BUSINESS ANALYTICS MATURITY FRAMEWORK FOR INDIAN FIRMS

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ABSTRACT

In the digital era, data is the new fuel, and analytics is the engine leading Organisations to be more competitive. A relatively new phenomenon, the Global Intelligent Enterprise, is increasingly on the agenda of many Organisations. These enterprises are built completely on the fundamentals of data and analytics. The literature demonstrates that the benefits of being analytically competitive are widespread and impactful across many Organisational functions, such as finance, marketing and operations. This is also true for Indian enterprises.

The above can only be accomplished, however, if an Organisation has the correct level of capabilities in adopting and executing analytics initiatives. Previous research on Business Analytics (BA) maturity models seems to have been adapted from the traditional Capability Maturity Model (CMM) for software that is mostly qualitative and points directionally towards the factors driving BA capability in a firm. These factors are Leadership, Information Technology, Human Capital and Organisation. More recent and upcoming literature reveals that these models may need to be updated with additional factors, given the increased scope of the previously understood analytics landscape and the changing business environment.

There is also very little or almost no literature currently available on the factors driving BA maturity for Indian enterprises. This study aims to address this lack by identifying the variables driving BA maturity in Indian enterprises and build a maturity framework that is referred to herein as the Business Analytics Maturity Framework for Indian Enterprises (BAMFIE).

The study empirically indicates that while Leadership, Information Technology, Human Capital and Organisation which are global variables have a strong influence on building analytics maturity, a new variable referred to as 'Analytics Catalyst', not only significantly influences analytics maturity but also has the highest impact on business outcomes (value) for Indian enterprises.

Keywords: Business Analytics Maturity, Business Analytics, Maturity Models.

INTRODUCTION

Digital technologies have evolved to encompass the utilisation of data capabilities to guide informed decision-making in businesses (Vial, 2019; Huang, 2018). As asserted by Thomas Davenport (2018), data analytics integrates the access of data, with digital technologies, to influence business performance, and is also termed as business analytics. Business analytics is further defined as the business technique in which the data are effectively collected, stored, analysed, and interpreted, which can be used for business decisions. Business managers further leverage business analytics to take different analyses, including predictive, descriptive, prescriptive and diagnostic analysis (Ariyarathna & Surrey, 2019), and even add to the competitive advantage of the organisation (Whitelock, 2018). The Indian business landscape has been evolving over the last decades, as the Indian analytics industry is experiencing double-digit growth (Bhatia, 2019). It is further predicted that the business analytics industry in India will grow to double by 2025.

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Organisations also reap several benefits through business data analytics, including refining business processes, supporting business initiatives, enabling innovation, improving supply chain performance, understanding consumer behaviour, and forecasting market trends (Grover et al., 2018; Ramakrishnan, Jones & Sidorova, 2012; Viaene & Van den Bunder, 2011). Along similar lines, the study by Xavier, Srinivasan and Thamizhvanan (2011) and Srivastava & Gopalakrishnan (2015) postulated that Indian enterprises can benefit from using business analytics, by improving decision quality, effectively aligning the firm's resources to business strategy, enhancing competitiveness, understanding customer needs and enhancing financial performance.

Statistics show that the value of the global analytics industry is at $17 billion, out of which, 33% is accounted by India (Xavier et al., 2011). It is further found that in 2020, the revenue generated by the Indian analytics industry stood at $35.9 billion, which is expected to grow by 30% by the year 2025 (Deoras, 2020). Although the Indian business landscape is embracing and growing with digitalisation and utilising data capabilities, with digital payments, digital identity, open data platforms, artificial intelligence and other such infrastructure developments (Prakash, Thangaraj & Rajesh, 2022; Biswas & Ashish, 2022; Mir et al., 2020), there are numerous challenges in exploiting these capabilities towards business analytics. There is a dire need to understand the key capabilities that help establish the analytics maturity of Indian firms. Thus, the study aims to explore and test the key capabilities that can help assess the analytical maturity of Indian business firms.

Related Works

Business analytics is defined as the process of improving operational efficiency and decision-making by putting data to effective use, through information technology, quantitative modelling, and mathematical and computational-based models (Davenport & Harris, 2007). Boyd (2012) further contends that business analytics transforms data into managerial insights, facilitating decision-making.

Several academicians and researchers have further identified many benefits of leveraging business analytics in managerial decision-making. For instance, Chen, Chiang, and Storey (2012) and Mikalef et al. (2019) provide that big data and business analytics help the organisational achieve an edge over the competitors, and earn enhanced business performance. Business analytics also aid organisations in terms of better innovative outcomes (Lehrer et al., 2018), higher agility (Ashrafi et al., 2019), turning data into actionable insights (Vidgen, Shaw, & Grant, 2017), higher business performance (Whitelock, 2018; Gupta & George, 2016), and resolve business problems and improved decision-making capabilities (Golfarelli et al., 2012; Gavin, 2019).

To reap these benefits, businesses must identify different data capabilities and integrate them into the business strategy, to build the business analytical maturity model. The study by LaValle et al. (2011) identifies that the benefits of business analytics can be realised by businesses by having the right data and business capabilities. Chuah & Wong (2011) further state that more than 150 versions of capabilities and frameworks are currently been used to establish business analytics initiatives. These maturity models help assess the maturity levels within the organisations, which depicts the analytical adoption capabilities, thereby translating into better organisational outcomes. According to Röglinger, Pöppelbuß & Becker (2012), maturity models are vital for an organisation since they depict the current analytical status, as well as the areas that need improvement, to gain operational and financial benefits. The maturity models measure the organisational capabilities that are utilised to transform and develop the required organisational competencies to initiate the change process for meeting the desired outcomes (Wendler, 2012). The importance of maturity models is

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further recognised by the fact that they design the future vision for organisational growth, facilitate benchmarking parameters for comparing performance between other firms in the industry, and establish objectives for future line of action (Felch, Asdecker & Sucky, 2019; Leino et al., 2017).

Having learnt the importance and advantages associated with maturity models and their application to the organisation, it is vital to understand and select the best maturity model for the industry, and firm. The literature is flooded with many maturity models, making it difficult for the organisation to select the best one that suits the needs of the organisation. Some of the famous maturity models that are majorly implemented by organisations worldwide are the Delta model (Davenport et al., 2010), the Data Analytics Maturity Model for Associations, the BLAST Analytics Maturity Framework, the Analytics Maturity Quotient Framework (Król & Zdonek, 2020), the Business Analytics Capability Framework (Cosic, Shanks & Maynard, 2015), the Analytic Processes Maturity Model (Grossman, 2018), the Web Analytics Maturity Model (Hamel, 2009), the HP Business Intelligence Maturity Model (Hewlett-Packard, 2007), the TDWI Business Intelligence maturity model (TDWI, 2009), the Gartner Business Intelligence Maturity Model, the Enterprise Business Intelligence Maturity Model (Chuah and Wong, 2012), and many others. However, it is difficult to select the optimal model to gauge the analytical maturity of the organisations, thereby, requiring further research.

Despite so many maturity models that have been identified in the literature, most of these models are generic and cannot be implemented as it is in different countries and industries. Banerjee & Banerjee (2017) further reveals that very few studies can be implemented in emerging nations, like India. Thus, one needs to develop a novel maturity model that can be readily applied to gauging the maturity of Indian firms.

After studying different maturity models, it has been found that all the maturity models comprise different capabilities. The study by Schmidt, van Dierendonck, and Weber (2023) shows that leadership is an essential driver of big data analytics as organisational leaders support and provide the climate for analytics initiatives. Grover et al. (2018) further contend that leadership is a core element of business analytics, and implementing it enhances the functional and strategic advantages of the organisation. Even the study by Caputo et al. (2019) asserts that big data is vital in influencing the behaviours and attitudes of leaders and helps in effectively utilising business data analytics. Leadership is also vital since the leaders from all the functional departments of the organisation deal with big data, and guide informed decision-making (Ciarli et al., 2021). The importance of leadership in business data analytics is also vital since the implementation of data analysis requires new leadership skills in adopting and adapting advanced technologies (Mikalef et al., 2021). Thus, from the existing literature, it can be asserted that leadership and managerial skills represent one of the core drivers for business data analytics, helpful in assessing the analytical maturity of the organisations.

Information technology is another vital capability that drives the analytical maturity in organisations. Sahay (2016) provides that studying data and driving meaning out of it helps address business problems, relevant to the analytical maturity of organisations. Data management facilitates business analytics by integrating and managing quality data (Davenport & Harris, 2007). Seddon et al. (2012) further reveal that organisations integrate information technology tools with their niche functionality, to complement data requirements and fulfil business analytical endeavours. Along these lines, Myerson (2002) points out that business analytical capabilities within the organisation are achieved by integrating the data tools with the organisational operating system. Moreover, Lavelle et al. (2011) suggest that the agenda of big data analytics spans from roadmaps that integrate information technology information with business resources and analytics. Thus, it can be derived that information

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technological tools and infrastructure represent another core element for assessing the analytical maturity of the firms.

Yet another factor recognised in the literature, and important for driving business analytics is human capital and talent. The study by Ransbotham et al. (2015) concludes that organisations that innovate with analytical capabilities can achieve a competitive edge, by exploiting resources through the right talent. As suggested by McAfee and Brynjolfsson (2012), the right set of human skills is needed to analyse and drive insights from the data. Human skills comprise technological, business and management skills, which are needed to not only drive analytical insights but also translate and communicate its value to the organisation (Cosic et al., 2015). Analytical skills are further important for implementing analytical insights, and require the human competencies for interpreting analytical outcomes to the organisational decision-makers (Davenport, 2005). The research by Akter et al. (2019) also concludes that talent capability within an organisation mediates the relation between information technology and the performance of the firm, thereby emphasising the importance of human capital in assessing analytical maturity. Hence, based on these literature excerpts, human capital is the third important capability driving business analytical maturity in organisations.

The analytical maturity framework also comprises the organisational factors that support the analytical initiatives in a firm. The study by AT Kearney (2019) considers organisation as the most important factor for driving business analytics and suggests that it leads to cross-functional data-driven decision-making, and embeds analytical capabilities within the organisational processes. A study by Foshay et al. (2015) suggests that analytical maturity requires robust processes and governance, to enable business analytical capabilities within the firms. Barrett & Barton (2006) also emphasise organisational governance as an important factor in successful analytical projects, since poor prioritisation, and mismatch in aligning between analytical initiatives and business requirements, cause backlog and failure in analytics implementation. Organisation and governance are also essential in putting a firm's resources (including data and analytical) to best use and manage any resistance to change (Williams & Williams, 2007). According to Sharma et al. (2010), structured and well-managed units of people and systems support business analytics. Thus, in light of the existing literature, it can be asserted that organisation represent an important driver for analytical maturity, and be considered as a capability for the maturity model.

Next, the analytics catalyst is another vital factor that contributes to assessing and measuring the analytical maturity of any firm. The study by Saravanabhavan, Riaz and Das (2022) unveils the importance of analyst maturity catalyst, along with other generic factors, in driving analytics maturity in Indian firms. Catalyst use cases are also considered important by Gartner (2023), which guide decision-making and combine predictive and prescriptive capabilities, vital for responding to dynamic business conditions. The importance of analytical use cases is also explained by Balasubramanian et al. (2017), who advocate that its implementations can enhance predictive capabilities. The study further states that to optimise the benefits, the added value and outcomes of implementing analytics should be predicted, and then the use cases be selected accordingly. Organisations taking the Use Cases approach can ensure a better machine learning perspective, by effectively listing the organisational problem (McKinsey & Company, 2016). This approach can help resolve multiple problems, including real-time optimisation, strategic optimisation, predictive analysis, predictive maintenance, and radical personalisation, discovery of new trends, forecasting and processing of unstructured data. Similarly, when the companies identify, size, prioritise and phase the relevant use cases, the managers can create an effective analytical strategy, with the potential to create organisational value (Chin et al., 2017). Apart from use cases, translators, who understand and apply data science to the business, also contribute to business analytics (Chin

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et al., 2017). Translators are imperative for analytical success as they enable organisations to derive real value from the analytical initiatives taken by the managers. They integrate the technical expertise of data engineers’ data scientists, and functional managers (Henke, Levine & McInnerney, 2018). These analytics translators even train the business managers to acquire requisite technical skills enabling them to translate business needs into data-oriented solutions (Brown et al, 2019). Another important analytical catalyst is advocacy or evangelisation. Flores (2016) asserts that data advocates help facilitate analytical maturity in the organisation, as they boost the data culture, and enhance the competitiveness and data-driven capability internationally. Similar findings are made by Germann et al. (2021), concluding that organisations implementing top management team advocacy can influence higher success rates in customer analytics. Thus, it can be asserted that analytics catalyst (comprising of use cases, translators, and advocacy) significantly contributes to the analytical maturity of the firms.

So far, the literature has identified the importance of analytical maturity and even investigated different variables that add to the analytical capability of the firms. The study now aims to study the applicability of these variables towards measuring the analytical maturity of Indian firms.

METHODOLOGY

The research makes use of a cross-sectional quantitative research strategy by sourcing primary information on the importance of key capabilities that help gauge the analytical maturity of Indian firms. The research instrument used to collect information is the survey questionnaire, which is circulated among the managers and professionals in the Indian analytics industry. The managers are selected from the ET500 companies as well as Large/ Medium size listed member companies from NASSCOM, who specialise in information services, business analytics and data sciences. The population for the survey consists of 500 and 800 companies listed on ET500 and NASSCOM, respectively. Using simple random sampling, the firms are selected, and the managers from the identified sample firm are selected using purposive sampling, such that the respondents possess relevant (at least 5 years) experience in the discipline of data analytics. All the surveys are filled using online media (Google Firms) to maximise the response rate in minimum time. A total of 324 respondents participated in the survey, and the collected data is analysed using ADANCO.

The survey instrument comprises three sections, such that the first section gauges information on the profile of the respondents (as given in Table 1). The majority of the respondents possess a vast work experience of more than 20 years, and they belong to different industry sizes, with the majority working in very large organisations. Also, they belong to different metropolitan cities in India and hold different senior-level organisational positions. Thus, it can be asserted that the respondents comprise of representative sample of the population, and their responses can be applied to the entire Indian analytical industry (Table 1).

Table 1
DEMOGRAPHIC PROFILE OF SURVEY RESPONDENTS

Location	
Ahmedabad	10
Bengaluru	137
Chandigarh	2
Chennai	32
Delhi NCR	55
Hyderabad	14

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Kochi	6
Kolkata	11
Mumbai	56
Work Experience	
0 – 5 years	40
11 – 15 years	51
16 – 20 years	78
20 + years	86
6 – 10 years	68
Organisational Role	
Associate Director	36
Managing Director	50
Senior Analyst Manager	34
General Manager	29
President/ CO/ CEO	23
Vice President	67
Group Leader	19
Senior Director	65
Organisational Size	
Large	62
Medium	25
Micro	8
Small	19
Very Large	209

Thereafter, the next sections of the instrument gauge the responses on the level of agreement on the five drivers of analytical maturity, namely leadership, information technology, human capital, organisation and analytics catalysts. The level of agreement has been gauged on a 5-point Likert scale, such that 5 denotes strongly agree, while 1 represents strongly disagree. Based on this, the conceptual model of the research is presented in Figure 1.

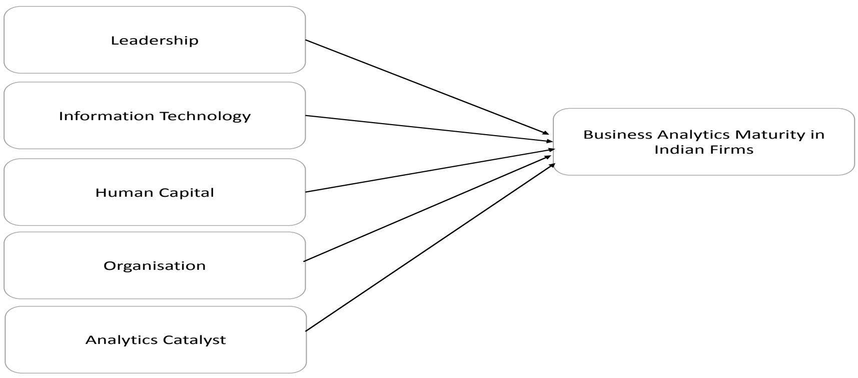

FIGURE 1
CONCEPTUAL FRAMEWORK FOR RESEARCH

The respondents have been communicated the purpose of the research, and their due consent was obtained for collecting the data, without infringing their privacy rights and meeting all ethical considerations.

RESULTS

Model Reliability and Validity

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Firstly, the reliability and validity of the proposed model using five drivers of analytical maturity of Indian firms are tested, namely leadership, information technology, human capital, organization and Analytics Catalyst (Table 2).

Table 2
RELIABILITY INDICES FOR FIVE DRIVERS OF ANALYTICS MATURITY

Construct	Dijkstra-Henseler's rho (ρ)	Jöreskog's rho (ρ)	Cronbach's alpha(α)
Leadership	0.82	0.88	0.82
Information Technology	0.81	0.88	0.79
Human Capital	0.82	0.89	0.82
Organization	0.77	0.87	0.77
Analytics Catalyst	0.77	0.87	0.76

Four out of five drivers of analytics maturity have a Dijkstra–Henseler's rho of more than 0.80, representing good reliability. All five factors have Joreskog's rho score of more than 0.80, showing high reliability. Finally, Cronbach's alpha (α) values for all constructs are more than 0.75, showing high reliability. Next, to find the Convergent Validity, the Average Variance Extracted (AVE) for all these five drivers of analytical maturity is computed (Table 3).

Table 3
CONVERGENT VALIDITY OF FIVE DRIVERS OF ANALYTICS MATURITY

Construct	Average variance extracted (AVE)
Leadership	0.644
Info Technology	0.706
Human Capital	0.738
Organization	0.687
Analytics Catalyst	0.680

All the five factors surpassed the threshold value for convergence (which is created than 0.5). Next, the Fornell-Larcher Criterion is performed to find the discriminant validity (Table 4).

Table 4
DISCRIMINANT VALIDITY

Construct	Leadership	Information Technology	Human Capital	Organisation	Analytics Catalyst
Leadership	0.644				
Info Technology	0.541	0.707			
Human Capital	0.616	0.593	0.738		
Organisation	0.564	0.586	0.492	0.687	
Analytics Catalyst	0.390	0.521	0.416	0.611	0.681

Discriminant validity exists since the main diagonal (AVE values) have the highest value for each row and column.

Structural Model

The structural model is developed (showing the path coefficients) and the different variables and their relationships are computed. The model is recursive u nature, with no causal loop and correlation between the residual values (Figure 2).

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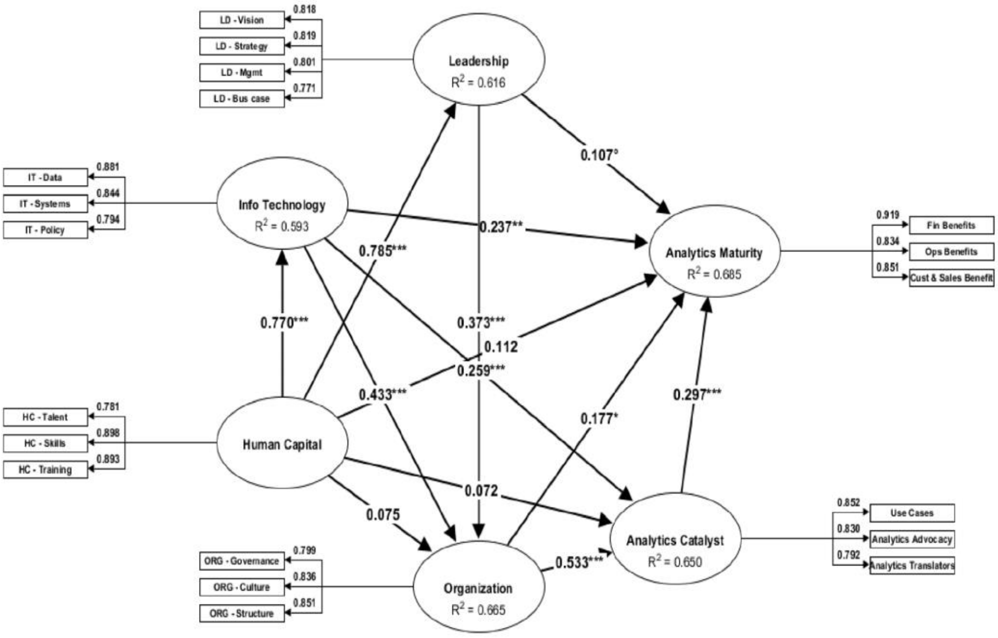

FIGURE 2
STRUCTURAL MODEL FOR RESEARCH

Relationship between variables

In this section, the path coefficients between different various variables are computed, to find their association with the analytical maturity of Indian firms.

Table 5
PATH COEFFICIENTS

Independent variable	Dependent variable				
	Leadership	Information Technology	Organization	Analyst Catalyst	Analyst Maturity
Leadership			0.3732		0.1071
Info Technology			0.4334	0.2587	0.2375
Human Capital	0.7849	0.7703	0.0749	0.0720	0.1117
Organization				0.5328	0.1774
Analytics Catalyst					0.2971

Table 5 shows the path coefficients between different variables. It can be found that all the path coefficients are directionally positive with their strength ranging between 0.07 to 0.78 for human capital to the organisation, and human capital to leadership, respectively.

A total of 13 hypotheses are tested, and the reliability of each of these hypotheses is tested against the recorded t-values of the variables. The direct effects are presented in Table 6 for testing these hypotheses. Moreover, the indirect effect inferences for different variables are found using the Sobel test (Table 6).

Table 6
DIRECT EFFECTS INFERENCE TABLE

Effect	Original coefficient	Standard bootstrap results					Percentile bootstrap quantiles			
		Mean value	Standard error	t-value	p-value (2-sided)	p-value (1-sided)	0.5 %	2.5 %	97.5 %	99.5 %
LD -> ORG	0.373	0.373	0.067	5.634	0.000	0.000	0.192	0.241	0.499	0.534

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Table 6 DIRECT EFFECTS INFERENCE TABLE										
Effect	**Original coefficient**	**Standard bootstrap results**					**Percentile bootstrap quantiles**			
		Mean value	**Standard error**	**t-value**	**p-value (2-sided)**	**p-value (1-sided)**	0.5 %	2.5 %	97.5 %	99.5 %
LD -> AM	0.107	0.111	0.061	1.752	0.08	0.039	-0.038	-0.007	0.237	0.277
IT ->ORG	0.433	0.431	0.051	8.422	0.000	0.000	0.273	0.321	0.522	0.549
IT -> AC	0.258	0.26	0.069	3.721	0.000	0.000	0.089	0.131	0.400	0.450
IT -> AM	0.237	0.234	0.081	2.948	0.003	0.002	0.024	0.071	0.385	0.432
HC -> LD	0.759	0.783	0.034	22.762	0.000	0.000	0.678	0.707	0.842	0.860
HC -> IT	0.770	0.767	0.041	18.552	0.000	0.000	0.638	0.678	0.838	0.856
HC -> ORG	0.075	0.076	0.080	0.929	0.352	0.176	-0.116	-0.076	0.242	0.287
HC -> AC	0.072	0.069	0.062	1.167	0.245	0.122	-0.095	-0.054	0.187	0.221
HC -> AM	0.112	0.112	0.091	1.232	0.218	0.109	-0.112	-0.063	0.293	0.361
ORG -> AC	0.533	0.531	0.047	11.427	0.000	0.000	0.41	0.441	0.622	0.652
ORG -> AM	0.177	0.189	0.084	2.11	0.035	0.017	-0.029	0.024	0.352	0.419
AC -> AM	0.297	0.296	0.0717	4.141	0.000	0.000	0.108	0.153	0.435	0.478

The direct effects inference suggests the presence of a significant relationship between leadership and analytical maturity, with a t-value of 1.752. The effect is positive, since the path coefficient, $\beta_{\text{L-AM}}$ = 0.102, suggesting that leadership is a predictor of analytical maturity in Indian firms. Also, when the indirect path coefficient effect for leadership and analytical maturity, is tested by mediating the relationship with the organisation. The indirect inference between these variables [$\beta_{\text{L-O}}$ = 0.373 (t value of 5.367) and $\beta_{\text{O-AM}}$ = 0.177 (t value of 2.11)], suggests that $\beta_{\text{L-MA through O}}$ = 0.373 x 0.177 = 0.066, leadership is mediated by information technology for the implementation and adoption of analytical maturity within Indian firms.

There is a significant relationship between information technology and analytical maturity, with a t-value of 2.947, showing a positive effect, given by the path coefficient of $\beta_{\text{IT-MA}}$ = 0.237. The relationship between information technology and analytical maturity is further mediated by the organisation and analytic catalyst variables, given by [$\beta_{\text{IT-O}}$ = 0.433 (t value of 8.422) and $\beta_{\text{O-AM}}$ = 0.177 (t value of 2.11) for organisation and [$\beta_{\text{IT-AC}}$ = 0.259 (t value of 3.721) and $\beta_{\text{AC-AM}}$ = 0.297 (t value of 4.141), and finally, $\beta_{\text{IT-MA through HC}}$ = 0.259 x 0.297 = 0.077] for analytic catalyst, and finally, $\beta_{\text{IT-MA through O}}$ = 0.433 x 0.177 = 0.077]. Thus, it shows that information technology contributes, both directly and indirectly through organisation and analytic catalysts, to enhance the analytical maturity of Indian firms.

Next, it is found that there does not exist any direct positive relationship between human capital and analytical maturity, given by $\beta_{\text{HC-MA}}$ = 0.112 and t-value of 1.232), since the level of significance is t < 1.65. Similarly, when the relationship between these two

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variables is checked for medication by the organisation and analytic catalyst variable, they are also not significant, given by-

Organisation: [$\beta_{\text{HC-O}}$ = 0.075 (t value of 0.929) and $\beta_{\text{O-AM}}$ = 0.177 (t value of 2.111), and finally, $\beta_{\text{HC-MA through O}}$ = 0.075 x 0.177 = 0.0133], it is rejected as t = 0.851 < 1.96, p = 0.394 > 0.05).

Analytic catalyst: $\beta_{\text{HC-AC}}$ = 0.072 (t value of 1.163) and $\beta_{\text{AC-AM}}$ = 0.297 (t value of 4.141), and finally, $\beta_{\text{HC-MA through AC}}$ = 0.072 x 0.297 = 0.021], it is rejected as t = 1.119 < 1.96, p = 0.263 > 0.05.

However, when the mediation between human capital and analytic maturity is checked for the leadership and information technology variables, the relationship comes to be significant-

Leadership- [$\beta_{\text{HC-L}}$ = 0.785 (t value of 22.762) and $\beta_{\text{L-AM}}$ = 0.107 (t value of 1.752), and finally, $\beta_{\text{HC-MA through L}}$ = 0.785 x 0.107 = 0.085]. This association is significant since t = 1.746 < 1.96, p = 0.081 > 0.05.

I nformation Technology- [$\beta_{\text{HC-IT}}$ = 0.77 (t value of 18.55) and $\beta_{\text{IT-AM}}$ = 0.237 (t value of 2.945), and finally, $\beta_{\text{HC-MA through IT}}$ = 0.77 x 0.237 = 0.183], is significant since t = 2.911 > 1.96, p = 0.004 < 0.05.

Thus, human capital leads to the analytical maturity of Indian firms, only in the presence of strong leadership.

Next, the direct effects inference further shows the existence of a significant relationship between the organisation and analytical maturity (t-value of 2.114, $\beta_{\text{IT-MA}}$ = 0.1774). This relationship is also found to be significant when mediated by the variable analytical maturity [$\beta_{\text{O-AC}}$ = 0.533 (t value of 11.427) and $\beta_{\text{AC-AM}}$ = 0.297 (t value of 4.141), and finally, $\beta_{\text{O-MA through AC}}$ = 0.533 x 0.297 = 0.158]. Both these relationships are significant at a 1% significance level (t > 1.96).

Finally, the direct inference test shows that analytics maturity significantly contributes towards the analytical maturity of Indian firms [t value = 4.411 > 1.96, $\beta_{\text{AC-MA}}$ = 0.297].

DISCUSSION

The paper provides vital findings and implications for the managers in Indian firms since they stated as well as tested the key variables that impact the analytical maturity in the organisations. In simple words, by working on these variables, the firms can enhance the adoption, implementation and underlying benefits from the analytical maturity.

It is found that leadership plays a pivotal role in enhancing analytical maturity, both directly and indirectly through organisation. Supported by Raber, Winter and Wortmann (2012) and Lauren and Thorlund (2010), it is found that leaders and managers in leadership positions contribute towards business analytics.

It is further found that information technology, both directly and when mediated through organisation and analytics catalysts, also positively impacts the analytical maturity in Indian firms. Verhoef, Kooge and Walk (2016) and Lavelle et al. (2010) support these findings, and conclude that data and information technological tools are key strengths in enhancing the analytical capability of firms.

Human capital is the only variable that does not directly influence the analytical maturity in Indian firms, but the relationship is significant only when mediated by leadership and information technology. It implies that human talent and skills can only drive analytical capabilities in firms when they are provided with the right resources. In this respect, even Akter et al. (2019) suggest that human capital mediates between information technology and enhanced performance of the firms. McAfee & Brynjolfsson (2012) also contend that when

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Human Resources are integrated with data and technology, they have the potential to scale up the analytical capabilities in business.

The organisation is another key driver of analytical maturity in Indian firms, both directly and through analyst catalysts. The study by AT Kearney supports this finding and suggests that the organisational structures, systems and processes are instrumental in facilitating analytical capabilities in firms.

Finally, analytics catalysts have evolved as the most significant driver for analytical maturity in Indian firms. This factor is not generally directly involved in any of the existing analytical maturity models and is a core contribution to this study.

CONCLUSION

In conclusion, the paper provides significant theoretical and managerial implications, and motivates the managers to enhance these drivers to build analytical maturity in firms. However, this study is confined to the quantitative data collected from the managers of Indian firms, which may not be representative of firms outside India. Also, the findings are made for the entire business sector, without providing for weights of different weights for different industry sizes. Thus, further research in this subject will help in substantiating the results and generalising the findings to global businesses.

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