relationship within the context of E-commerce firms using big data analytics in Hangzhou. Based on the literature and the identified research gap, the following hypothesis is proposed:

H4: Global sourcing has significant impact on firm performance.

2.3 Competitive Advantage (CA)

Competitive advantage reflects a firm's ability to maintain superior market positioning through unique assets, capabilities, or strategic initiatives (Potjanajaruwit, 2018). Traditionally associated with resources such as brand equity or innovation (Barney, 1991), today's competitive advantage increasingly depends on how well firms utilize data-driven capabilities to respond to market changes (Behl, 2022).

In the E-commerce sector, big data analytics empowers firms to personalize offerings, optimize pricing, and respond quickly to demand shifts, contributing to sustained advantage (Lee & Yang, 2023). Yet, empirical studies on the direct link between data-enabled competitive advantage and firm performance remain scarce, especially in emerging digital economies.

This study fills that gap by examining how competitive advantage, fueled by analytics and strategic resource deployment impacts performance in E-commerce firms. Unlike earlier studies that focus on static assets, this research considers competitive advantage as a dynamic, capability-based construct. Based on the literature and the identified research gap, the following hypothesis is proposed:

H5: Competitive advantage has significant impact on firm performance.

2.4 Business Value (BVL)

Business value refers to the measurable benefits an organization gains from leveraging technological and data-driven capabilities. Early studies categorized business value into informational, automation, and transformational outcomes (Zuboff, 1988), and later expanded it into strategic, transactional, and transformative dimensions—each offering long-term positioning, operational efficiency, and organizational change, respectively (Gregor et al., 2006). In the context of big data analytics, business value is viewed as a bridge between advanced data capabilities and firm outcomes (Ji-Fan Ren et al., 2017). The resource-based view frames business value as the result of leveraging rare, valuable, and data-driven assets to support firm performance. Studies show that big data analytics enhances decision-making, market responsiveness, and agility—ultimately translating into performance gains (Li & Liu, 2023; Vitari & Raguseo, 2020). In E-commerce, this value is especially relevant due to the fast pace of digital transactions and customer interactions (Zhao & Wang, 2022). However, extracting business value requires addressing challenges like information overload and redundancy. Poor data quality can significantly diminish the value of analytics initiatives (Ghasemaghaei, 2022).

Despite growing interest, empirical research exploring how business value affects both user satisfaction and firm performance in E-commerce contexts remains limited. This study fills that gap by examining business value as a key outcome of big data analytics in digitally advanced E-commerce companies in Hangzhou. Based on the literature and the identified research gap, the following hypothesis is proposed:

H2: Business value has significant impact on satisfaction.

H6: Business value has significant impact on firm performance.

2.5 Satisfaction (SAT)

Satisfaction, in the context of data-driven environments, reflects users' or employees' emotional responses and evaluative judgments toward systems, services, or work environments. Spreng et al. (1996) defined satisfaction as users' subjective experiences when interacting with systems such as big data analytics platforms. Building on this, Wixom and Todd (2005) emphasized satisfaction as an affective response to information quality, system usability, and service performance.

Satisfaction is particularly relevant in two key domains: employee (job) satisfaction and customer (user) satisfaction. Job satisfaction is shaped by factors such as work-life balance, compensation, growth opportunities, and organizational environment (Deb et al., 2023; Lu et al., 2021). It influences not only employee engagement and productivity but also organizational performance. Similarly, customer satisfaction plays a vital role in influencing behavioral outcomes such as loyalty, repurchase intentions, and advocacy. Factors such as trust, perceived value, and service performance are commonly identified as key drivers (Kalinić et al., 2019; Marinkovic & Kalinic, 2017).

In E-commerce, satisfaction with digital platforms is critical. Trust and perceived usefulness significantly shape user satisfaction in mobile and online shopping contexts (Chong, 2013; Kalinić et al., 2019). Higher satisfaction with information systems is linked to increased usage, stronger reliance on big data analytics, and improved decision-making (Langenberg et al., 2012; McAfee & Brynjolfsson, 2012). Recent studies confirm that user satisfaction also serves as a performance indicator in technology-driven firms (Kong & Liu, 2023), yet few have explored its role as a mediating factor between business value and firm performance in data-intensive E-commerce environments.

This study contributes by investigating satisfaction as a multidimensional construct, encompassing both employee and user perspectives and examining its direct influence on firm performance in the context of big data-enabled E-commerce firms in Hangzhou. Based on the literature and the identified research gap, the following hypothesis is proposed:

H7: Satisfaction has significant impact on firm performance.

2.6 Firm Performance (FP)

Firm performance is broadly defined as an organization's ability to achieve superior outcomes relative to competitors. It encompasses financial metrics such as profitability, sales growth, and return on investment, as well as non-financial indicators like customer acquisition, process improvement, and product quality (Galbreath et al., 2020; Miah et al., 2017). In dynamic markets, firm performance is increasingly viewed as the result of effective resource deployment and strategic alignment, consistent with the dynamic capability view (Gupta et al., 2018; Pratono, 2024).

Competitive advantage, global sourcing, and integration have all been identified as critical drivers of performance. Prior studies have shown that strategic global sourcing practices, supported by managerial expertise, positively impact firm outcomes (Foerstl et al., 2013; Gualandris et al., 2014). Similarly, integration across supply chains enhances data flow and decision-making, improving competitiveness and performance (Lin et al., 2017). Big data analytics further amplifies these effects by improving information quality, generating insights, and enhancing responsiveness (Ji-Fan Ren et al., 2017; Mikalef et al., 2020). Business value derived from analytics is increasingly recognized as a key intermediary that connects technological investments to tangible firm outcomes (Li & Liu, 2023; Vitari & Raguseo, 2020). Satisfaction, both customer and employee also contributes to performance by fostering loyalty, improving service delivery, and enhancing workforce productivity (Kalinić et al., 2019; Kong & Liu, 2023).

Despite growing research, few studies have explored how these variables interact within a unified framework in data-intensive E-commerce settings. This study contributes by examining the integrated effects of business value, satisfaction, global sourcing, integration, and competitive advantage on firm performance—offering a more holistic view of performance drivers in the big data era.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework for this study is grounded in three foundational theories: the Resource-Based View (Wernerfelt, 1984), the Dynamic Capability View (Teece & Pisano, 1994), and the Information Systems Success Model (DeLone & McLean, 2003). Together, these theories provide a comprehensive lens for examining how data-driven capabilities influence the performance of E-commerce firms.

A theoretical framework consists of key concepts and assumptions that guide the research and explain the relationships between variables. In this study, the framework is supported by previous models developed by leading scholars. The first relevant framework, introduced by Razaghi and Shokouhyar (2021), explores how big data analytics capabilities enhance supply chain integration and firm performance, particularly within the context of global sourcing strategies. The second framework, proposed by Behl (2022), draws on the dynamic capability perspective to explain how data-related competencies improve competitiveness and business performance, especially in digital startups. The third framework, developed by Wamba et al. (2018), focuses on how perceived business value and user satisfaction mediate the effect of data analytics on firm performance. It is based on the appraisal-emotional response-coping model, often used to understand how users evaluate and respond to technology. These three perspectives collectively inform the structure of this study, enabling a deeper understanding of how E-commerce companies in a data-intensive environment like Hangzhou can achieve better performance through integration, sourcing strategies, competitive advantage, business value, and satisfaction.

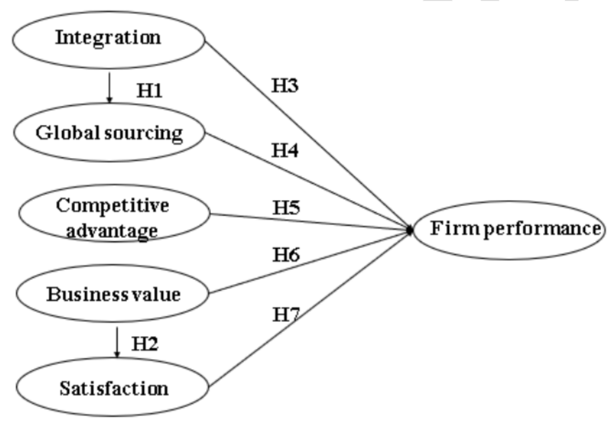

Figure 1: Conceptual Framework

Figure 1 proposes the conceptual framework of this study. As illustrated, this framework outlines all the variables examined in the study and depicts the causal relationships among them, including INT, GS, CA, BVAL, SAT, and FP. It aims to analyze all the factors influencing FP in the E-commerce era in Hangzhou, China, relying on BDA.

3.2 Research Methodology

This study adopted a quantitative research design, using structured questionnaires to gather data from employees working in E-commerce companies in Hangzhou. The data collection process was conducted online through the Questionnaire Star platform, which enabled wide distribution and efficient management of responses. A mix of sampling methods were employed to ensure that the sample reflected diversity across eight distinct types of E-commerce companies, capturing a variety of operational models. This mix methods enhances the internal generalizability of the findings within the E-commerce sector. However, since the data were collected from firms located in a single city, caution should be exercised when generalizing results to broader national or international contexts.

The questionnaire consisted of three sections. The first section included screening questions to filter out participants without practical experience using big data analytics. The second section gathered demographic information such as gender, age, years of experience with big data technologies, and the specific contexts in which these technologies were applied. The third section used a five-point Likert scale (ranging from 1 = strongly disagree to 5 = strongly agree) to measure six latent constructs: Integration (5 items), Competitive Advantage (5 items), Business Value (6 items), Global Sourcing (4 items), Satisfaction (4 items), and Firm Performance (4 items), for a total of 28 items.

To ensure the validity of the questionnaire, expert judgment was used during the development phase. Three professionals from academia and industry assessed the content validity through the Item-Objective Congruence (IOC) method. Items with IOC values above 0.80 were retained, confirming their relevance and clarity. A pilot test involving 30 participants was also conducted to further assess the clarity and reliability of the questionnaire. Feedback from this test was used to refine the final instrument.

Once the survey was finalized and distributed, a total of 500 valid responses were collected. Cronbach's Alpha was used to test the internal consistency of the constructs, confirming acceptable reliability levels. Further statistical analysis was conducted using Jamovi and AMOS software. Confirmatory Factor Analysis (CFA) was applied to assess the model fit, and Average Variance Extracted (AVE) and composite reliability were calculated to evaluate convergent and discriminant validity. Finally, Structural Equation Modeling (SEM) was employed to test the proposed hypotheses and examine the structural relationships among the variables in the conceptual model.

3.3 Population and Sample Size

The target population of this study consisted of employees from eight types of E-commerce companies based in Hangzhou, China. Hangzhou was selected due to its position as a national leader in digital innovation and E-commerce development. Home to major firms like Alibaba, the city offers a mature digital infrastructure and advanced application of big data technologies, making it an ideal context for studying analytics-driven firm performance. Participants were required to have at least one year of experience in the E-commerce sector and practical exposure to big data analytics. This ensured relevant and informed responses.

To determine the appropriate sample size, the researcher followed Kline's (2011) recommendation of at least 200 cases for structural equation modeling (SEM). A sample size calculator, based on the number of indicators and variables, suggested a minimum of 403. To increase statistical power and reliability, a total of 500 valid responses were collected.

A mixed sampling approach was adopted. Purposive sampling was used to select eight E-commerce business types in Hangzhou. Stratified random sampling determined proportional quotas for each type of company shown in table 1, and convenience sampling was used to reach eligible respondents. Screening questions ensured all participants met the study's criteria.

Table 1: Population and Sample Size by Company

Type of Company	Population Size	Proportional Sample Size
Cosmetic Company	1,200	146
Furniture Company	500	61
Electric Equipment Company	350	43
Advertising Company	460	56
Toys Company	340	42
Foods Company	580	71
Clothes Company	420	51
Books Company	240	30
Total	**4,090**	**500**

4. Results and Discussion

4.1 Demographic Profile

As shown in Table 2, the demographic data is for 500 participants, of which male respondents accounted for 40.2% and female respondents accounted for 59.8%, which is consistent with the situation that females account for most practitioners in the E-commerce industry. The largest group in this study is 21-30 years old, accounting for 47.4% of the respondents, followed by 31-40 years old 34.8%. In general, there are more young practitioners, which is also consistent with the characteristics of the industry. Regarding work experience, 1-3 years accounted for 42%, and 4-7 years accounted for 36.8%, consistent with the application history of big data, an emerging technology, in the e-commerce industry. Regarding the application of BD, research, promotion, customer service, and market operation are similar. In terms of the role of big data analysis in promoting corporate performance, predicting trends, getting more customers, saving money on marketing, and advancing products have played a roughly consistent role, among which the role of acquiring more customers accounts for a slightly higher proportion, accounting for 28.8%, which is also consistent with the reality of e-commerce industry drainage.

Table 2: Demographic Profile

Demographic and Behavior Data (N=500)		Frequency	Percentage
Gender	Male	201	40.2
	Female	299	59.8
Age	Less than 21 years old	25	5.0
	21-30 years old	237	47.4
	31-40 years old	174	34.8
	41-50 years old	52	10.4
	More than 50 years old	12	2.4
Experience	less than 1 years	74	14.8
	1-3 years	212	42.4
	4-7years	184	36.8
	More than 8 years	30	6.0
Aspect	Research	122	24.4
	Promotion	131	26.2
	Customer service	129	25.8

Demographic and Behavior Data (N=500)		Frequency	Percentage
Effect	Market operation	118	23.6
	Predict trends	119	23.8
	Get more customers	144	28.8
	Save money on marketing	120	24.0
	Advance products	117	23.4

4.2 Confirmatory Factor Analysis (CFA)

This study conducted CFA, a specific format of factor analysis, and can be considered a submodel and key starting point of the SEM (Hair et al., 2010). CFA is an interrelated statistical technique used to test the hypothesized model proposed by the researcher (Sarmento & Costa, 2019). It can verify the interrelationships between manifest variables and latent factors when testing multiple assumptions of the measurement model (Arbuckle, 2008). The evaluation of the CFA measurement model helps to understand the extent to which the measurement items reflect the latent variables and measure the reliability and validity of the variables (Khan & Qudrat-Ullah, 2021). The measurement model in the SEM was first analyzed using CFA. As shown in Table 3, the CFA results showed that all items in each variable were important and had factor loadings to demonstrate discriminant validity. The guidelines recommended by Hair et al. (2006) were also adopted to define the importance of each item's factor loading and the acceptable values for goodness of fit. The factor loadings were above 0.50, and the p-values were below 0.05. Furthermore, the composite reliability (CR) was greater than the cutoff point of 0.7, and the AVE was greater than the cutoff point of 0.5, as Fornell and Larcker (1981) recommended.

The CFA test used GFI, AGFI, NFI, CFI, TLI, and RMSEA as model fit indicators. The values in Table 4 show that the model measurement results are greater than the acceptable values. In addition, the square root of AVE determined that all correlations were greater than the corresponding correlation values of the variable in Table 5, which verifies the convergent validity and discriminant validity and the discriminant validity to measure the validity of the subsequent structural model estimation.

Table 3: Confirmatory Factor Analysis (CFA), Composite Reliability (CR), and Average Variance Extracted (AVE) Results

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Integration (INT)	Yu and Fang (2023)	5	0.895	0.743 - 0.858	0.895	0.630
Competitive advantage (CA)	Potjanajaruwit (2018)	5	0.892	0.711 - 0.857	0.891	0.622
Business Value (BVAL)	Gregor et al. (2006)	6	0.893	0.688 - 0.848	0.893	0.583
Global sourcing (GS)	Jia et al. (2017)	4	0.805	0.580 - 0.816	0.836	0.561
Satisfaction (SAT)	Wixom and Todd (2005)	4	0.843	0.670 - 0.850	0.805	0.512
Firm performance (FP)	Galbreath et al. (2020)	4	0.864	0.701 - 0.844	0.863	0.614

Note: CR = Composite Reliability, AVE = Average Variance Extracted

Table 4: Goodness of Fit for Measurement Model

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (Barrett, 2007)	2.253
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.897
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.876
NFI	≥ 0.80 (Wu & Wang, 2005)	0.906
CFI	≥ 0.90 (Hair et al., 2006)	0.945
TLI	≥ 0.90 (Hair et al., 2006)	0.938
RMSEA	< 0.08 (Hair et al., 2006)	0.050

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

Table 5: Discriminant Validity

Variable	Factor Correlations					
	INT	CA	BVAL	GS	SAT	FP
INT	**0.793**					
CA	0.360	**0.789**				
BVAL	0.385	0.324	**0.764**			
GS	0.339	0.376	0.344	**0.749**		
SAT	0.375	0.357	0.400	0.317	**0.716**	
FP	0.304	0.384	0.368	0.376	0.349	**0.784**

Note: The diagonally listed value is the AVE square roots of the variables

4.3 Structural Equation Model (SEM)

Structural Equation Modeling (SEM) was conducted using SPSS AMOS version 26 to assess the relationships among latent variables and evaluate overall model fit. Following guidelines from prior research, several fit indices were examined. The initial model showed an acceptable fit, though one index (TLI) was slightly below the threshold.

After model adjustment, all key indices—including GFI, CFI, and TLI—met the recommended standards, indicating a good fit between the theoretical model and the observed data. This confirms that the proposed framework effectively captures the interactions among integration, global sourcing, competitive advantage, business value, satisfaction, and firm performance.

Table 6: Goodness of Fit for Structural Model

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (Barrett, 2007)	2.992
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.864
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.838
NFI	≥ 0.80 (Wu & Wang, 2005)	0.872

Index	Criterion	Statistical Value
CFI	≥ 0.90 (Hair et al., 2006)	0.911
TLI	≥ 0.90 (Hair et al., 2006)	0.901
RMSEA	< 0.08 (Hair et al., 2006)	0.063

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

The hypothesis testing was conducted using the structural model, with each path evaluated by standardized regression weights (β) and t-values. The coefficient (β) represents the strength and direction of the relationship between variables, while the t-value indicates whether that relationship is statistically significant. A t-value greater than 1.96 generally indicates significance at the 0.05 level ($p < 0.05$). Table 7 summarizes the results of the hypothesis testing.

Table 7: Hypothesis Testing Result

Hypothesis	Standardized path coefficients (β)	t-value	Test Result
H1: INT → GS	0.415	8.048*	Supported
H2: BVAL → SAT	0.484	9.617*	Supported
H3: INT → FP	0.056	1.077	Not Supported
H4: GS → FP	0.235	4.216*	Supported
H5: CA → FP	0.222	4.715*	Supported
H6: BVAL → FP	0.190	3.435*	Supported
H7: SAT → FP	0.177	3.108*	Supported

Note: *=p-value<0.05

H1: The relationship between integration and global sourcing was statistically significant (β = 0.415, t = 8.048). This suggests that when internal systems and external partners are well integrated, firms can execute sourcing strategies more effectively. This finding aligns with Razaghi and Shokouhyar (2021), who argued that integration across departments and suppliers enhances coordination, enabling smarter and more agile sourcing decisions.

H2: Business value had the strongest effect in the model (β = 0.484, t = 9.617), showing that perceived value from big data analytics leads to higher satisfaction among users or employees. This supports Vitari and Raguseo (2020), who highlighted how analytics-generated value improves user experiences and contributes to job or customer satisfaction, especially in competitive, data-rich environments.

H3: The path from integration to firm performance was not significant (β = 0.056, t = 1.077). This suggests that integration alone may not lead directly to improved performance. While integration can support smoother operations, it might require complementary factors—such as digital capabilities or strategic alignment—to significantly affect firm-level outcomes. This is consistent with Stank et al. (2001) and Swink et al. (2007), who found that integration may have an indirect or conditional effect on performance.

H4: Global sourcing positively influenced firm performance (β = 0.235, t = 4.216). Firms that effectively manage sourcing across international suppliers tend to gain cost advantages, access better inputs, and improve responsiveness—factors that enhance competitiveness. This supports findings by Gualandris et al. (2014), who emphasized the strategic value of sourcing in improving firm outcomes.

H5: The relationship between competitive advantage and firm performance was significant (β = 0.222, t = 4.715). This indicates that firms with unique resources or capabilities—such as innovation, brand equity, or analytics expertise—are better positioned to outperform competitors. The result echoes studies by Fahy (2000) and Ismail et al. (2010), who linked sustainable advantage to long-term firm success.

H6: Business value from big data analytics positively impacted firm performance (β = 0.190, t = 3.435). This supports prior work by Ji-Fan Ren et al. (2017), who found that analytics-driven value such as improved decisions or market insights enhances overall performance metrics including revenue, efficiency, and growth.

H7: Satisfaction also contributed positively to firm performance (β = 0.177, t = 3.108). This suggests that when employees or users are satisfied—due to better tools, services, or working conditions, they are more engaged, productive, and loyal, which benefits firm performance. Luo and Homburg (2008) described satisfaction as an intangible yet critical factor for building firm competitiveness and customer retention.

5. Conclusions and Recommendation

5.1 Conclusions

This study examined how E-commerce companies in Hangzhou enhance firm performance through big data analytics, using a framework grounded in the Resource-Based View, Dynamic Capability View, and Information Systems Success Model. By analyzing responses from 500 employees across eight E-commerce business types, the findings offer both theoretical and practical insights.

The results confirm that big data analytics contributes to firm performance, primarily through indirect pathways. Business value and satisfaction emerged as central mediators, reinforcing the idea that it is not the technology itself but the perceived value and experience it delivers that drive organizational outcomes. These findings align with recent studies (Ghasemaghaei, 2022; Li & Liu, 2023), which stress the importance of analytics-driven decision quality and user engagement.

Integration was found to be more of an enabler than a direct driver of performance, particularly valuable in supporting functions like global sourcing. This supports the evolving view that structural alignment must be complemented by data capability to deliver measurable gains (Wang et al., 2023).

The study highlights that firm performance in the digital economy is best achieved by combining strategic sourcing, competitive positioning, and data-driven value creation, all supported by strong user and employee satisfaction. These insights offer a roadmap for E-commerce firms seeking to translate analytics investments into sustainable business success.

5.2 Recommendations

This study contributes to closing a key research gap by providing an integrated understanding of how big data analytics can influence firm performance in the E-commerce sector, particularly within the highly digitalized and globally competitive environment of Hangzhou. The findings offer actionable insights not only for business managers but also for policymakers seeking to support innovation and performance in the digital economy.

To maximize the benefits of big data analytics, E-commerce firms must go beyond data collection and focus on extracting business value that informs strategic decision-making. As business value and satisfaction emerged as the most influential drivers of firm performance, companies should invest in analytics platforms that deliver real-time, actionable insights and ensure that both employees and customers perceive tangible benefits from these tools. For example, business-to-consumer (B2C) platforms could use predictive analytics to improve personalization and customer satisfaction, while business-to-business (B2B) firms might focus on data-driven procurement or market intelligence.

Global sourcing also plays a critical role in enhancing firm performance. Companies should strengthen supplier relationships through digital supply chain integration, using data to evaluate supplier risk, monitor performance, and optimize sourcing locations. This is especially important for cross-border E-commerce firms, which must manage regulatory complexity, logistics challenges, and price fluctuations across markets. The adoption of big data–driven supply chain visibility tools can help improve agility and resilience.

To maintain a sustainable competitive advantage, firms should identify whether they compete through cost leadership or differentiation. Big data analytics can support both strategies—by reducing operational inefficiencies for cost leaders, or by enabling advanced customer insights and innovation for differentiators. For example, niche E-commerce startups could use analytics to identify underserved markets, while large-scale platforms may leverage customer sentiment analysis to enhance user experience and brand loyalty.

While integration did not directly impact firm performance, it significantly influenced global sourcing, suggesting it should still be prioritized as an enabling capability. Firms should focus on aligning internal departments such as engineering, procurement, and logistics through integrated data systems and process standardization. This is particularly valuable for platform-based E-commerce models, where operational complexity is high and cross-functional coordination is critical.

Satisfaction, both user and employee, also emerged as a performance driver. Human resource departments should develop strategies for enhancing employee experience with analytics systems, such as ongoing digital skills training and involvement in decision-making processes. At the same time, marketing and customer service functions should leverage analytics to monitor user satisfaction in real time and respond proactively to feedback. Customer-centric firms, in particular, should prioritize satisfaction as a strategic asset that drives retention, loyalty, and advocacy.

For policymakers and digital economy strategists, these findings underscore the importance of supporting infrastructure for data-driven innovation. Policies that promote open data access, data literacy, and investment in analytics technologies—especially among small and medium-sized E-commerce enterprises—can accelerate digital transformation and competitiveness at the regional and national levels. Furthermore, regulatory clarity on data privacy and cross-border data flows will be crucial in enabling firms to scale their big data strategies globally.

This study provides a clearer understanding of how E-commerce firms can strategically deploy big data analytics to drive performance. By focusing on value creation, global sourcing optimization, satisfaction enhancement, and strategic positioning, businesses can move from data collection to data-driven growth. This research fills a gap in the literature by offering an evidence-based framework tailored to the E-commerce context, and it can serve as a guide for practitioners, strategists, and policymakers navigating the future of digital business.

5.3 Limitation and Further Study

This study is subject to several limitations that should be considered when interpreting the results. First, the sample was limited to eight types of E-commerce companies in Hangzhou, China—mostly sales-driven and consumer-focused. This may limit the generalizability of findings to other regions or industries where big data analytics is applied differently, such as software development or gaming.

Second, the study focused on a defined set of variables and did not account for other potential performance drivers such as innovation, information quality, leadership, or policy influences, which could be explored in future research.

Third, the use of self-reported survey data introduces possible response bias, and the cross-sectional design restricts the ability to examine causal relationships or changes over time. Longitudinal studies could help assess how analytics capabilities evolve and impact performance across different business stages.

Finally, while a mix of sampling methods was used to ensure representation, the inclusion of purposive and convenience sampling may introduce selection bias. Broader, multi-industry, and multi-regional studies, possibly using mixed methods, are recommended to enhance the robustness and applicability of future findings.

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