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IMPACT OF BUSINESS ANALYTICS AND INNOVATION ON FIRM PERFORMANCE

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Abstract

The field of business analytics has seen some research, but far less effort than is needed has been put into accumulating and disseminating a comprehensive understanding of the connection between analytics and performance. To address this gap in understanding, this study provides a holistic framework for describing the many types of business analytics, the connections between them, and the impact of business analytics use on innovation and financial success. A cross-section of Mumbai's small and medium-sized enterprise (SME) sector was analyzed empirically. The study uses a structural equation modeling (SEM) analysis using a mediation model to investigate the possible causal relationship between the research constructs. This study analyzed the connection between innovation, exogenous independence, and firm performance (endogenous) using product and process innovations as a second-order component, business analytics as an exogenous independent variable, and firm performance as a dependent variable. According to the findings, business analytics have a significant role in predicting the creativity and success of small and medium-sized enterprises.

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1.1 Introduction

Firms need to be more creative and nimbler in their ability to anticipate and meet their consumers' ever-evolving requirements and wants in today's fast-paced, worldwide business climate. These companies' chances of success or even survival hinge on how well and fast they can adapt to the ever-changing conditions of the global market. As a result, IS (Information science) and IT (Information technology) become metaphors that supply varied resources and approaches to help organizations face and conquer the challenges of such settings (Sharda, Delen, & Turban, 2016). In recent years, businesses have gained access to vast amounts of data made possible by their use of digital infrastructure. It's also important to acknowledge how the widespread adoption of IT has led to the rise of digitalized enterprises that amass both structured and unstructured data. For businesses to gain a competitive edge, they need to be able to analyse and interpret the information contained in these massive data sets (Bichler, Heinzl, & van der Aalst, 2017).

There are many uses for IS, each requiring a unique mix of resources and methods for dealing with massive data volumes. These days, firms use a suite of tools and techniques known as business analytics (BA) to make sense of their data and use that information to make informed decisions (Delen & Zolbanin, 2018). They are meant to handle the "big data" (increasingly large amounts of data with a high rate of change) that businesses and individuals are collecting (Sharda et al., 2016).

Investments on the Busine analytics regarded by both middle- and upper-level managers as valuable investments (Cosic, Shanks, & Maynard, 2015). The use of business analytics (BA) is revolutionizing the way companies collect and analyse information (Ramanathan, Philpott, Duan, & Cao, 2017). The academic and professional communities have been paying more attention to them because of the significant operational and strategic potential they hold in many fields.

It has been discovered that BA has a lot of potential for making business decisions and resource and capacity planning more resilient to the future (Sheng et al., 2020). Due to the limited resources available to modern digital SMEs, it is crucial that they take advantage of digital technology, such as business analytics, to aid in the transition from one business model to another for improving firm performance (Griva et al., 2021b).

Research question

Organizations need in-depth knowledge of markets, consumers, goods, regulations, competitors, suppliers, employees, and more to thrive in today's globally interconnected economy. To gain this insight, data analytics must be used efficiently. Business operations can be improved with the help of data analytics by zeroing in on the most profitable customers, setting the most optimal prices, mapping out the most efficient supply chain routes, and selecting the most qualified candidates (J. Bughin 2010). Therefore, it's very important to understand what is the impact of business analytics on SMEs performance and innovation. And how innovation can further boost firm performances.

2.1 Literature review and hypothesis development

Wójcik (2015) argues that in the future, businesses will need to focus on their ability to renew themselves in order to remain competitive. One way to do this is through business analysis (BA), which can help businesses gain a competitive edge by improving their learning experiences and implementing the knowledge they uncover. (Ramanathan et al., 2017).

Understanding the specific techniques through which IT applications boost business performance is essential (Zhang &

Dhaliwal, 2009). This is why Bharadwaj (2000) demonstrated how advanced IT capabilities are a major differentiator between high- and low-performing businesses. Earlier research (Delen & Nam, Lee & Lee, 2018) has claimed that BA skills make it possible for a rich analysis to assist businesses gain a competitive edge.

There is a lot of research showing that BA improves both organizational and operational performance (Huang, Pan, & Ouyang, 2014) Data-driven decision making is one way that BA may help businesses improve their performance, as suggested by research by Brynjolfsson, Hitt, and Kim (2011), for instance.

The ability of businesses to solve market problems and opportunities is what is meant by the phrase "innovation" (Song, 2015). Innovation is widely recognized as one of the most important strategic gains made possible by the implementation of information technology (Wang, Kung, Wang et al., 2018). In accordance with the work of Wang and Dass (2017), "a firm's ability to produce, accept, and implement new ideas, processes, products, or services" is the definition of innovation capability. When it comes to improving a company's capacity for innovation, IT capabilities center on the use of internal IT resources. One group of researchers (Zain, Rose, Abdullah, and Masrom, 2005) contended that businesses' use of IT skills boosts performance by helping with innovative activities.

Analytics is used by startups for client acquisition and retention planning and for product development (Sayyed-Alikhani et al., 2021); however, it is rarely used to improve internal workflow (Behl et al., 2019). Even in these cases when BA is not being fully utilized, it still represents a huge opportunity for startups and SMEs (Sheng et al., 2020). The combination of a small company's proximity to its customers and its lack of high-level knowledge about its partnerships and collaborations with the insights gained from business analysis might help it remain competitive despite its meagre resources (O'Connor & Kelly, 2017). It is clear that the lack of resources and capabilities pushes smaller organizations to leverage BA, typically for customer objectives; however, the use of BA to enhance internal processes and modify business models has been relatively understudied. Such an effort necessitates proper BA implementations and the cautious incorporation of BA into preexisting organizational procedures in order to improve the practice (Wang & Wang, 2020).

2.2 Hypothesis Development

Business analytics and performance of SMEs

An important conceptual distinction between big data analytics and big data analytics capabilities is provided by Mikalef, Pappas, et al. (2017), who also stress the necessity of the latter when thinking about performance improvements. The authors provide a study framework that emphasizes the significance of aspects related to processes, people, technology, organization, and data in determining the business value of big data analytics. Improved data-driven decision making and novel approaches to organization, learning, and innovation are made possible by Business analytics (Kiron, 2013, Yiu, 2012), which in turn strengthens customer relationship management, better manages operational risk, boosts operational efficiency, and boosts firm performance (Kiron, 2013).

Business analytics and innovation

Y. Duan & G. Cao (2015) Based on the results of the study, it appears that BA has a direct effect on environmental scanning, which in turn increases the company's innovation in terms of the uniqueness and significance of its new products. Data-driven culture acts as a mediator between BA's contribution and the company, amplifying the former's impact. Cultures that place a premium on data have an immediate effect on the originality of new products, and indirectly on their utility by means of constant environmental monitoring. Additionally, the results show that environmental scanning has a direct impact on the originality and significance of new products, both of which boost competitive advantage.

Innovation and firm performance

A study by Lööf (2000) found a favourable correlation between sales innovation and elasticity across five key performance metrics (Rising Employment, Rising Value Added, Rising Sales, Rising Operating Profit, Rising Operating Profit to Assets Ratio, and Rising Return on Assets). There is little correlation between creative production and profit margin. When businesses are broken down into their manufacturing and service components, it becomes clear that the correlation between inventive production and job growth weakens significantly for service organizations. Accenture and GE found that 89% of businesses fear losing market share unless they implement big data and BA (Business analytics) strategies. (Columbus, 2014)

Research hypothesis:

H1: Business analytics has a direct and significant impact on the performance of SMEs.

H2: Business analytics has a direct and significant impact on Innovation.

H3: Innovation has a direct and significant impact on the performance of SMEs.

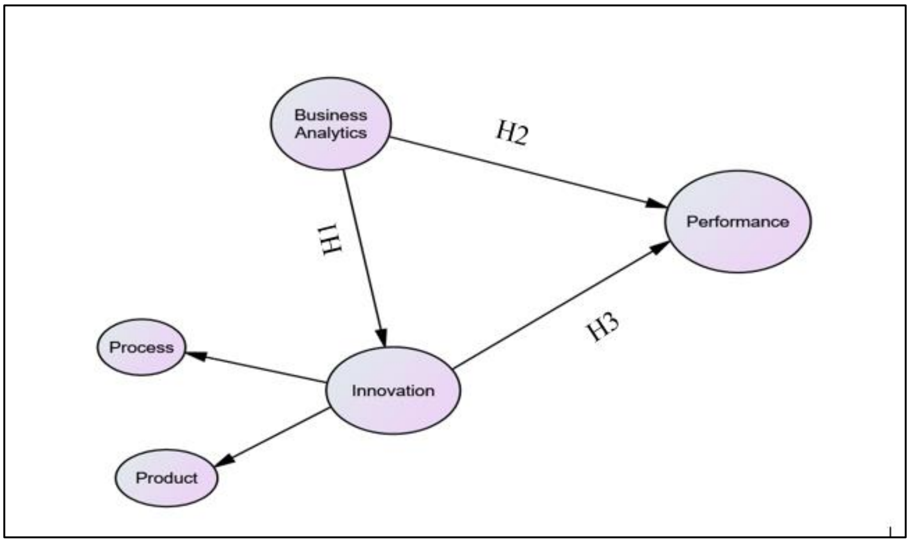

Figure 1: Conceptual framework of the study

3. Research methodology:

The empirical analysis was performed on sample of SMEs industries present in Mumbai. The target respondents for the study are owner/managers who has knowledge of every detail of firms and survey was conducted through random sampling method. A semi-structured questionnaire was prepared constitutes of two sections: one about details of respondents and enterprise, another section contains questions on research variables. The respondents were requested to give their opinion on 5-point Likert scale (where 5-strongly agree and 1-strongly disagree). Out of 230 questionnaires returned back by respondents, during data screening process, data having missing values were rejected and finally 218 samples were selected for further analysis.

The measure for the scale of were derived and adapted from previous studies. For measuring performance of firm were selected from the Venkatraman (1989) and Aydiner et al., (2019) studies. Innovation scales were derived from the studies of Atalay et al., (2013) and the item for business analytics were adapted from Aydiner et al., (2019) study.

Descriptive and inferential statistics were used to examine the data with the assistance of SPSS and AMOS version 26. Overviews of the data, as seen in tables 1 and 3, are provided by descriptive statistics.

The study began with an exploratory factor analysis (EFA) to discover the underlying structure of the measurement data, and then moved on to a confirmatory factor analysis (CFA) to establish the robustness of the derived constructs. Structural Equation Modelling (SEM) was then used to finally put the research idea to the test.

Table 1 Details of respondents from selected SMEs (N=218):

Measures	Items	Frequency	Percentage
Gender	Male	178	82
	Female	40	18
Age	Below 24	3	1
	25-30	24	11
	30-35	62	28
	35-40	73	34
	40 & above	56	26
Education	Secondary	13	6
	Undergraduate	117	54
	Postgraduate	74	34
	Others	14	6
Type of business	Micro	28	13
	Small	53	24
	Medium	137	63
Industry	Food and beverages	33	15
	Products that last, like electronics and heavy machinery	48	22
	Chemicals, pharmaceutical and plastics	57	26
	Merchandise involving textiles, leather, and apparel	41	19
	Other manufacturing	39	18

Source: Primary survey

Factor analysis:

A preliminary factor analysis was performed to ensure that selected scale items were loaded properly with a factor loading score of >0.5, and no cross-loading was observed. The Kaiser–Meyer–Olkin (KMO) value determines if a sample size is adequate for further study. A high value of KMO (0. 841) and small value of significance (<0.05) of the results of Bartlett's Sphericity Test suggest that factor analysis would be beneficial for our data. Principal Component Analysis (PCA) using Varimax Rotation Method Kaiser Normalization was applied to the 13 elements.Based on factor extraction criteria having Eigen values greater than 1, results into four factors, explaining total variance of 80.927%.

Table 2: Factor loadings of variables

Factor	Items	Item loadings
Business analytics	BA1: We have implemented data processing and analytics via cloud services.	.866
	BA2: Use of predictive analytics such marketing intelligence system, data mining	.864
	BA3: We've used open-source big data analytics software.	.856
Product innovation	PDi1: Many product lines are available from our company.	.818
	PDi2: According to market needs, we introduce specialized products.	.877
	PDi3: Our business expands into untapped niches through new product development (NPD).	.869
Process innovation	PCi1: At our organization, we use cutting-edge methods of real-time process control.	.900
	PCi2: Our business deals with the import of high-tech, programmable machinery.	.884
	PCi3: Our company innovates marketing methods	.875
Performance	P1: The percentage of the market that we control is growing.	.859
	P2: Our company has a very healthy rate of return on sales.	.849
	P3: An increased level of customer loyalty has been established at our company.	.858
	P4: Our firm's administrative expenses have been reduced	.886

Table 3: Cronbach's alpha, Mean, Std. deviation and Correlation of the variables

	Business analytics	Innovation	Performance
Reliability (Alpha value)	.890	.781	.927
Mean	3.5841	3.3593	3.4725
Standard deviation	.85348	.64348	.61644
Business analytics	1	.248**	.499**
Innovation	.248**	1	.384**
Performance	.499**	.384**	1

Note: ** indicates Correlation is significant at the 0.01 level (2-tailed)

The descriptive statistics table of perception of SMEs owner/mangers towards Business analytics is highest as mean value (M=3.58) above neutral value 3. The mean values of innovation (M=3.36) and performance (M=3.47) are near to agreement degree it indicate respondents are agreeing on involvement of analytics, innovation and performance of their firm.

The above table also shows Correlation of the independent variables with each other and dependent variables. The correlation coefficients of all relationships with performance are positive and significant highlighting that increase in innovation and business analytics leads to improvement in performance of SMEs.

Finally, table 3 shows the Cronbach's alpha value, which was used to assess the reliability of the research variables. According to the threshold requirements, the alpha value for all four components is greater than 0.7, verifying the data's reliability.

4.2 Reliability and Validity using CFA:

CFA was performed by considering all the four factors as exogenous constructs. The fit indices of the measurement model are $\chi2$ = 506.614, CMIN/df =1.262; p =0.015, RMSEA = 0.026, CFI = 0.985, NFI = 0.930 and AGFI = 0.898. This shows that the proposed scale fits for measurement (Hair et al., 2010).

To determine whether indicators of each latent variable conceptually explain the constructs, the researcher examined Convergent validity using average variance extracted (AVE). According to the threshold value, all the AVEs are more than 0.5, indicating that the constructs can explain 50% of the variance in their items. The four reflectively measured components have composite reliabilities ranging from 0.709 to 0.854, above the minimum threshold of 0.70. (Hu & Bentler, 1999).

Discriminate validity shows how well one construct may be separated from another with similar or dissimilar value profiles (Sarstedt et al. 2014). Hair et al. (2010) state that the maximum shared variance (MSV) must be less than the average variance estimate (AVE) to meet the discriminant validity condition.

Table 4: Validity and reliability of research constructs

	CR	**AVE**	**MSV**
Performance	0.928	0.762	0.304
Business analytics	0.890	0.731	0.304
Innovation	0.891	0.732	0.214

4.3 Hypothesis testing using Structural Equation Modelling:

The study runs SEM analysis using maximum likelihood method to test the causal relationship between research constructs. The study assessed innovation as a second-order factor constituted of product and process innovations, business analytics as an independent variable (exogenous), and firm performance as a dependent variable (endogenous). The criteria for accepting or rejecting a study hypothesis are based on a critical ratio value of 1.96 and a p value less than 0.05 at the 5% level of significance.

Table 5 displays the findings of the path analysis and hypothesis testing. All significant relationships are represented by a standardized path coefficient and associated p-value. The standardized path coefficient is calculated using Table 5 and Figure 3. (β) of business analytics to innovation is positive and significant as β =0.455 with p=0.000. Since p value <0.05

and CR (3.826) >1.96, thus hypothesis H1 accepted.

The impact of business analytics on performance of SMEs is positive and significant having β = 0.314, CR = 2.647and p =0.008 ($p < 0.05$), provided sufficient evidence to accept hypothesis H2. Similarly, performance of SMEs positively influenced by innovation with β =0.521. p= 0.009. This relation is significant as p value less than 0.05, therefore hypothesis H3 was supported from this finding.

The findings also revealed that influence of innovation is more on performance compared to business analytics as standardized regression value is higher for innovation.

The coefficient of determination (R^2) value is 0.207, for innovation inferred 20.7% of variation in attainment is explained by retention. The two predictors of performance, i.e., business analytics and innovation explained 52% of the total variance in SMEs' performance.

The fit indices of the measurement model are CMIN/df =2.161; , RMSEA = 0.026, CFI = 0.989, NFI = 0.958 and AGFI = 0.954. The results indicate that the structure model fits prediction and interpretation.

Figure 2: Casual model

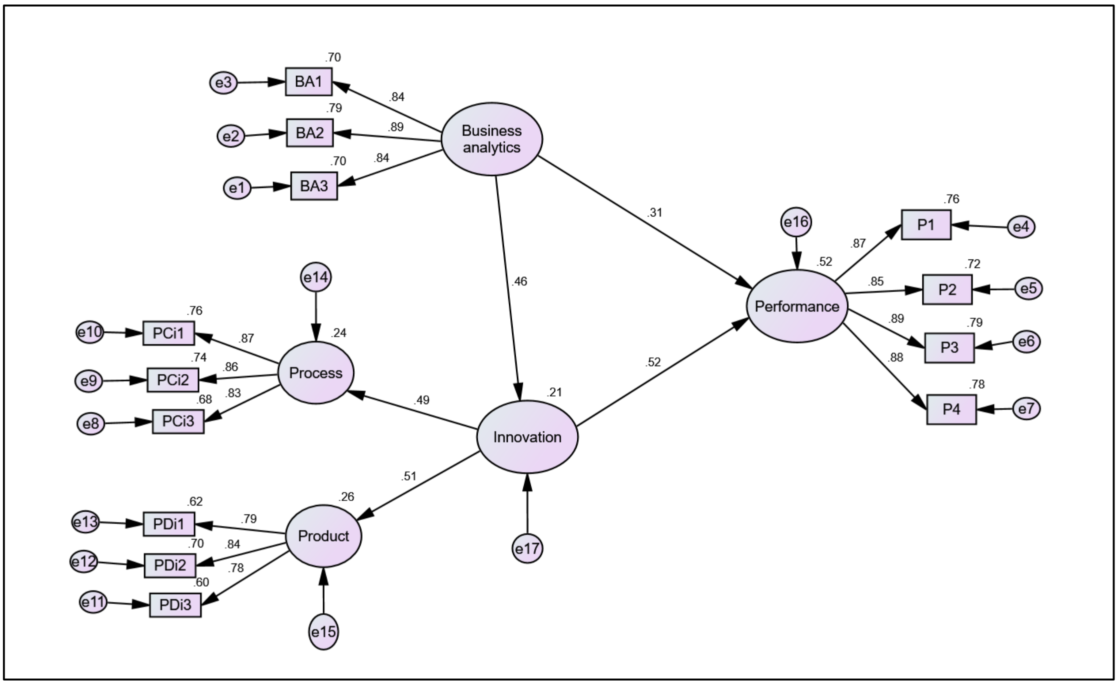

Table 5: Path coefficients of the Structural model

Hypo-theses	Outcome variables		Causal Variables	SE.	CR.	P	Path coefficient	Result
H1	Innovation	←	Business analytics	.061	3.826	***	.455	Accepted
H2	Performance	←	Business analytics	.094	2.647	.008	.314	Accepted
H3	Performance	←	Innovation	.313	2.597	.009	.521	Accepted

*Note: SE; Standard error, CR; Critical ratio, Path coefficient: Standardized regression weights and p: probability of significance. *** indicates p<0.000.*

Table 6: Overall Model Fit

Indices	Recommended criteria	Model values
Chi square ($\chi 2$)	pval>0.05	0.064
Normed chi square ($\chi 2$/DF)	$1<\chi 2/df<3$	2.161
Goodness-of-fit index (GFI)	>0.90	0.967
Adjusted GFI (AGFI)	>0.80	0.954
Comparative fit index (CFI)	>0.95	0.989
Root mean square error of approximation (RMSEA)	<0.05 good fit <0.08 acceptable fit	0.026
Tucker-Lewis index (TLI)	0<TLI<1	0.925

(Source: Researcher's calculation based on primary survey). Threshold criteria suggested by Hair et al., (2010) study.

Discussion and Implications:

The current study has explored the effects of business analytics and innovation on the performance of select SMEs in Mumbai. The findings of the study are elaborated below:

The results of research confirmed that business analytics are important predictor of innovation and performance of SMEs. The findings proved that adoption of business analytics in the form of data driven technologies, intelligence system, data mining or advance analytics methods improves a firm's ability to sense and respond to opportunities in the market and also helps organization to be innovative in their product and process.

The present study explored the positive and significant influence of innovation on the performance of SMEs. This finding is aligned with the findings of the study by Atalay et al., (2013) and Kijkasiwat & Phuensane (2020) meaning that small and medium-sized enterprises (SMEs) may use innovation to boost their performance and raise their likelihood of survival.

The results also revealed that product and process are important determinants of innovation. For current study the strength of product innovation is more compared to process innovation, those are in line with previous research (Kijkasiwat & Phuensane (2020). SMEs embracing innovation in their products and process will survive in a competitive world and perform better. It is essential to have both internal and external R&D, product modification in accordance with market requirements, and the development of staff skills in order to generate product innovation. (Pereir and João Leitão. 2016). The process innovation is driven by use of latest technology or re-engineering in SMEs.

Managerial Implications:

Based on research findings, it is recommended that involvement of business analytics tools by firm during production and marketing of products is very important aspect to consider for success the organization. It is advisable for the managers to give attention to business analytics tools in organization as it can lead to overall innovation in firm.

The importance of business analytics in the creation of new products and services is ubiquitous. Managers rely on data analysts to build products and strategies across the board, from making internal organisational changes to promoting those changes. If the future lies in innovation, then data analytics is the tool that any business can use to herald in that era.

Limitations & Future Scope

The current research collects data from SMEs present in Mumbai. This study can be extended to other regions of county. Secondly study has selected only two predictors of performance: business analytics and innovation and for measuring innovation also only product and process innovations are taken. The study concludes the results based on cross-sectional data, future research can be performed using pre and post impact of business analytics on success of SMEs by considering moderator and mediator variables. issues that may affect results. Instead of online surveys, one can go for personal interviews to get accurate results.

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