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Research Article

Does Big Data Drive Innovation In E-Commerce: A Global Perspective?

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ABSTRACT

Objective: Literature indicates big data is a competitive edge, which boasts a firm's overall performance. With the rise of big data (BD), e-commerce firms are using the tools to engage more with customers, offer better products, and innovate more to gain a competitive advantage. Nevertheless, past empirical studies have shown conflicting results.

Design: Building on the capital-based perspective and the firm's inertia concept, we created a model to explore how BD and BD analytics capability impact innovation results in e-commerce businesses. We carried out a two-year empirical investigation project to secure empirical data on 1703 data-driven innovation tasks from USA and Asia.

Findings: We showed that there is a tradeoff between BD and BD analytics capability, in which the optimum balance of BD depends on the amount of BD analytics ability. BD analytics ability exerts a good moderating impact, that is, the better this capability is, the higher the effect of BD on gross margin and sales growth. For U.S. innovation tasks, BD has an inverted U-shaped relationship with sales innovation. For Asian innovation tasks, when major data capital is minimal, promoting big data analytics capability improves sales innovation and disgusting margin up to a specific point.

Policy Implications: Establishing BD analytics capability over that time could prevent innovation efficiency. Our findings offer guidance to e-commerce firms on producing strategic choices about source allocations for BD and BD analytics ability.

Originality: A limited research has been carried out to show the impact of using BD analytics tools to drive innovation. This is one of the first articles that dive into using BD to foster innovation in the e-commerce business.

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Introduction

Recently, the accumulation and implementation of big data (BD) have attracted a lot of interest. Both executives and academics have emphasized the benefits of BD. Many e-commerce firms have invested a lot in BD, with the target of deriving important insights to gain lasting competitive edges (Bresciani, Ciampi, Meli, & Ferraris, 2021). The latest literature has recommended that the innovation process must create long-lasting abilities, for instance BD analytics ability. BD (BD) can help e-commerce businesses process the overwhelming amounts of data available to determine market trend, predict consumer needs, and evaluate consumer purchase choices. Certainly, the task of BD in the innovation process is becoming more visible in practice and recognized in the literature (He, 2021). Past scientific studies suggest that BD innovations promote innovative long-lasting capabilities. Regardless of the buzz that involves BD, minimal focus is given on the systems and processes through what big BD add value to e-commerce firms.

Long-lasting performance and growth are becoming a great topic in the literature. The literature has recommended that organizations must create long-lasting capabilities like BD (Alrumiah & Hadwan, 2021). Prior research has indicated that BD is a crucial long-lasting tool for e-commerce enterprises, as they require new technologies to control and analyse substantial information and data. The growth of BD has transformed the initial creation and high performance of e-commerce enterprises. Lots of big e-commerce enterprises want to develop long-lasting BD analysis capability to enhance their market competitiveness. Since BD can help e-commerce enterprises use advanced analytical abilities to extract valuable information from BD, it can help e-commerce enterprises obtain higher operational efficiency and long-lasting performance. Nevertheless, past scientific studies claim that if e-commerce firms do not take note of the sustainability of BD, the impact will be temporary (Kayser, Nehrke, & Zubovic, 2018). BD can promote long-lasting innovation in fields that are many, including the e-commerce, retail, manufacturing etc and long-lasting innovation in supply chain.

Though literature indicates that big BD is a long-lasting competitive benefit that improves firm's advancement, empirical analysis is inadequate, and the limited studies have shown conflicting results on the importance of BD for firm's innovation and long-lasting innovation (Issa, Byers, & Dakshanamurthy, 2014). The problems of whether and under what circumstances investments in BD can improve solid functionality remain unsettled. There is hardly any empirical proof to guide executives on how to use BD to achieve sustainability of firm's performance and innovation. We try to pack the literature gap by examining how BD contributes to sustainability of firm's innovation, and how data analytics ability might moderate this relationship. Consequently, two investigate questions are developed.

RQ1: Does big data have an inverted U-shaped relationship with sustainability of firm's innovation?

RQ2: Does BD fortify or weaken the consequences of big information on sustainability of firm's innovation?

To respond to these, we construct on two of the most crucial theories of firm's innovation: the resource-based principle and the firm's inertia principle. We suggest that BD might have an inverted U-shaped relationship with sustainability of firm's innovation. That is, a reasonable level of BD energy is ideal, though many BD materials decrease sustainability of firm's innovation (Hao, Zhang, & Song, 2019). BD might help managers better leverage big data resources and conquer the inertia of routines and resources. As an outcome, BD has the potential to reinforce the results of big information on sustainability of firm's innovation. We try these hypotheses with information by 800 U.S. and 903 Asian e-commerce companies that are using big data for innovation tasks.

Literature Review

Organizational learning principle is seated in the resource-based perspective, which says other firms easily replicate a firm's learning skill. This theory grew out of a concern in how businesses acquire, analyze, and use info to correct firm performance (Lee, Kao, & Yang, 2014). Organizational learning concept indicates that exploration for new info will be the foundation of firms' innovation abilities, as combining new information could fix the prototypical strategic trouble of locating the best rewarding use for a firm's energy sources by lowering causal ambiguity (Antons & Breidbach, 2018). Therefore, the organizational learning principle focuses on firms' need to construct a capability to find out by combining, processing brand new details and attaining new insights (Wright, Robin, Stone, & Aravopoulou, 2019). This principle was used in various contexts, including information integration, marketing assistance, along with firm customer and innovation metrics (Aversa, Hernandez, & Doherty, 2021). Innovation is also strongly related to organizational learning, since development consists of the destruction of old knowledge and the integration of information that is new to produce modern solutions.

Development is essential for sustainable competitive advantage. Development is usually undertaken in response to unexpected, unfamiliar, or non-routine problems. Consequently, innovation involves organizational intelligence and learning, as it takes replacing a firm's existing cognitive paradigms and resources (Zhuang, Wang, Nakamoto, & Jiang, 2021). In performing innovations, firms must initially gather data from different sources, and then analyze and understand the information. This is the procedure of organizational learning (Lee H. L., 2018). Learning is improved by gaining greater cognizance of the influence and action-outcome relationships of events on these interactions, as companies generally attempt to make logical options in the face of causal ambiguity (Zhang & Guo, 2021). Making rational choices requires a significant investigation of different usual options, the consequences, and the outcomes. The perspective argues that firms must constantly attempt to understand what is happening around them to improve the quality of their decisions (Hao, Zhang, & Song, 2019). For instance, firms might experience many alternative investment opportunities with unknown results (Lekhwar, Yadav, & Singh, 2019). To improve their learning about the outcomes of various investment alternatives, firms should incorporate information from external and internal sources (Yang, Huang, Li, Liu, & Hu, 2017). Collecting a lot of info in time that is real helps firms learn precisely and quickly what consumers want that remaining firms do not supply, that will help them improve the decisions before competitors corner the market, their information is exhausted, or consumers' interests change.

In line with the above-mentioned conversation, we think firm outcomes are stochastic: that is, they lie somewhere between random and deterministic experimentation (Ying, Sindakis, Aggarwal, Chen, & Su, 2021). While first exploration on the resource-based perspective has centered on the job of blind luck in determining how firms acquire and develop distinctive, inimitable, non-substitutable, along with useful online resources, newer conceptualizations have centered on the development activity as inherently stochastic (Yu, et al., 2021). Conceptualizations of firm results as stochastic might be rooted in earlier studies' claims that, as info advances, ambiguity declines (Bresciani, Ciampi, Meli, & Ferraris, 2021). Because of this assumption, decision-creators pursuing innovation encounter ambiguity surrounding cause-effect relationships, but tend to, given sufficiently abundant information, identify organizational attributes or even develop resources that are much more apt to boost firm performance (Wise, 2022). Thus, to boost organizational learning of the innovation process, enhanced use of existing development, plus more proactive acquisition, and assimilation of new information, start to be essential (Li & Zhang, 2021).

If the exploration of new information will be the grounds for organizational learning, then major information provides a big chance for firms to study and improve their performance (Shakya & Smys, 2021). In the era of big data, earlier research has considered information a crucial firm aid for development (Keskar, Yadav, & Kumar, 2021). With a great number of advanced technologies and available data to process them, firms can promptly exploit information that is new to create and implement different concepts (Montoya-

Torres, Moreno, Guerrero, & Mejía, 2021). Organizational learning through grave data can be regarded as a constant, disruptive mixture of abduction, deduction, and induction to recognize patterns and relate them to possible remedial actions (Silva, Hassani, & Madsen, 2020). Big data has raised discussions regarding the need for analyzing and interpreting raw details to gain from the integration of big volumes of data. Big data could improve organizational learning, as it can offer surprising and interesting glimpses into places outside what companies currently understand.

Big data can be useful in different customer places, enhancing innovation, for example, buy behavior, issue recognition, and usage. Big data has changed the capabilities firms have to perform effectively. Trabucchi and Buganza (Trabucchi & Buganza, 2018) argued that firms that can process new data tend to be more successful. Especially firms that can use big data in their business processes might have a much better possibility of enhancing their efficiency and revenue growth than their competitors (Wang, Wu, Yu, Shen, & Zhao, 2021). Hence, big data is a brand-new type of capital in enhancing firm innovation efficiency.

Nevertheless, big data is a new resource and might not yet be properly optimized by many firms. This study leverages the organizational learning principle to investigate whether great data has a good effect on firm innovation efficiency and, consequently, firm performance. Whereas several studies argue for an optimistic relationship between big data and tight performance, other scientific studies suggest that using big information might not result in improved firm efficiency. Thus, several factors could facilitate, or perhaps stymie, the relationship between big performance and data (Wise, 2022). One element is the organization's capacity to learn about and adjust to the environment. Based on organizational learning theory, an organization searches for and collects information to find out about and adjust to its surroundings through innovation in internal processes and business models by utilizing this system, an organization's body.

Thus, performance is enhanced within a specific niche or context. Thus, this study uses organizational learning literature to check out the mediating role of firm development efficiency (i.e., innovation efficacy and originality efficiency) on the effect of big data on tight efficiency (Wang, Wu, Yu, Shen, & Zhao, 2021). A bunch of performance measures may explain the lack of results in previous work. As opposed to many earlier studies, this analysis thinks of numerous kinds of performance groups (i.e., operational excellence, financial returns, and client perspectives) to calculate the general functionality of the firm. Even though previous labor demonstrates that you can find numerous big data methods (Morabito, 2015). Much research has considered this variable an alternative idea (Niebel, Rasel, & Viete, 2019). Nevertheless, in the present analysis, we operationally and conceptually differentiate among the key attributes of big data instead of treating it as an alternative idea.

Methodology

Model

Firm inertia refers to how the patterns and processes that companies have determined to capitalize on the effectiveness of their business operations can develop powerful inner resistance against extreme changes. Gobble (Gobble, 2013) has suggested you find 2 kinds of firm's inertia: routine and resource. The former describes inertia-based capital-allocation patterns, and the latter relates to inertia in the firm's tasks that use the materials. BD refers to high volume, high-velocity, and high variety info that cannot be easily processed using conventional methods. Service innovation projects' investments in BD include the materials allocated to info and the firm's tasks that use these properties, each susceptible to inertial pressures. The capital-based perspective indicates that materials are essential for e-commerce firms to get a long-lasting competitive edge. Ghasemaghaei and Calic (Ghasemaghaei & Calic, 2020) created the capital-management design, suggesting that source management contributes much more to better performance than merely owning information. Adhering to this reasoning, we argued that acquiring BD sources is not enough. Innovations should also have the power to process, regulate, and deploy their BD materials - that is, they require BD. As these, this powerful company intelligence capability can enhance the effect of BD materials on the sustainability of innovation and the firm's innovation. We used purposive sampling to select companies with more than $100 million in annual sales, to ensure that the selected companies had been in the industry for a while and had enough resources to implement big data tools.

We drew out of the capital-based view and firm's inertia principle to create a theoretical design illustrating how BD materials impact the sustainability of a firm's innovation. The framework even suggested that the impact of big data on the sustainability of a firm's innovation depends on the amount of BD.

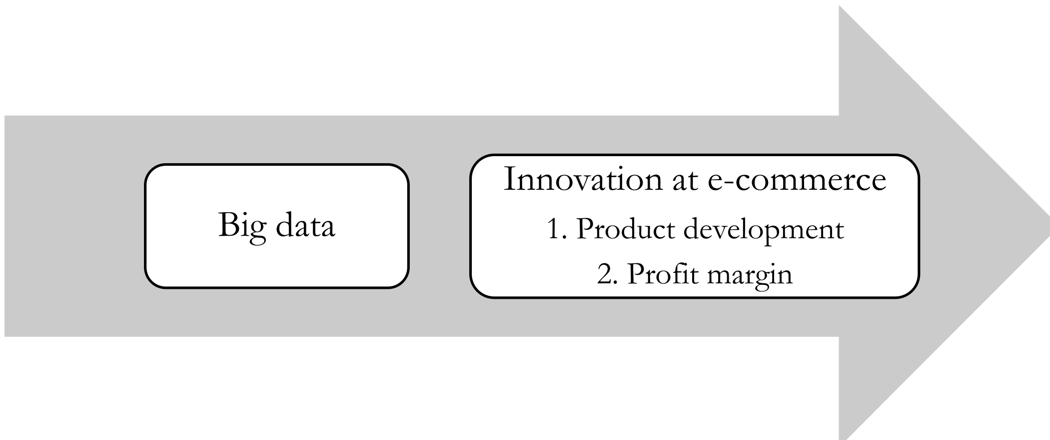

Figure 1: Theoretical framework

Research Hypothesis one: BD & Innovation Performance

The capital-based perspective describes how e-commerce firms achieve a long-lasting competitive edge via methods and hypothesizes that big data can offer e-commerce firms with long-lasting competitive by nature edge. Certainly, an appearing stream of studies has highlighted that BD favorably impacts the sustainability of a firm's innovation. For instance, Bresciani et al., (Bresciani, Ciampi, Meli, & Ferraris, 2021) suggested that BD allows remedies that have a significant impact on the company. Nevertheless, we hypothesized that the beneficial impact of big information on the sustainability of a firm's innovation could drop as the amount of BD gets to a crucial point for two reasons. For starters, due to source and regular inertia, when new tasks increase their investment in BD, they might also count on the fundamental information to get knowledge and information. They also do not modify the way they assign resources, ignore various other capital-allocation patterns, and inhibit their ability to adapt to changing ecological conditions. More to the point, projects are usually capital-constrained, which will weaken the rewards from BD and reduce service performance. Consequently, we proposed the following hypothesis:

Hypothesis 1: Big data has an inverted U-shaped relationship with the sustainability of a firm's innovation.

Research Hypothesis two: The Moderating Effect of BD Analytics Capability

BD describes a firm's expertise in handling and leveraging its BD to enhance performance. We hypothesized that BD improves the beneficial impact of big information on the sustainability of a firm's innovation. As BD improves, the result of BD materials on the sustainability of the firm's innovation increases and innovation. The capital-management model claims that materials alone do not ensure a long-lasting competitive edge. Next, BD enables innovation teams to integrate and reconfigure their information resources and business processes to adapt to rapidly changing environments. In so carrying out, BD can help innovation teams overcome their capital-and regular inertia. Collectively, these arguments claim that BD can perform a facilitating task in the connection between BD energy and innovation efficiency. Consequently, we proposed the following hypothesis:

Hypothesis 2: Big data strengthen the consequences of big information on the sustainability of a firm's innovation.

Methods and materials to test our model, we collected data included in a multi-year panel study. By the website, we selected program innovation projects from each participating organization in 5 industries in 2 countries. The information reported in this study showed just the tasks with sales growth rate and task yucky margin for the first 3 decades after the commercialization.

Overall Research Design

There were 3 parts to our research design. To ensure the suitability of research scales and techniques for a cross-national comparative analysis of a theoretical version, we followed the methods suggested by and extended by Alrumiah and Hadwan (Alrumiah & Hadwan, 2021). Next, to evaluate the causal associations between variables, we collected information on BD energy and BD analytics abilities. Lastly, we tracked the tasks over time and collected product sales and gross profits information for the first 3 decades after the commercialization.

Measurement Innovation Procedures

We created the measurement scale through the procedures found by Parry and Song. We conducted in-depth case studies and focus group interviews with program innovation teams in Asia and the United States, follow-up interviews with staff, and consultations with academic pros from 2 national business administration facilities. We utilized the findings to enhance measurement scales in the literature on big information and BD analytics abilities.

In the focus group interview, we incorporated semi-structured and open-ended issues. Workers were asked to define the primary key constructs of BD and BD analytics abilities. We examined the conceptual equivalence of the constructs with the first set of concerns. We assessed the purposeful equivalence of the constructs with the next set of concerns. Team members evaluated how good the theoretical model of our data was in their one service innovation knowledge. We assessed the group equivalence of the constructs, together with the final concerns that tackled the perceptions of the importance and completeness of the machine products from literature and last case research. The outcomes of these case studies & interviews suggest that many scales used in the academic study must be customized for cross-national relative exploration of the program innovation process.

Variable Measurement

Our study variables include BD, BD analytics innovations, and task efficiency. Aside from project efficiency, measured using objective data, the various other variables have been assessed using scales we used out of the literature or even developed based on the measurement innovation as described. Prior research suggests a 0-10 rating scale mirrors the metric system of structure, and it is easier to understand in overseas surveys than 1-7 or maybe 1-5 score scales. The measurement scale for BD energy innovations 5 things that evaluate how sufficient the project staff has the BD materials on client requirements, user behavior, naturally competitive intelligence, engineering advancement intelligence, and merchandise usage. The scale for the typical gross margin was used. These variables are estimated using the following formulas:

Average sales growth rate= average of sales growth for two years

Data Collection Procedures

To ensure that the individuals in both countries have the same comprehension of the machine products, we used the double translation strategy to convert the questionnaire. 2 translators translated the English model into Asian, then 2 additional translators on their own translated the Asian variant in English. The 4 translators reviewed and solved inconsistencies they discovered and consulted with many case study participants to identify the appropriateness of the Asian questionnaire. We afterward performed 2 pretexts on the questionnaire, one in which individuals finished the questionnaire in the presence and raised questions regarding unclear wording, and another where a professionally drafted questionnaire surveyed individuals within true learn. Due to this preliminary investigation, we made small modifications to produce the last survey.

Each participating firm was requested to provide information on a recently available service innovation project, a regular service innovation project, a booming, and a failure service innovation task. We administered the survey by express mails & messages. We 1st directed a package/email which included a personalized sales letter, the survey, and a prepaid go-back envelope. A week later, we mailed a follow-up letter/email to every business to inspire their participation. And then, we sent 2 follow-up letters/emails & made telephone calls to non-responding e-commerce firms to enhance the response rate. The last information in each country is discussed below.

Results

Cronbach's alpha was used to evaluate construct reliability for big BD. and data. The alpha coefficients of big BD and data, respectively, are 0.891 and 0.803 for the U.S. test and 0.814 and 0.767 for the Asian test. Thus, the study measures for these two theoretical constructs are reliable.

We offered the construct median, mean and standard deviations in Table one. Exploratory factor analysis was conducted to assess the construct validity. These outcomes suggested that the research methods should be properly loaded onto the corresponding element. Most retained methods lack double loadings of more than 0.40. Therefore, the constructs had convergent validity.

Table 1: Descriptive Statistics of the data

US Sample: 800	**Median**	**Mean**	**S.D.**	**Big Data**
Sales	28.60	51.20	52.10	
Margin	55.30	74.30	50.10	
Big Data	6.19	5.30	2.70	0.86
Asia Sample: 903	Median	Mean	S.D.	Big Data
Sales	22.42	40.14	40.85	0.00
Margin	43.36	58.25	39.28	0.00
Big Data	4.85	4.16	2.12	0.67

The theoretical model in Figure one includes the following two equations:

Typical sales with the very first 2 yrs = $\alpha + \beta 1\ x + \beta 2\ x\ 2 + \beta 3\ x + \beta 4\ x\ x + \beta 5\ x\ 2\ x + \varepsilon$.

Typical margin with the very first 2 yrs = $\alpha + \beta 1\ x + \beta 2\ x\ 2 + \beta 3\ x + \beta 4\ x\ x + \beta 5\ x\ 2\ x + \varepsilon$.

To evaluate the hypotheses, the above mentioned 2 formulas are approximated for every nation individually utilizing Proc Reg in SAS 9.4 system. We conducted two standard minimum square regression analyses for every nation utilizing task general performance measures: the project's two-year typical sales growth rate and disgusting margin information. We estimated the same equations using data for each year and discovered that the main conclusions didn't change. Consequently, we reported the outcomes of the common sales growth and the average gross margin.

Table 2: Estimates of the variables

Sales		**USA**			**Asia**	
	Parameter estimate	Standard error	standardized estimate	Parameter estimate	Standard error	standardized estimate
Intercept	43.81	4.50	0.00	34.44	2.61	0.00
Big Data	4.58	0.76	0.22	5.06	0.54	0.29
e-commerce	-2.20	0.19	-0.01	0.38	0.08	-0.15
Margin		USA			Asia	
	Parameter estimate	Standard error	standardized estimate	Parameter estimate	Standard error	standardized estimate
Intercept	39.09	4.02	0.00	30.73	2.33	0.00
Big Data	4.08	0.68	0.20	4.52	0.48	0.26
e-commerce	-1.96	0.17	-0.01	0.34	0.07	-0.13

From table 2 above, the study shows that the values of $\beta 1$ are 4.58, $\beta 2$ is -2.20, $\beta 3$ is 4.08, $\beta 4$ is -1.96, and $\beta 5$ is 1.32. All the values are statistically significant except for the $\beta 5$, showing that they confirm the hypothesis.

Research Hypothesis one: Direct Effects of BD and Innovation Performance

Hypothesis one predicts an inverted U-shaped relationship between BD and the sustainability of a firm's innovation. The result differs based on the functionality measure being considered; for the common income innovation, Table two shows that for the U.S. test, big information had a major beneficial connection, while Table 2 had a major damaging connection. These results suggest that big information had an inverted U-shaped connection with the sustainability of firm's innovation, as assessed by the common income innovation in the U.S. test, around support of Hypothesis one.

For the Asian test, the connection with big data was again drastically good, whereas 2 had a bad, however, not great connection. In comparison to the U.S. test, big information had a good impact on the common sales innovation but did not come with an inverted U-shaped connection with the common sales innovation. Consequently, the Asian test did not back H_1.

For the two-year typical gross margin, Table two shows that for the U.S. test, big information had a beneficial connection, whereas Table 2 had a bad, however, not great connection. For the Asian test, big information had a significant beneficial connection, and the connection with 2 had also been good but not substantial. Consequently, countertop to H_1, these outcomes suggest that BD possessed a positive linear connection with the sustainability of firm's innovation as assessed by the typical gross margin.

Research Hypothesis two: The Moderating Effects of BD

To evaluate Hypothesis two, we had to assess the coefficient estimates of x BD plus 2 x BD. Results in Tables two and four suggest that each x BD plus 2 x BD had a significant beneficial connection with the common income innovation and the typical yucky margin. For the Asian test, x BD had a good, although not significant, connection with both the common income innovation and the typical yucky margin, while 2 x BD had a major negative association with the typical income innovation and the common gross margin. These results hence suggest that big information received a U-shaped connection with the sustainability of firm's innovation. Nevertheless, for the Asian test, there seemed to be an inverted U-shaped relationship.

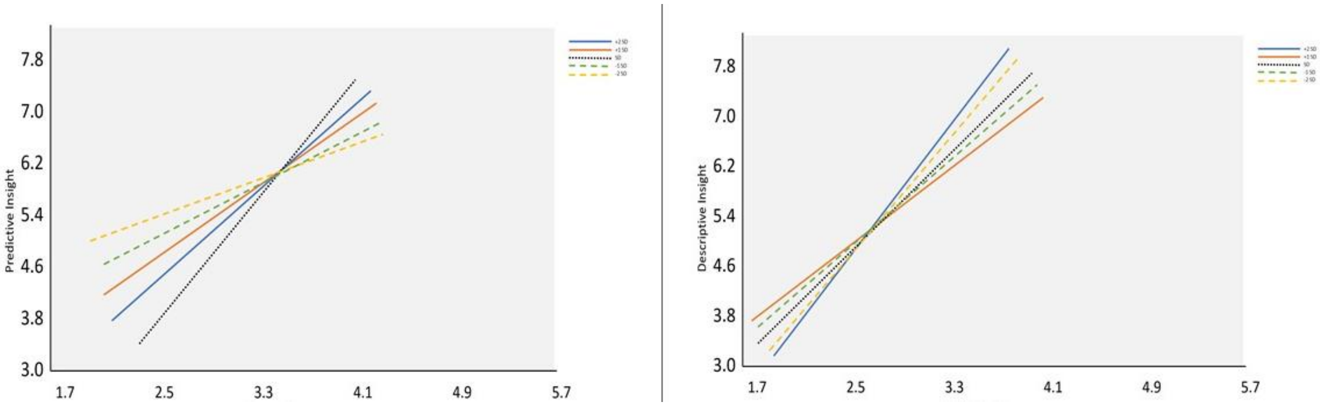

Figure 2: Test of the relationship between data analytics and innovation

Figure 2 demonstrates how data analytics impacts the descriptive and predictive insights to drive innovation efforts of an e-commerce business. As the study shows, the predictive insight is very strong with data analytics which means that as big data's attributes become larger in size, variety, and velocity, the ability to predict also increases significantly. Predictive analytics is more responsive than descriptive analytics.

To further illustrate these fascinating relationships, we presented Figure two show the relationships. Figure 3 displays the connection between BD and the typical income innovation at various amounts of BD for the U.S. program innovation tasks. As we can discover by using Figure 3, when BD was zero, big information had an inverted U-shaped impact on common income innovation. When BD was one or even greater, there seemed to be a half U-shaped connection between BD and the typical income innovation. Additional increases in BD enhanced the typical sales innovation. These findings offer empirical support for hypotheses one and two.

Figure 3 displays the connection between BD and a typical small margin at varying levels of BD for U.S. innovation tasks. When BD was zero, BD possessed a positive linear connection with disgusting margin. That is, spikes in BD favourably impacted a disgusting margin.

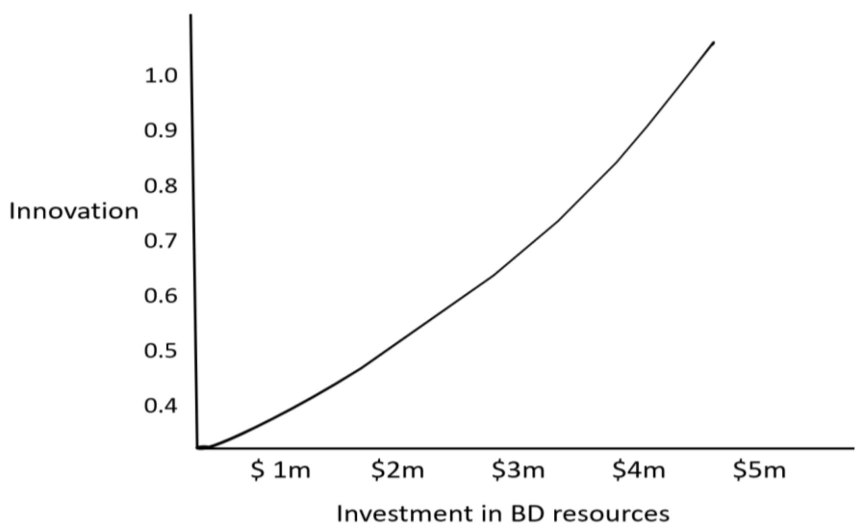

Figure 3: Relation between big data investment and innovation

Discussion and implications

Building on the capital-based view and firm's inertia concept, we presented a model which specified how innovation teams could leverage BD that might be leveraged by innovation teams to achieve exceptional performance. Using samples from the country and Asia, we empirically tried the product and discovered two fascinating results that are surprising.

For starters, our findings offered a far more nuanced understanding of the effect of big information on the sustainability of firm's innovation. Past studies have highlighted the role of BD in following long-lasting competitive edge. In line with this logic, we discovered that BD enhanced gross margin and sales growth. Much more surprisingly, for U.S. service innovation tasks, we discovered that big information had an inverted U-shaped connection with product sales innovation: a reasonable degree of BD was associated with the greatest level of product sales innovation, whereas a lot of BD essentially inhibited revenue innovation. A description for this may be that capital-and regular inertia may lead innovation teams to rely way too much on BD to get knowledge and information. Therefore, they overlook different capital-allocation patterns needed to boost sales innovation and increase positive innovation results. These results help with the extant literature by demonstrating and detailing the restricted edge of improving investment in big information.

Next, we extended the current literature by presenting and confirming empirically which BD strengthened the good effect of BD on the sustainability of a firm's innovation. As found in Figure 2 for the U.S. test, improved lots of data purchase was a far more crucial precursor to innovation tasks gross margin and sales growth if we had a reason to the high amount of BD. Thus, innovation teams will acquire much more from their investment in BD if they commit to creating their BD. As unraveled in Figure 2 the results just for the Asian test were much more complicated: BD strengthened the consequences of BD on sales innovation and disgusting margin just prior to a point, but beyond this stage, BD exerted a bad moderating impression.

The study has several implications, from showing why BD tools are important for e-commerce to how BD can improve the innovation aspect of a business. With detailed study, it shows, that big data can lead to more innovation, resulting in further sales and increased profitability.

Conclusion

Our findings showed several interesting insights for innovation leaders regarding big data analytics. It is recommended that leaders in both Asia and the U.S. can improve innovation efficiency by making sure the teams have enough big data materials on client requirements, user behaviour, competitive advantage, services, products, marketing, and technology advancement intelligence (Hao, Zhang, & Song, 2019).

Even though these big information materials can boost gross margin and sales growth, executives in U.S. service innovation teams should be aware of the limits of their BD resources and comprehend that a lot of buy-ins BD could harm sales innovation of the program innovation tasks. The innovation teams also need to build the BD to harness the possibility of BD resources (Aversa, Hernandez, & Doherty, 2021). For U.S. service innovation teams, dedicating to BD is better than more buy-in BD. The better the BD is, the more outcomes BD can have in boosting gross margin and sales growth. To us, the variables in the data of ours, U.S. innovation teams must do the following to attain a lot of BD:

1. Use much more complex resources to acquire values from big data.
2. Develop the power to discover dependencies and relationships from big data.
3. Develop the ability to perform predictions of behaviours and outcomes from big data.
4. Develop the power to explore new correlations from grave data to identify industry demand trends and predict operator behaviour; plus employ and grow BD analytics personnel who have the proper abilities to do their tasks effectively.

Managers of Asian service innovation tasks must be mindful that building BD may have downsides. When investment in big information is minimal, advertising BD can boost gross margin and sales growth. Nevertheless, after a point, allocating additional resources to BD could inhibit the sustainability of firm's innovation. Asian managers might also use the suggested tactics to boost BD analytics ability. Our findings, therefore, showed insights to Asian innovation teams and the U.S. on the skilful ways in which major information could lead to exceptional performance and help them optimize their BD usage.

Limitation and Future Direction

Although this study helped understand how BD and BD analytics abilities affected long-lasting innovation performance in e-commerce, there were a minimum of 2 limits, which additionally provide upcoming research opportunities. For starters, the modified R^2 of our models has been below 0.33 since we focused on the effect of BD and BD analytics innovations on long-lasting innovation efficiency in e-commerce. Past research suggests that other capabilities like technology, market-linking, marketing, and info technology capabilities also affect innovation performance. Collecting data and including these innovations in the proposed model must improve R^2 and offer additional interesting findings. This constitutes a fascinating avenue for future studies. Next, there are new and emerging capabilities like AI capabilities and machine learning capabilities. It will be fascinating to conduct future studies to study how these new abilities combined with BD and BD analytics abilities impact long-lasting innovation performance.

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