Amplifying organizational performance from business intelligence: Business analytics implementation in the retail industry

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Abstract

***PURPOSE**: The concept of business analytics (BA) and business intelligence (BI) is just emerging in the Philippines. Since these are new concepts, it is important to investigate their impact on organizational performance and the performance metrics in business industry. The aim of this study is to examine the impact of business analytics generating business intelligence and how it affects organizational performance by developing a structural model. Consequently, the impact of organizational performance on other performance metrics was also established. **METHODOLOGY:** The partial least squares – structural equation modeling was utilized, which proposed a model that shows how business intelligence, generated by business BA, affects organizational performance, which consequently leads to improved marketing, financial, and business process performance. A survey was conducted on business analysts and executive managers of retail companies that have already been implementing BA for at least three years. **FINDINGS:** BA capabilities have a significant positive effect on the level of BI. BI has a significant positive effect on organizational performance. However, the result of the moderation analysis indicated that the level of readiness for BA implementation could not be considered a moderating factor on the relationship between BI and organizational performance. **IMPLICATIONS:** Out of the different BA capabilities, the decision support system and business process management were found to be the most beneficial functions in generating BI. BI amplifies organizational performance and consequently improves the marketing and business process performance of retail firms. However, the readiness for BA implementation does not significantly affect how BI improves organizational performance. Overall, it is recommended that in order to enhance marketing and business process performance, retail firms should focus on the BA capabilities of decision support system and business process management. **ORIGINALITY AND VALUE:** This would be the first empirical study in*

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the Philippines which has assessed how business analytics and business intelligence impact organizational performance. This study is original in determining what BA capabilities generate BI, which translates to improved organizational performance. This study is also unique in defining what key performance metrics are much improved as a result of its implementation. This may serve as a viable reference for other researchers interested in business analytics and other technology about data management applied in business operations.

Keywords: *structural equation model, knowledge-based view, business analytics, business intelligence, organizational performance, retail industry*

INTRODUCTION

The perpetual revolution of information technology has genuinely dictated how industries conduct business today. Nevertheless, with the Fourth Industrial Revolution's advent, the fusion of technologies blurs the lines between the physical, digital, and biological spheres. It elevates the importance of data to become an integral part of conducting business (Beltran, 2018). Data have become the most important intangible resource of a firm, especially in the retail industry.

Retail trade in the Philippines has blossomed in recent years. The Philippine National Statistics Office (2019) counted 637,325 establishments engaged in retail trade in 2018. The Philippine retail industry has fragmented as different overseas companies enter the country. However, it is assumed that the industry will likely experience more significant consolidation and respond to incoming paradigm shifts (Rabo & Ang, 2018). Gomez, Arranz, and Cillan (2012) suggested that in order to be successful, it is critical for retailers to make use of its information resources efficiently and to pursue new strategies promptly. This may be achieved with the help of analytics in the retail supply chain (Gutierrez, 2014). In the Philippines, building customer loyalty is a primary goal for retailers. A retailer's ability to plan and implement measures toward customer retention may be provided by comprehensive business intelligence systems.

Beltran (2018) affirmed that there is still a gap between available technology and how firms use such technology to improve their business efficiency and customer response, both of which lead to better performance. It is where the concept of business analytics comes in. Several studies have already supported how BA generates BI and how these technologies impact organizational performance. But even if some studies have proved that BA generates BI, it can have different results for different situations and locations (Corte-Real, Oliveira, & Ruivo, 2016; Aydiner et al., 2019; Akter et al., 2016; Ashrafi et al., 2019). Current studies also lack exploration as to how each

BA capability generates BI and its specific impact on the key performance metrics of marketing, finance, and business process performance. This study also finds rationale for several contradicting results found in the previous literature on the impact of BI on organizational performance (Laursen & Thorland, 2010; Sharma et al., 2010; Aydiner et al., 2018; Bedeley et al., 2016; Grover et al., 2018).

Based on these gaps, this study aims to formulate a structural model that may predict and/or explain the quantitative relationship between business intelligence generated by BA capabilities and organizational performance, further translated to the key performance metrics of finance, marketing, and business efficiency. A survey was conducted on 62 retail companies in the Philippines that have already been implementing business analytics for at least three years. These companies represented by 124 respondents (one from top management and one analytics implementer for each company) already using business analytics are surveyed through questionnaires. This is the first empirical study in the Philippines to assess how business analytics and business intelligence impact organizational performance.

LITERATURE REVIEW

This study draws its framework from the knowledge-based view (KBV) of the firm, first theorized by Grant (1996) and extended by Kaplan et al. (2001). According to this theory, knowledge is the most significant intangible resource of a firm. It proposes a model that relates knowledge with the firm's capabilities by which it increases organizational performance. Such knowledge can be taken from internal and external sources. It also perceives the firm's resources as the key factors in its performance, thus suggesting that management should focus on harnessing internal capacities and capabilities rather than cogitating on external factors over which the firm has no control. Proponents of this view argue that organizations should focus on the inner strength of the company for its competitive advantage instead of comparing themselves with the competition. It is the knowledge that is the source of organizational performance (Wickramasinghe & Lubitz, 2007).

Business analytics and its capabilities

The earliest literature on business analytics (BA), such as Davenport and Harris (2007), defines it as a successive process of gathering, storing, analyzing, and interpreting meanings of data in order to improve decision-making and organizational performance. Definitions have somehow evolved through time as more organizations become more perceptive of what BA is all about. Stubbs (2013) defined business analytics as the generation of data-driven insight to produce value. It does so by requiring business relevancy, actionable insight, performance measurement, and value measurement. Laursen and Thorlund (2017) concluded that BA goes beyond just providing intelligent reports. Min (2016) connected business analytics with various quantitative techniques such as statistics, data mining, optimization tools, and simulation. Defining BA becomes more extensive as time passes. BA capabilities that generate competitiveness can be perceived through customer and product dashboards (Glaister et al., 2008). These are real-time reports of the current customer engagement on the different products of the company. It concluded that BA's predictive ability could bring the right raw material and products to the company's delivery chain at the right time and place. BA is also seen to go beyond the advantages of traditional financial analysis (Ouahilal, El Mohajir, Chahhou, & El Mohajir, 2016), stating that with the explosion of data made through digital technology, data analysis has acquired greater prominence than mere financial accounting to be the basis for financial analysis. The most crucial capability of BA is its ability to support decisions based on data analysis. Through the inputs of data, the BA system can see through its algorithms the factors that cause different yields of business operations that guide managers in coming up with sustainable decisions (Glaister et al., 2008; Mithas et al., 2011; Ordanini & Rubera, 2009; Santhanam & Hartono, 2003; Ramanathan et al., 2017; Troilo et al., 2016.).

The researcher used the variables data dashboard, financial analysis, business process management, and decision support systems of business analytics based on the aforementioned literature.

Business analytics generating business intelligence

Sabherwal and Fernandez (2011) supported the idea that "organizations derive strategic decisions from hierarchical layers from data to intelligence." Business intelligence (BI) is the outcome of careful analysis of data through the support of analytics technology (Grossman & Rinderle-Ma, 2015). It can be considered the result of the manifestations of technology, methodology, practices, systems, and techniques involved in analyzing data to help an organization understand its operations, leading to timely decisions. Foley and Gullemente (2011) concluded that BI is a function of business analytics capabilities. Mishra, Hazra, Tarannum, and Kumar (2016) also supported such a conclusion by finding that business analytics significantly affects business intelligence, especially in decision-making activities. Chen et al. (2012) described BA as factors and part of BI. The main difference between

BI and BA is the fact that BA is more specific in its focus, and an argument can be made that BA are factors of BI (Mashingaidze & Backhouse, 2017). This description aligns with the relationships described in Kowalczyk and Buxmann (2014), Chen et al. (2012), and Williams (2016). BI can be manifested through a descriptive understanding of the market. Firms can predict growth opportunities from internal and external data (Parra & Halgamuge, 2018). With the help of business analytics, companies are able to reflect on their internal strengths by deepening their knowledge of what is really happening inside the walls of their organization (Kearns & Sabherwal, 2007; Larson & Chang, 2016). Sabherwal (2007) suggests that BI can be assessed through understanding customer preferences, coping with competition, identifying growth opportunities, and enhancing internal efficiency. Also, Larson and Chang (2016) confirmed that BI is an enabler for the organization to work smarter, which rises from the fact that data analyses are turned into useful information. BI-related factors indeed affect the perceived decision quality (Visinescu, Jones & Sidorova, 2016). Overall, BI is seen when each executive in the organization confidently makes decisions backed up by rigorous data analysis (Grossman & Rinderle-Ma, 2015). Through the understanding of the discussion above, this hypothesis is therefore formulated:

H1: Business analytics capabilities are significant factors of business intelligence.

Business analytics and business intelligence linked with organizational performance

The importance of BA and BI in improving corporate and organizational performance is well acknowledged in the literature (Wixom et al., 2013). Several pieces of literature provide evidence of a relationship between BI, BA, and organizational performance. Price optimization and profit maximization are found to be outputs of comprehensive business intelligence (Davenport & Harris, 2007; Schroeck et al., 2012). Sales, profitability, and market share are greatly affected by analytics implementation (Manyika et al., 2011). Aydiner et al. (2018) found that business analytics capabilities generating business intelligence affect the overall business performance of the firm. According to Wixom et al. (2013), BI can increase performance by increasing productivity, which has both concrete (i.e., reduced paper reporting) and intangible (i.e., improved business reputation) benefits. Thus, a firm that creates superior BA should maximize organizational performance by facilitating the pervasive use of insights gained from its business intelligence derived from analytics (McAfee & Brynjolfsson, 2012; Prahalad & Ramaswamy, 2013).

Ramanathan et al. (2017) argue that there appears to be a link between business performance and BA adoption. Corte-Real et al. find that BA and BI add value to the firm by amplifying organizational performance. Businesses that incorporate BA into their operations can outperform their competitors in productivity and in profitability. Many of the previous studies indicate a positive link between the adoption of BA and organizational performance in terms of increased business value (Cosic et al., 2015; Elbashir, Collier & Davern, 2008; Ramanathan et al., 2017). Elbashir, Collier, and Davern (2008) established a strong relationship between business intelligence systems and organizational performance.

However, few works of literature negate the positive link between business intelligence and organizational performance. Gartner (2016) revealed that while investments in big data continued to proliferate, some data reveal contradicting inference. This is due to the fact that there were big data projects that yielded disappointing results. According to Gartner, 60% of big data projects will fail to progress beyond piloting and experimentation in 2017 and will be abandoned. Grover et al. (2018) also identified that some companies find it hard to see a valuable return on their investment, with analytics supporting the idea that business analytics may not have a significant impact on organizational performance. Based on the foregoing, it is therefore hypothesized:

H2: Business intelligence has a significant effect on organizational performance.

Business analytics implementation and its role as a moderating factor between business intelligence and organizational performance

In order to implement BA, business organizations must be aware of their infrastructure. Davenport and Harris (2007) found that the essential elements of any analytics infrastructure are the software, number of nodes, data capacity, and the processes involved. This study has adopted this view as it is supported by different literature discussing the same topic. Several studies having different views were shared in using the abovementioned list in defining the infrastructure of any analytics system, such as those of Laursen and Thorland (2010), Sharma et al. (2010), Aydiner et al. (2018), Bedeley et al. (2016), and Grover et al. (2018). The number of nodes refers to the number of devices (e.g., computers and smartphones) wherein they are installed and utilized for such purposes. Data capacity refers to the average number of data involved regularly in the given traffic period and is usually measured in terabytes (Stubbs, 2013). The intangible component is all about the human resource: its knowledge and technical skills in implementing BA.

Several literature works have linked the firm's readiness for BA implementation with organizational performance outcomes and business intelligence. Jain, Narayanan, and Lee (2019) formulated a model that positively links a firm's BA readiness with business intelligence generated by firms. Ghasemaghaei (2019) found that structural readiness has a positive impact on organizational performance. It identifies the significance of technology infrastructure capability, tool functionality, data volume, and employee analytics capability in determining a firm's structural readiness to use big data analytics. Continuous usage of BA infrastructure leads to more success in the firm's performance (Ramarakrishnan, Khuntia, Kathuria, & Saldanha, 2016). Barton and Court (2012) emphasized a fast return on investment from analytics infrastructure. Gürdür, El-khoury, and Törngren (2019) concluded that in order to increase data analytics usage, firms needed to improve their tools and employee analytics skills. It was stated as an example that if companies continue to train employees and expose them to opportunities in their analytics knowledge, it will probably also enhance analytics capabilities. Prior research has shown that the relationship between business intelligence from big data analytics and organizational performance is influenced by the firm's infrastructure and readiness to implement analytics as a moderating factor (Wamba et al., 2015; Côrte-Real et al., 2017). Their research framework commonly exhibits a triangular setup between BA infrastructure, business intelligence, and organizational performance. Such a triangular relationship was explored further by Grossman and Siegel (2014), who concluded that the capacity or readiness to implement business analytics does not affect organizational performance unless it is organized well and BA capabilities are enhanced. With a good understanding of the related literature, this hypothesis is therefore formulated:

H3: Readiness of business analytics implementation moderates the effect of business intelligence on organizational performance.

Organizational performance and other performance metrics

Organizational performance refers to how a business organization achieves and realizes its goals (Li et al., 2004) as well as how it enhances competitiveness that strengthens its edge over its competitors (Rahman et al., 2018; Chen et al., 2013; Hogan & Coote, 2014; Carter & Greer, 2013; Lee & Raschke, 2016). To appraise organizational performance, Elbashir, Collier, and Davern (2008) proposed metrics used to capture organizational performance that represent organizational objectives, competitiveness, and market responsiveness, strengthening the organization's overall performance.

In measuring marketing performance, lead generation can be used as retail companies use online platforms to track customer interactions, whether expressing interest or making an inquiry (Artun & Levin, 2015). Rothman (2014) enumerated different types of leads that can be used as metrics of marketing performance: marketing leads, sales leads, and product leads, which form a marketing funnel.

In measuring business process performance, Aydiner et al. (2019), on the other hand, proposed that business efficiency be gauged through efficient inventory management, transaction time with customers, and the efficiency in delivering products. In measuring transaction time, Jaff and Ivanov (2015) used the metrics of input resources order time, move time, product and service processing time. Treville, Shapiro, and Hameri (2013) described transaction lead-time as the functions of setup time, batch processing, waiting time, and delivery of products or services. Financial performance is measured through the marginal increase in sales, net profit, return on assets and return on equity (Ordanini & Gubera, 2009).

Several pieces of literature relate organizational performance with financial performance, marketing performance, and business process performance (Li et al., 2006; Elbashir, Collier, & Davern, 2008; Aydiner et al., 2019; Corte-Real, Oliveira, & Ruivo, 2016) and business process performance (Aydiner et al., 2019; Rahman et al., 2018). In the framework of Corte-Real, Oliveira, and Ruivo (2016), organizational performance affects other performance metrics. Therefore, it is hypothesized that:

H4: Organizational performance affects other performance metrics such as marketing performance, financial performance and business process performance.

The related literature supporting the formulation of the hypothesis mentioned can be summarized in this conceptual framework (Figure 1).

Based on the knowledge-based view of the firm, which theorizes that the knowledge of the firm is crucial in increasing organizational performance, this conceptual model postulates that BA capabilities of data dashboard, financial analysis, business process management and decision support system affect and explain the level of business intelligence that a retail company has. Business analytics capabilities and business intelligence represent the knowledge of a firm and are part of the independent variables. Organizational performance is hypothesized to affect the constructs of financial performance, marketing performance, and business process performance.

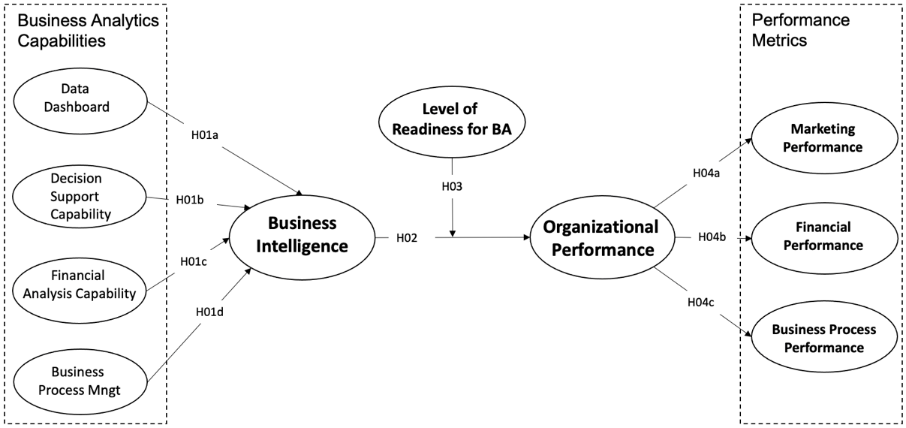

Figure 1. Conceptual framework on the relationship between business intelligence and organizational performance with intervening variables

The model proposes that the level of business intelligence (knowledge) affects and explains the level of organizational performance. The level of readiness of the firm to implement business analytics is theorized to have a moderating effect between business intelligence and organizational performance. It is also hypothesized that the strength of the relationship between business intelligence and organizational performance is moderated by the value of companies' readiness level to implement BA. This conceptual model is the basis for establishing the proposed structural equation model on business analytics implementation in the retail industry.

METHODOLOGY

Research design

Since the objective is to determine the relationship between the variables of the study, the strength of their correlation and the probability of predicting another variable through the value of a predictor variable, Structural Equation Modeling (SEM) is utilized (Eriksson, 2014; Waljee, Higgins, & Singal, 2014). SEM is used to explain associations, interactions, or correlations between variables by incorporating unobservable variables (e.g., latent variables) measured indirectly by indicator variables (Hair et al., 2017).

To establish the intended output of this study, the Partial Least Squares Regression – Structural Equation Model (PLS-SEM) was used to evaluate each relationship of our constructs. PLS-SEM is selected in this study since, according to Hair, Ringle, and Sarstedt (2011), it is more appropriate to use for theory development and when the sample size is small. It is also an advantage of PLS if the data violates normality assumption because it is a non-parametric type of statistical tool. The evaluation of the measurement model and the structural model was conducted based on the PLS-SEM approach of Hair et al. (2017).

Research data

The locale of the study is the retail companies that have been implementing any form of business analytics technology from 2016 to 2019. Retail companies are composed of Food and Non-Food firms. Since business analytics is relatively new in the Philippines, only a limited number of qualified respondents can participate. Consequently, total population sampling is utilized as an approach to enlisting participants. Laerd (2012) defines total population sampling as a technique where we choose to examine an entire but small population with a particular set of characteristics. From the prescribed characteristics, 69 retail companies who are qualified to take part in the study were identified, but only 62 companies were available to participate.

Data comes from the responses to the survey questionnaire given to the two sets of respondents – (1) Managers in charge of implementing BA technology and (2) Managers or Directors who are in charge of marketing, finance, and operations. Overall, 124 respondents (2 for each retail firm) participated in the study.

The following Table 1 showcases the profile of the respondents as they are sorted according to their organizational position, number of analysts, and years in implementing business analytics.

Table 1. Respondent's profile distribution

Characteristic	Frequency	Relative	Rank
Position/Title for BA Implementers			
Head/Lead Analyst	48	77.4%	1
Business Analyst	14	22.6%	2
Total for BA Implementers	62		
Position/Title for Corporate Officers			
Chief Information Officer	47	75.8%	1
Corporate Relations Officer	12	19.4%	2
Administration/Operations Officer	3	4.8%	3
Total for Corporate Officers	62		
Total Respondents	**124**		

Characteristic	Frequency	Relative	Rank
Number of Analysts			
1 to 10	82	66.1%	1
11 to 20	24	19.4%	2
21 to 30	12	9.7%	3
More than 30	6	4.8%	4
Retail Category			
Food	96	77%	1
Non-Food	28	23%	2
Number of Years of BA Implementation			
Less than 3	0	0%	
3 years and above	124	100%	

Note: 62 retail companies were represented by the 124 respondents.

With the minimum absolute significant path coefficient in the structural model of 0.216, Type I error of 0.05, and statistical power level of .80, the minimum required sample sizes are as follows: 94 for gamma exponential method and 108 for inverse square root (see Figure 2). The required minimum sample size must be between 104–117; thus, the actual sample size of 124 is sufficient enough to explain the results of the structural model.

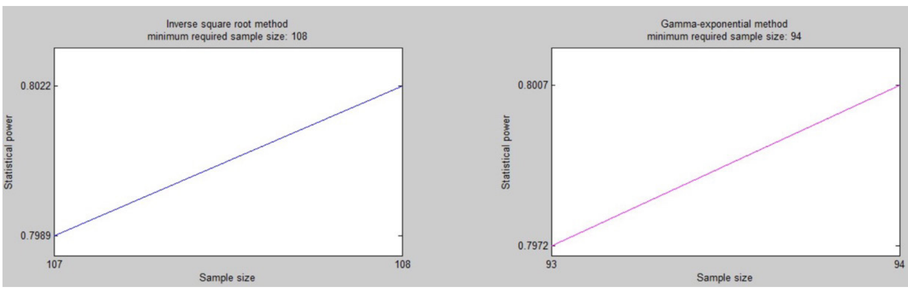

Figure 2. Results of the inverse square root and Gamma-exponential method

Research instrument

The questionnaire items are indicators intended to measure each construct or latent variable presented in the conceptual framework. Answers for each item in the questionnaire are given through a 4-point scale. Each item was evaluated using a numerical scale based on the respondent's knowledge of the variables of the research questions. For the survey questionnaire for business analysts, the items inquire about the quality or capacity of analytics infrastructure and capabilities. If this is the case, the following scale descriptors suggested by McLeod (2019) and Boone et al. (2012) are deemed appropriate: 1 – Poor; 2 – Lacking; 3 – Good; 4 – Excellent (1st questionnaire).

The survey questionnaire for top-level managers has a list of definitive statements serving as indicators, where respondents rate statements based on the level of their agreement with each one (Hair et al., 2017). It has the following scale descriptors: 1 – Strongly disagree; 2 – Disagree; 3 – Agree; 4 – Strongly agree (2nd). All questionnaire items are shown in Table 2.

Data gathering procedure

Two data gathering methods were used in evaluating the hypothesis: Survey strategy and Financial statement analysis. The survey was conducted in December 2019. Financial data were also inquired from the retail companies to measure their financial performance. There were separate survey questionnaires for business analytics and organizational performance. It is one of the ex-ante approaches to avoid the rampant dilemma in survey methods called the common method bias, in which only one class of respondents answers both questionnaire items for the independent and dependent variable (Chin, Thatcher, & Wright, 2012; Hair et al., 2017). In this scenario, a respondent being the sole source of information can easily taint the results of the study.

Table 2. Scale items per construct

Construct	Item	Items
Level of Readiness of BA Implementation	AVETSA	Technical skills level of analysts
	AVEBSA	Analytics infrastructure of the firm
	AVEBAN	Network capacity of the firm
	AVEBAI	Number of implementers and/or analysts
	AVEBAY	Years of BA implementation
Data Dashboard	DD01	Integration with third party applications
	DD02	Track progress against key customer experience and operational targets
	DD03	Organize, track and maintain CRM-related data to have a hub for managing all customer-related information helping employees prioritize workload
	DD04	Organize, track and maintain product related data to have a hub for managing all produce product-related information helping employees prioritize workload
Decision Support System	DSS01	Sensitivity analysis
	DSS02	Backward analysis sensitivity models
	DSS03	Optimization analysis
	DSS04	Forecasting models
Financial Analysis Capability	FA01	Liquidity real time report
	FA02	Leverage real time report
	FA03	Solvency real time report
	FA04	Forecasting capability
	FA05	Prescriptive capability

Construct	Item	Items
Business Process Management	BPM01	Order fulfillment
	BPM03	Logistics Management
	BPM04	Operations monitoring
	BPM05	Customer onboarding
Marketing Performance	MP01	We continue to increase our customer contacts
	MP02	We continue to increase our marketing leads
	MP03	We continue to increase our qualified sales leads
	MP04	We continue to increase our qualified product leads
Business Process Performance	BPP01	We continue to reduce Input Resources Order time
	BPP02	We continue to reduce the processing time of products
	BPP03	We continue to reduce move time
	BPP05	We continue to reduced batch processing time
Business Intelligence	BI01	We have a thorough understanding of customer preferences
	BI02	We can effortlessly cope with heightened competition through anticipation
	BI03	We can easily identify growth opportunities
	BI04	We are adept in improving our internal efficiency
	BI05	We work smarter through data-driven decisions
Organizational Performance	OP01	We consistently realize our organizational objectives
	OP02	We continue to increase the competitiveness of our products
	OP03	We continue to penetrate current and potential markets
	OP04	We are able to respond quickly to changes in trends and demands of the market

Financial data analysis

In order to establish a high degree of accuracy in terms of financial data, analysis was also used for the financial indicators under financial performance (Table 3). Financial statements for the years ending 2016, 2017, 2018, and 2019 were requested from research participants. Some of the financial statements were downloaded from the official website of retail companies represented by the respondents that post their financial statements online (e.g., publicly listed). Other financial statements were given directly by the research participants.

Table 3. Numerical range from averaged index of annual growth rate evaluating financial performance

Scale	Sales	Net profit	Net worth and return on equity
1	1.17 to 1.33	1.03 to 1.06	1 to 1.03
2	1.34 to 1.41	1.07 to 1.08	1.04 to 1.05
3	1.41 to 1.48	1.09 to 1.11	1.06 to 1.08
4	Over 1.48	Over 1.11	Over 1.08

The annual growth rate was computed using the Averaged Index method to facilitate the scaling of financial performance. Each figure for the succeeding years (2017, 2018, and 2019) is divided by the base year – 2016. The pedagogic objective was to determine the increase or decrease of the financial performance by comparing it to the base year. The advantage of this method is it yields small variances, which is favorable for statistical analysis. The average annual growth rate index is then grouped into quartiles to match the 4-point numerical scale similar to the scale responses in the questionnaire to be appropriate for statistical analysis. Since the range of average indexes is different between these financial metrics (i.e., sales are higher and more varied than the net profit or return on equity), each has a different bracket for each scale point.

Validity and reliability test results

Content validity

Content validity was established through the scrutiny of BA experts, managers, and research experts. The experts were requested to specify whether a questionnaire item is necessary for operating a construct in a set of items or not. To this purpose, they were requested to score each item from 1 to 4 with a four-degree range of "not necessary, useful but not essential, essential, and highly essential," respectively (Zamanzadeh et al., 2015). Based on the content validity result for all the questionnaire items to measure the latent variables, all items passed the given standard, which is > 0.70, having a rating of either Good or Excellent. Four items were excluded having a score of < 0.40. It shows that the remaining items are good indicators of the constructs they are trying to measure.

Construct validity and reliability

In order to verify the construct validity and reliability of the survey instrument, a pilot study was conducted by inviting 25 respondents to answer the survey questionnaire. Their responses were used as raw data for the construct validity and reliability tests. These respondents were consequently excluded from the proper survey of the study to avoid the pre-testing effect (Richland, Kornell, & Kao, 2009).

Construct validity was established through convergent and divergent validity measures using confirmatory factor analysis. Based on the statistical analysis performed on the pilot test data, two items were removed due to indicator scores falling below the standard. All remaining items have factor loadings that are statistically significant with $p < 0.05$ (two-tailed) and are more than the minimum recommendation of Hair et al. (1987 & 2009) >= 0.50. The average variances extracted for all the constructs are also more than 0.50, which is the minimum postulated by Fornell and Larcker (1981). Discriminant validity is established when the square root of the average of each concept is larger than the correlations with the other constructs (Fornell & Larcker, 1981). For the measure of internal consistency, all constructs have composite reliability of at least 0.90, which is considered very high, taking into account that the conservative criterion is only > 0.70 (Fornell & Larcker, 1981; Nunnally & Bernstein, 1994).

RESULTS

Measurement model evaluation

The validity of the measurement model should be evaluated first before the structural model can be built (Hair et al., 2012). The constructs of BA capabilities (1st order) are measured formatively while the construct of BI (2nd order), organizational performance (3rd order) up to the key performance metrics (4th order) are measured reflectively. For constructs that have been measured reflectively, the following tests are applied: (1) convergent validity through average variance extracted; (2) discriminant validity through the Fornell and Larcker index; and (3) internal consistency through composite reliability. Reflective constructs in this study are marketing performance, financial performance, business process performance, organizational performance, and business intelligence.

On the other hand, formative constructs have been evaluated based on convergent validity, collinearity between indicators, and the relevance of outer weights (Hair et al., 2017). Collinearity is measured through the Variance Inflation Factor (VIF), which should not exceed a value of 5. In order to evaluate the significance and relevance of outer weights, all indicator loadings were statistically significant (i.e., $p < 0.05$), and the R^2 adjusted are > 0.30 (Dijkstra & Henseler, 2015). R^2 adjusted is used instead of the common R^2 since it is more appropriate considering the number of indicators to avoid overestimation of variance.

Table 4. Loadings and cross-loadings for the reflective measurement model

Construct	Questionnaire item	MP	FP	BPP	BI	OP
Marketing Performance (MP)	MP01	**0.634*****	0.114	0.332	0.366	0.233
	MP02	**0.715*****	0.386	0.18	0.45	0.454
	MP03	**0.977*****	0.323	0.272	0.115	0.128
	MP04	**0.720*****	0.193	0.191	0.129	0.384
Financial Performance (FP)	FP01	0.426	**0.850*****	0.183	0.165	0.103
	FP02	0.376	**0.749*****	0.307	0.2	0.289
	FP03	0.424	**0.887*****	0.176	0.464	0.135
	FP04	0.47	**0.803*****	0.275	0.279	0.298
Business Process Performance (BPP)	BPP01	0.164	0.486	**0.785*****	0.406	0.177
	BPP02	0.32	0.138	**0.984*****	0.115	0.418
	BPP03	0.446	0.283	**0.618*****	0.366	0.47
	BPP05	0.363	0.131	**0.764*****	0.413	0.381
Business Intelligence (BI)	BI01	0.131	0.491	0.363	**0.844*****	0.383
	BI02	0.344	0.454	0.498	**0.966*****	0.444
	BI03	0.37	0.156	0.444	**0.674*****	0.246
	BI04	0.243	0.158	0.373	**0.619*****	0.238
	BI05	0.366	0.356	0.185	**0.710*****	0.415
Organizational Performance (OP)	OP01	0.467	0.116	0.406	0.155	**0.682*****
	OP02	0.182	0.468	0.178	0.456	**0.741*****
	OP03	0.136	0.279	0.431	0.251	**0.906*****
	OP04	0.417	0.46	0.202	0.497	**0.725*****

Note: The figures in bold represent the indicator loadings of the construct while those not in bold are cross-loadings. Significant at p values : *< 0.05, **< 0.01, and ***<0 .001.

Table 4 reveals that only indicators that have loadings above 0.50 were considered. Only one item (BPP04) was eliminated under the construct of BPP. Since the indicator loadings are all above 0.50, its average variance is also greater than 0.50. Further, all loadings are statistically significant. Hence, all reflective indicators laid above have convergent validity.

The results for the reflective measurement model are provided in Table 5. The composite reliability coefficient evaluates construct dependability by taking into account indicators with varying loadings. The composite reliability of all structures in the table above is greater than 0.70, indicating that they have internal consistency. To test discriminant validity, the study uses the Fornell-Larcker criterion and cross-loadings. First, according to Fornell and Larcker (1981), the square root of AVE should be greater than the correlations with other latent variables.

Table 5. Correlation matrix, composite reliability, and square root of average variances

Construct	CR	MP	FP	BPP	BI	OP
Marketing Performance (MP)	0.78	**0.77**				
Financial Performance (FP)	0.85	0.57	**0.82**			
Business Process Performance (BPP)	0.82	0.50	0.24	**0.80**		
Business Intelligence (BI)	0.84	0.34	0.29	0.60	**0.77**	
Organizational Performance (OP)	0.77	0.46	0.40	0.44	0.51	**0.77**

Note: (1) First column is CR (composite reliability); (2) Diagonal and bold figures are the square root of average variance extracted; (3) Off-diagonal elements are correlations.

It reveals that the square roots of AVEs (in bold) are higher than the correlation between constructs. Second, the loading of each indicator should be greater than all cross-loadings. Accordingly, Table 5 shows that the loadings of all indicators are greater than their cross-loadings. These results, therefore, support the fact that all the constructs have discriminative measurement capacity.

For the formative measurement model, the indicators are checked for: (1) collinearity through the variance inflation factor (VIF); and (2) significance and relevance through p-value and regression weights, accordingly.

Formatively measured constructs of this study are exhibited in Table 6. To test for the validity of these latent variables, there should be no multicollinearity issues among them and their outer regression weights should be statistically significant. It can be realized that the VIF values are not exceeding 5, which is the alarm value for multicollinearity. However, six items were removed in the construct of readiness for BA implementation due to the critical level of their VIF values.

Table 6. Variance inflation factor and outer regression weights

Construct	Item	VIF	Outer Weights
Level of Readiness of BA Implementation (LRBA)	AVETSA	1.744	0.289**
	AVEBSA	1.616	0.293***
	AVEBAN	1.537	0.275**
	AVEBAI	2.071	0.473***
	AVEBAY	1.854	0.382***
Business Analytics Capabilities			
Data Dashboard (DD)	DD01	1.730	0.409***
	DD02	1.675	0.346***
	DD03	1.482	0.427***
	DD04	1.099	0.345***

Construct	Item	VIF	Outer Weights
Decision Support System (DSS)	DSS01	2.381	0.329***
	DSS02	1.905	0.317***
	DSS03	1.625	0.369***
	DSS04	1.420	0.312***
Financial Analysis Capability (FA)	FA01	1.685	0.329***
	FA02	2.112	0.230**
	FA03	1.689	0.405***
	FA04	1.800	0.245***
	FA05	1.343	0.332***
Business Process Management (BPM)	BPM01	1.866	0.402***
	BPM03	1.692	0.216***
	BPM04	1.823	0.320***
	BPM05	2.504	0.390***
	BPM06	2.708	0.478***

Note: Significant at p values: *< 0.05, **< 0.01, and ***< 0.001.

All outer weights are also statistically significant. Therefore, we can conclude that the constructs measured formatively have acceptable validity and reliability. Overall, the measurement model has good indicator reliability, construct reliability, convergent validity, and discriminant validity. As these criteria are met, the constructs can test the structural model.

Structural model evaluation

To evaluate the structural model, the following were established based on Hair's recommendation (Hair et al., 2013): (1) collinearity assessment, (2) structural model path coefficients, (3) coefficient of determination (R^2 value), (4) effect sizes (f^2 and q^2) and (5) predictive relevance (Q^2) (Hair, Hult, Ringle, & Sarstedt, 2014; Samani, 2016). Collinearity is assessed and the results present minimal collinearity among the constructs having 2.15 as the highest VIF among explanatory variables. This means that the predictors in the structural model do not suffer from multicollinearity issues. The significance of each path coefficient is computed by means of a bootstrapping technique with 5000 iterations with n = 124 (Chin, Kim, & Lee, 2013).

PLS-SEM, as proposed by Hair et al. (2017), is to be evaluated through the coefficient of determination expressed as R^2 – a measure of the predictive power and through Stone-Geisser's Q^2 value (Geisser, 1974; Stone, 1974) – a criterion of predictive accuracy was computed for the exogenous constructs. R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables can, as a rule of thumb used by scholarly studies, be respectively described as strong, moderate, or weak (Hair et al., 2011; Henseler et al., 2009). Furthermore, each path is evaluated through effect size. Two effect sizes are reported in this study: the effect size related to R^2 expressed as f^2 and the effect size related to Q^2 expressed as q^2. Criteria for evaluating f^2 and q^2 are that values of 0.02, 0.15, and 0.35, respectively, represent small, medium, and large effects (Cohen, 1988). Effect size values of less than 0.02 indicate that there is no effect. Table 7 shows the result of path evaluation, while Table 8 shows the coefficient of determination and predictive relevance results.

Table 7. Structural path evaluation results

Structural Path	Path Coefficient (β)	*t*-value	f^2	q^2	Conclusion
DD → BI	0.356	3.14**	0.201	0.116	H1a supported
DSS → BI	0.412	4.61***	0.378	0.371	H1b supported
FA → BI	0.216	2.18*	0.160	0.126	H1c supported
BPM → BI	0.362	3.71***	0.360	0.355	H1d supported
BI → OP	0.508	4.57***	0.355	0.249	H2 supported
OP → MP	0.423	4.12***	0.301	0.151	H4a supported
OP → FP	0.314	3.13**	0.416	0.263	H4b supported
OP → BPP	0.461	4.77***	0.463	0.377	H4c supported

Note: Significant at t critical values : *1.99 at p = 0.05, **2.66 at p = 0.01, and ***3.46 at p = 0.001.

The values of f^2 and q^2 effects can be considered < 0.149 – weak; 0.15 to 0.34 – moderated and => 0.35 – strong.

The results of the structural path evaluation shown in Table 6 support the acceptance of hypothesis 1 (H1) that there is indeed a significant effect of business analytics capabilities on business intelligence. It can be noted that the decision support system capability (DSS) of business analytics (BA) has the most effect among predictor variables of BI, having the largest coefficient explaining business intelligence (β = 0.412; p < 0.001). It implies that for 1 level of increase in DSS utilization, there is a high probability that the business intelligence of the firm increases by 41.2%. BA's capability to improve business processes is the second most impactful explanatory variable of BI (β = 0.362; p < 0.001). The significant effect of data dashboard capability (β = 0.356; p < 0.01) infers that it statistically increases business intelligence by 35.6%. The financial analysis capability (FA) of BA turns out to be the lowest but still a significant explanatory factor of BI (β = 0.216; p < 0.05). Every output of BA can probably increase the level of BI by 21.6%.

Hypothesis 2 (H2), which postulates the significant effect of business intelligence on organizational performance, is also evidenced ($\beta = 0.508$, $p < 0.001$). It indicates that for every 1 unit increase in the level of business intelligence, it predicts a positive increase of around 51% in the level of organizational performance of a firm.

Results also support hypothesis 4 (H4) that organizational performance significantly affects marketing performance, financial performance, and business process performance. Among the most positively affected by organizational performance is business process performance ($\beta = 0.356$; $p < 0.001$). Marketing performance ($\beta = 0.423$; $p < 0.001$) and financial performance ($\beta = 0.314$; $p < 0.01$) are also significantly increased by amplifying organizational performance.

Table 8. Coefficient of determination and predictive relevance of the endogenous constructs

Endogenous Constructs	**R^2 %**	**Explained Variance**	**Q^2**	**Predictive Relevance**
Business Intelligence (BI)	68.2	High	0.502	Moderate
Organizational Performance (OP)	71.5	High	0.671	High
Marketing Performance (MP)	63.5	High	0.567	High
Financial Performance (FP)	58.8	Moderate	0.319	Moderate
Business Process Performance (BPP)	67.1	High	0.578	High

Note: Hair's criteria =< 0.30 – Low; 0.31 to 0.60 – Moderate; > 0.60 – High.

The goodness of fit of PLS-SEM, according to Hair et al. (2017), is based on the evaluation of the coefficient of determination and predictive relevance, which should be moderate to high. Overall, we can conclude that the structural model of amplifying organizational performance through business intelligence generated by business analytics has significant explanatory and predictive power.

The Two-Stage approach proposed by Chin et al. (2003) was used to evaluate the moderating variable – level of readiness in BA implementation. This was done by computing an interaction term (i.e., level of readiness indicators x business intelligence indicators) and determining if it is statistically significant through bootstrapping. To determine the significance of the interaction term, we ran the bootstrapping procedure with 5,000 bootstrap samples (n = 124), using the No Sign Changes option, two-tailed testing, and the standard settings for the PLS-SEM algorithm.

Table 9. Moderating effect of the level of readiness of BA implementation

Interaction Term	*t*-value	*p*-value	Conclusion
-0.131	1.43	0.159	H4 rejected

Note: Significant at t critical values: *1.99 at p = 00.05, **2.66 at p = .01, and ***3.46 at p = 0.001.

The result of the moderation analysis performed using an interaction term is indicated in Table 9. Through the bootstrapping procedure, it is found that such an interaction term is not statistically significant where $t(123) = 1.43$, $p > 0.05$ is lower than the t critical, $t(123) = 1.33$, $p = 0.05$ causing the rejection of hypothesis 3 (H3), which states that there is a significant interaction effect of the level of readiness for business analytics implementation as a moderating variable between business intelligence and organizational performance. Accordingly, it implies that the relationship between business intelligence and organizational performance established does not change, given different levels of readiness in BA implementation.

Accordingly, this result supports Grossman and Siegel's (2014) claim that capacity or readiness to implement business analytics does not so much affect organizational performance. Thus, it negates previous studies that have shown that the relationship is influenced by the firm's infrastructure and readiness to implement analytics as a moderating factor (Wamba et al., 2015; Côrte-Real et al., 2017).

Below is the established structural equation model (Figure 3) which exhibits the relationships of the constructs with their path coefficients, statistical significance, explanatory power, and predictive power.

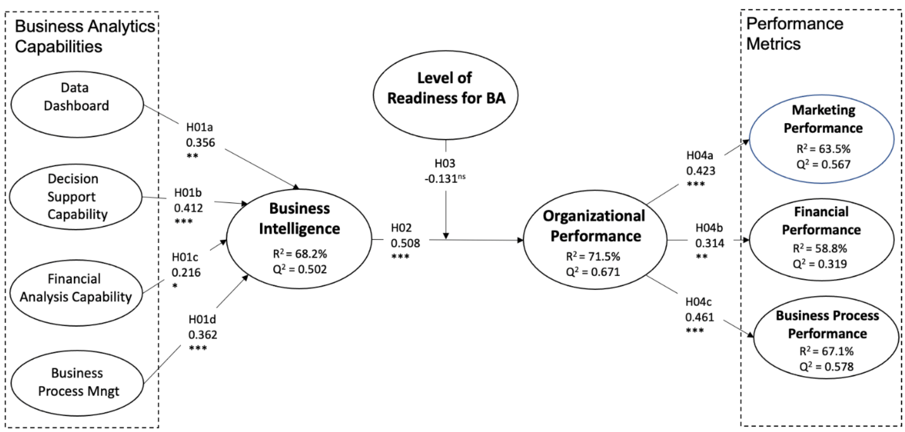

Figure 3. Structural equation model of amplifying organizational performance through business intelligence

DISCUSSION

Effect of business analytics capabilities on business intelligence

Based on the analysis, business analytics capabilities have a significant positive effect on the level of business intelligence (BI). This means that there is indeed a significant effect of business analytics capabilities as factors of business intelligence. It can be noted that the decision support system capability (DSS) of BA has the most effect among predictor variables of BI. This means that for 1 level of increase in DSS utilization, there is a high probability that the firm's business intelligence will increase by 41.2%. The BA capability of improving business processes (BPM) follows as the second most impactful explanatory variable of BI. This means that for 1 unit level of increase in BPM utilization, there is a high probability that the business intelligence of the firm increases by 36.2%. The significant effect of data dashboard (DD) capability infers that it statistically increases business intelligence by 35.6%. The financial analysis capability (FA) of BA turns out to be the lowest but still a significant explanatory factor of BI. Every output of FA can probably increase BI's level by 21.6%.

Business analytics capabilities indeed generate the business intelligence of a business organization. The BA capability that mostly affects business intelligence is the decision support system. This can be related to the previous fact that one of the strongest indicators of business intelligence is the firm's ability to make data-driven decisions. Another powerful BA capability that positively increases business intelligence is the business process management system. This is the reason why firms with high BI display the skill to harness internal knowledge for discovering areas for improvement in their business processes. BA's data dashboard capability provides a thorough market understanding as one of the core manifestations of BI. The BA capability in the real-time financial analysis also positively contributes to BI by providing internal knowledge in financial terms.

Effect of organizational performance on other performance metrics

Organizational performance significantly affects other performance metrics such as marketing performance, financial performance, and business process performance. As can be viewed from the findings, organizational performance has a higher effect on business process performance and marketing performance. Every time OP increases, both the business process and marketing performance are most expected to increase subsequently. Among these performance metrics, marketing and business process performance are more likely to increase given the similar positive increase in organizational performance.

Effect of business intelligence on organizational performance

PLS-SEM results show that business intelligence is a significant predictor of the organizational performance of a retail firm. The path coefficient indicates that for every 1unit increase in the level of business intelligence, it predicts a positive increase of around 51% in the level of organizational performance. The high degree of market understanding is translated into increased market leads and a consistent increase in sales. The excellent ability to produce data-driven decisions also leads to a continuous increase in sales and net profit. Prediction of growth opportunities is manifested through the consistent increase in the return on equity. Exceptional internal knowledge of a retail firm translates to a dramatic reduction in the lead-time of input resources to order, move, process, and deliver retail products. This also concludes that the benefits that business intelligence provides for retail companies far exceed the cost of acquiring a business analytics infrastructure. Such benefits positively affect different aspects of the business organization.

Moderating effect of the level of readiness of business analytics implementation

The result of the moderation analysis performed indicated that the interaction term is not statistically significant. This means that the level of readiness for BA implementation cannot be considered as a moderating factor on the relationship between business intelligence and organizational performance. The coefficient values between BI and OP do not change, given different levels of readiness in BA implementation. The level of readiness, in this case, does not affect the predictive power of BI to OP.

CONCLUSION

Theoretical implications

Business intelligence amplifies organizational performance supporting the knowledge-based view of the firm

Findings reveal that the business intelligence generated by business analytics significantly improves overall organizational performance. As a result, this confirms Grant’s (1996) knowledge-based view of the Firm, which asserts that knowledge is the most important intangible resource of a firm that aids in improving organizational performance. It was then extended by Kaplan et al. (2012) in which knowledge from internal and external sources through capabilities enhances organizational performance. In the structural equation model established, the business intelligence generated the knowledge of the firm. The business analytics capabilities represent the capabilities enhancing organizational performance. Therefore, management should focus on harnessing its knowledge from internal and external transactions to improve, consistently, organizational performance and other performance metrics such as marketing, finance, and business process.

Business analytics infrastructure not significantly affecting the link between business intelligence and organizational performance

Based on the results of the study, it was found that the level of readiness for implementing business analytics does not have a significant effect on the link between business intelligence and organizational performance. It concludes that the generation of business intelligence in amplifying organizational performance entirely depends on how business analytics capabilities are utilized. The generation of business intelligence in amplifying organizational performance does not depend, therefore, on the sophistication and the expensiveness of BA infrastructure, nor does it depend on the number of analysts.

Decision support system and business process management capabilities amplifying market performance and business process performance

Based on the proposed structural equation model on amplifying organizational performance through business intelligence, the business analytics capabilities of decision support systems and business process management capabilities are the best generators of business intelligence. Business intelligence amplifying organizational performance eventually leads to enhanced marketing performance and business process performance. Therefore, in order to improve marketing and business process performance, companies should focus their utilization of business analytics on decision support systems and business process management capabilities.

Understanding business analytics generating business intelligence

Despite potential benefits, some firms fail to capture value from the big data that flows into their company (Kaisler et al., 2013). Recent papers suggested research opportunities (Abbasi et al., 2016; Agarwal & Dhar, 2014), claiming that there is a need to conduct assessments of the actual impact of BA investments and use, and to understand how to achieve the benefits for organizational performance. The value chain of business analytics generating business intelligence remains relatively unexplored and requires further investigation. This study theoretically proposes and empirically validates a structural equation model based on a strategic management theory of the knowledge-based view of the firm, which considers the data or information that flows into the firm, which, if applied with business analytics, will be a source of enhanced organizational performance (Liu et al., 2014). Several pieces of literature studied business analytics and business intelligence separately as to their effects on different performance metrics (Elbashir, Collier, & Davern, 2008; Min, 2016; Aydiner et al., 2019, Akter et al., 2016; Grossman & Rinderle-Ma, 2015). This is the first study that empirically demonstrates how BA capabilities generate BI, which helps retail firms create organizational performance, leading to competitive advantage. Further studies could beneficially use this theoretical framework through the established structural equation model to assess the business value in other IT innovations at a process level and strategic level. Students, teachers, and other academics can use this paper for pedagogical support for learning about the value of business analytics and business intelligence.

Recommendations for future research and some limitations

Cost analysis and return on investment of business analytics

Gathering financial data on the exact cost or investment in analytics was not part of this study. This is because relying on financial statements will not give an exact figure of capital that can be solely attributed to business analytics. Therefore, a future study can be conducted to assess the exact financial figures invested in business analytics. After arriving at the cost of infrastructure, the research can include an objective to compare it with the same returns that business analytics provide for a company.

Financial metrics used in measuring the impact of business analytics

This study supports the conclusion that financial analysis capability and financial performance are on an acceptable level but rank the lowest among other variables. It was also found that Net Worth seems not that sensitive to the business analytics effect. Therefore, it would be beneficial if further studies were conducted to identify what specific metrics should be chosen by researchers that may accurately measure the impact of business analytics technology.

Repeated measures research design of business analytics implementation

Since this study is built on the PLS-SEM, data analysis is designed to evaluate data sets within one specific period, i.e., years included in the study are when business analytics is already being implemented. In order to determine the effect of business analytics, the average increase along the time periods was evaluated. Another exciting research that can be conducted is to ascertain the impact of business analytics through repeated measures research design. This is done by getting performance data (e.g., financial, marketing, operations) when business analytics is not yet utilized and comparing it to the gathered data from when business analytics is already being fully implemented. The objective would be to see the difference between the absence and presence of business analytics technology in its impact on any business objectives.

Mediating effect of organizational performance between business intelligence and other performance metrics

The proposed structural equation model on amplifying organizational performance through business intelligence as generated by business analytics showed that BI predicts OP, while OP predicts marketing, financial, and business process performance. OP is in the middle, which acts as mediating variable between BI and these performance metrics. To explore further this established SEM, further research can be conducted focusing only on the mediating effect of OP. Related literature may be scrutinized to substantiate the series of links between BI and OP, and OP to any of the other performance metrics.

Structural model for other industries

The locale of this study is in the retail industry. Since business analytics and business intelligence concepts are new, especially in the Philippines, future researchers' objectives can be adopted by future researchers to explore such concepts further using different industries in building their model. There is so much to learn about the impact of this technology from a different business perspective.

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Abstrakt

CEL: *Koncepcja analityki biznesowej (BA) i business intelligence (BI) dopiero pojawia się na Filipinach. Ponieważ są to nowe koncepcje, ważne jest zbadanie ich wpływu na wydajność organizacji i wskaźniki wydajności w branży biznesowej. Celem jest zbadanie wpływu analityki biznesowej generującej business intelligence oraz jej wpływu na wydajność organizacji poprzez opracowanie modelu strukturalnego. W konsekwencji ustalono również wpływ wydajności organizacji na inne mierniki wydajności.* ***METODYKA:*** *Wykorzystano modelowanie metodą najmniejszych kwadratów — równania strukturalne. Zaproponowano model pokazujący, w jaki sposób business intelligence, generowany przez biznesowe BA, wpływa na wydajność organizacji, co w kon-*

sekwencji prowadzi do poprawy wydajności marketingowej, finansowej i procesów biznesowych. Przeprowadzono ankietę wśród analityków biznesowych i menedżerów wykonawczych firm detalicznych, które wdrażają BA już od co najmniej trzech lat. ***WYNIKI:*** *Możliwości BA mają znaczący pozytywny wpływ na poziom BI. BI ma znaczący pozytywny wpływ na wydajność organizacji. Jednak wynik analizy moderacji wskazał, że poziom gotowości do wdrożenia BA nie może być uważany za czynnik moderujący związek między BI a wydajnością organizacji.* ***IMPLIKACJE:*** *Spośród różnych możliwości BA, system wspomagania decyzji i zarządzanie procesami biznesowymi okazały się najbardziej korzystnymi funkcjami w generowaniu BI. BI zwiększa wydajność organizacyjną, a w konsekwencji poprawia wydajność marketingu i procesów biznesowych w firmach detalicznych. Jednak gotowość do wdrożenia BA nie wpływa znacząco na to, jak BI poprawia wydajność organizacji. Ogólnie rzecz biorąc, zaleca się, aby w celu zwiększenia wydajności marketingu i procesów biznesowych, firmy detaliczne skupiły się na możliwościach BA systemu wspomagania decyzji i zarządzania procesami biznesowymi.* ***ORYGINALNOŚĆ I WARTOŚĆ:*** *jest to pierwsze badanie empiryczne na Filipinach, w którym oceniano wpływ analityki biznesowej i analizy biznesowej na wydajność organizacji. To badanie jest oryginalne w określaniu, jakie możliwości BA generują BI, co przekłada się na poprawę wydajności organizacji. Badanie to jest również wyjątkowe w określaniu, które kluczowe wskaźniki wydajności zostały znacznie ulepszone w wyniku jego wdrożenia. Może to służyć jako realne odniesienie dla innych badaczy zainteresowanych analityką biznesową i innymi technologiami dotyczącymi zarządzania danymi stosowanymi w operacjach biznesowych.*
Słowa kluczowe: *model równania strukturalnego, podejście oparte na wiedzy, analityka biznesowa, business intelligence, wydajność organizacyjna, branża detaliczna*

Biographical note

Emmanuel P. Paulino finished his master's degree in Business Administration at the University of the City of Manila. He is a graduate of Bachelor of Science in Commerce major in Information Management from the University of Perpetual Help in Las Pinas, Philippines. His employment career has mostly been spent in government service, working as an IT and Database Manager and Consultant. In 2012, he started his teaching career with St. Dominic College of Asia. He took the Teaching Certificate Program while teaching at the University of Perpetual Help Molino at the Senior High School department. In September 2019, he passed the Licensure Examination for Professional Teachers. He graduated from the Doctorate Program in Business Administration at the University of the City of Manila in 2021. He is currently a faculty member of San Beda College - Alabang as a faculty in business and management, teaching different courses related to business, entrepreneurship, and research.

Conflicts of interest

The author declares no conflict of interest.

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