iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL
FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 Issue: XII Month of publication: December 2021

DOI: https://doi.org/10.22214/ijraset.2021.39323

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue XII Dec 2021- Available at www.ijraset.com

A Study of Analysis and Trends for Embedded Business Intelligence Market

Tanmayee Tushar Parbat[1], Honey Jain[2], Rohan Benhal[3], Dr. Lalit Kulkarni[4]
[1, 2]B.E IT, Pune
[3]BBA IT, Pune
[4]Guide, Dr. Vishwanath Karad MIT World Peace University, Pune, Maharashtra, India

Abstract: Self-service Business Intelligence (SSBI) is an emerging topic for many companies. Casual users should be enabled to independently build their own analyses and reports. This accelerates and simplifies the decision-making processes. Although recent studies began to discuss parts of a self-service environment, none of these present a comprehensive architecture. Following a design science research approach, this study proposes a new self-service oriented BI architecture in order to address this gap. Starting from an in-depth literature review, an initial model was developed and improved by qualitative data analysis from interviews with 18 BI and IT specialists form companies across different industries. The proposed architecture model demonstrates the interaction between introduced self-service elements with each other and with traditional BI components. For example, we look at the integration of collaboration rooms and a self-learning knowledge database that aims to be a source for a report recommender.
Keywords: Business Intelligence, Big Data, Architecture, Self-Service, Analytics

I. INTRODUCTION

Among the 33 strategic business intelligence topics we currently study, embedded BI technology ranks 12th (fig. 1). This finding (identical to 2016), places embedded BI near the top third of all technologies and initiatives strategic to business intelligence, behind the most mainstream BI practices (reporting, dashboards, and end-user self-service) but ahead of other widely discussed initiatives including cloud, big data, and Internet of Things. This reflects continuing high demand for embedded technologies and an anticipation of future deepening business intelligence/analytics penetration.

Figure 1: Technologies and initiatives strategic to business intelligence

Across five years of study, the overall importance of embedded BI generally increases over time, either in perceived measures or actual usage (fig. 2). In 2017, "critical" scores slip from 28 percent to 24 percent, while most other measures improve slightly. Less than 1 percent say embedded BI is "not important," an all-time low for our study. As we note in fig. 1, adjusted mean importance by technologies ranked did not change. We continue to observe that embedded BI is very much in the mix of important strategic initiatives at organizations.

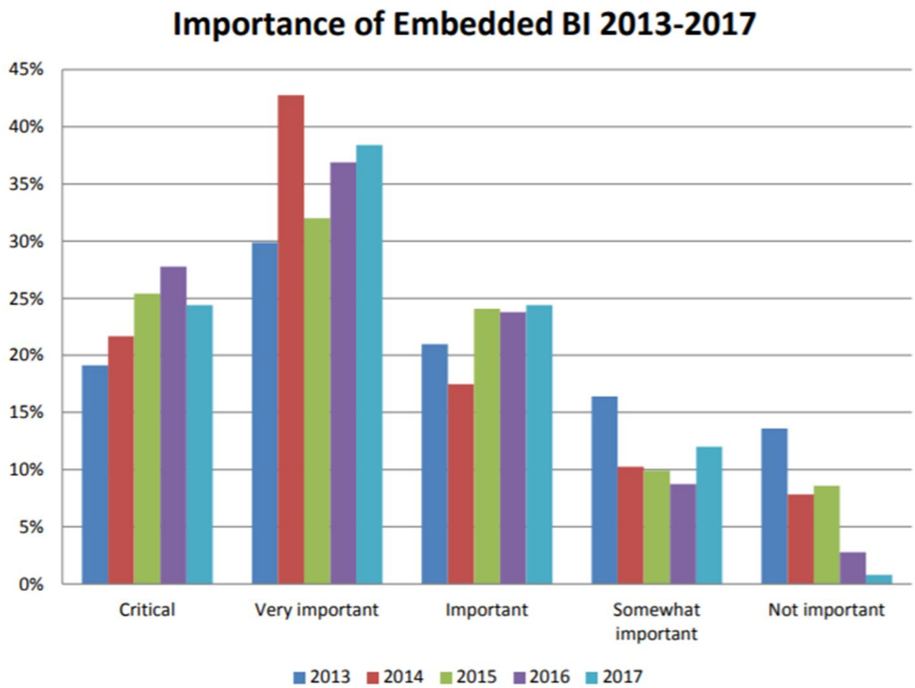


Figure 2: Importance of embedded BI 2013-2017

The perceived importance of embedded BI is highest in Asia Pacific, followed by North America, Latin America and EMEA (fig.3). Perceived "critical" importance is more than twice as high in Asia Pacific compared to North America and four times higher than in other regions. Mean levels of perceived importance across all geographies are less variable and fall in a range of 3.5 to 4.1, between "important" and "very important."

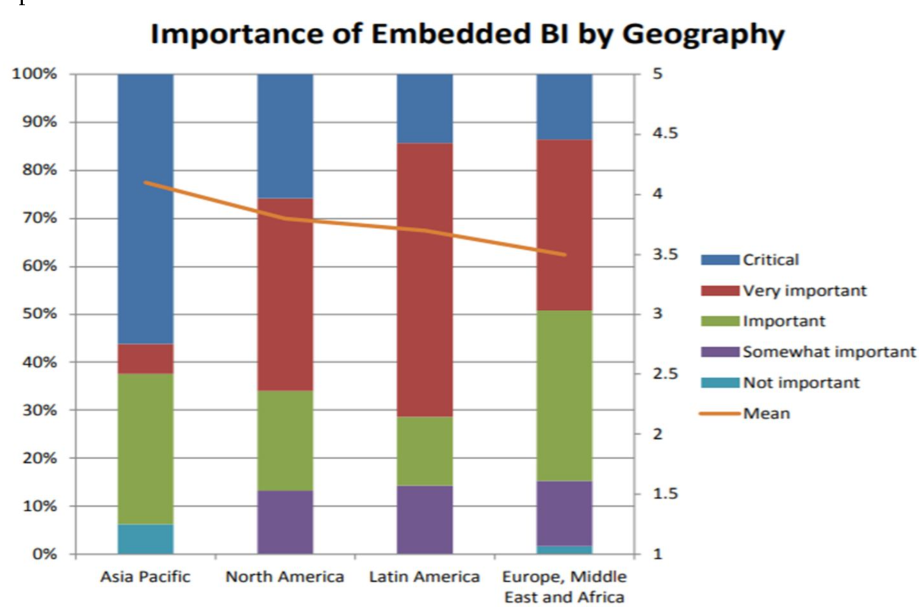


Figure 3: Importance of embedded BI by geography

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue XII Dec 2021- Available at www.ijraset.com

II. THE CHANGING DIMENSIONS AND EVOLUTION OF ANALYTICS

A. *The Rise of Business Analytics*

Analytics is “the science of analysis.” A practical definition of analytics is how a business arrives at an optimal or realistic decision based on existing data. The Institute for Operations Research and the Management Sciences defines analytics as “a set of technologies, processes, and techniques that use data to understand and analyze business performance and guide decision making.” (Koushik, 2011). Analytics have been used in business since the era of Scientific Management that was initiated by Frederick Taylor in the late 19th century. For example, Henry Ford measured pacing of the assembly line, thusrevolutionizing manufacturing. Today, businesses of allsizes use analytics(Strickland, 2015). Thomas Davenport identified three eras in the use of analytics—Analytics 1.0, 2.0 and 3.0. They are also referred to as before big data and after big data. These eras are described below and summarized in Figure 4 based on writings of Davenport and Phillips (Davenport, 2013; Phillips, 2014).

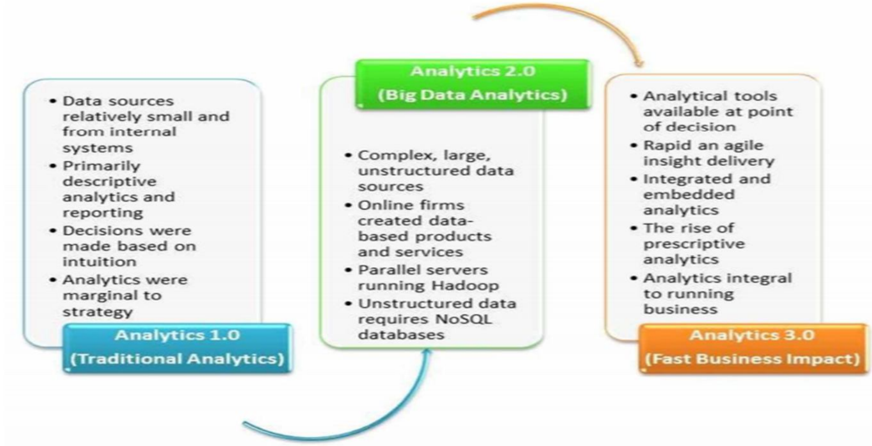


Figure 4: The evolution of business analytics

In the mid-1950s, descriptive analytics and reporting activity were used for internal data analysis. The purpose was for internal decision support and to gain an objective, deep understanding of important business phenomena. Spreadsheets and other tools were used that could produce and capture a larger quantity of information and discern patterns in it far more quickly than the human mind ever could. Data sources were relatively small and structured, and mostly from internal systems. Data about production processes, sales, customer interactions and more were recorded, aggregated, and analyzed. Analysts spent a good deal of their time on data preparation and relatively little time on the analysis itself. Analytics pricked up in the late 1960s when computers were used in decision support systems. Since then, analytics have evolved with the development of a wide variety of hardware and software tools and applications. Information systems were at first custom-built by large companies and later were commercialized by several vendors in generic forms. This era is characterized by the enterprise data warehouse, used to capture information, and of business intelligence software, used to query and report it (Philips, 2014).

B. *Benefits of Using Analytics*

Most people rely on their gut instinct when faced with important decisions. Human biases and heuristics are predominant in decision making. Human error and physical limitations often lead to mistakes. Henke et al. (2016) claimed that analytics overcomes limitations and improves four aspects of decision making:

1) *Speed:* When real time responses are needed, analytics can react in an instant. Analytics visualization tools can deliver results at the speed-of-thought and it is well suited to working with a very large volume of data coming from a variety of sources;
2) *Accuracy:* Provided with the right data, predictive models are able to provide a cleaner view of the future. They can make forecasts and predictions more accurate and precise;
3) *Reliability and Consistency:* Machines and analytics are reliable and predictable. Analytics tools can seamlessly connect with a wide range of structured, semi-structured, and unstructured traditional data sources enabling users to gain insight in a reliable and consistent way;
4) *Transparency:* Machines and algorithms improve transparency which allows for decisions to be reviewed and improved upon in the future.

C. Today's Landscape for Analytics

In today's business environment, analytics is increasingly strategic and is now central to most business roles. A recent study by Gartner, published in 2015, identified a shift in focus from IT-led reporting to business-led self-service analytics. Traditional reporting-based BI platforms are not designed to handle the exponential growth in terms of the sources, volume, and complexity of data. The traditional platforms enforce strict data and report governance, only allowing access by specialized reporting groups. In contrast, the modern approach views data governance as an important step in creating self-service analytics. Traditional BI platforms are being augmented with more agile solutions. Where traditional systems could take months to implement, the modern approach takes as little as a few hours. Latency is no longer tolerated. The advances in the Internet have resulted in greater expectations and less patience. Modern BI platforms support organizational needs for greater accessibility, agility, and analytical insight from a diverse range of data sources. Every business process is an analytics process, and every business user is an analytics user. To meet the time-to-insight demands of today's competitive business environment, many organizations changed the traditional BI model and end-user requirements. The modern BI platform aims to democratize analytics with self-service capabilities. It is characterized by agility, flexibility, and ease of use (Table 1) (Gartner Report, 2015).

D. Factors Fueling Progress

In the past five years, technology has set off waves of change in the BI landscape. Advances in data collection, computational power, machine learning, and deep learning have expanded the field of BI well beyond what was forecasted before. More sophisticated algorithms are being devised by scientists. Moreover, the growth of cloud-based platforms has given companies elastic scalability, up-to-date security, and the tools and storage capacity to conduct advanced analytics. Henke et al. (2016) found that the following technology trends and developments have contributed to a breakthrough in the field of BI and are helping rapid advances as they converge:

1) Exponential growth in the volume of available data;
2) Advances in algorithms such as deep learning;
3) Greater computational power;
4) Increased data storage capacity at reduced costs;
5) The growth of cloud-based platforms.

III. CATEGORIES OF ANALYTICS

Analytics is constantly evolving, has changed dramatically over the years and is advancing rapidly today. There are five categories of analytics: descriptive, diagnostics, predictive, prescriptive, and cognitive. These categories build on each other and enable enterprises to make faster and smarter decisions. As organizations evolve, they move from focusing on historical "what" and "why" questions to a more forward-looking predictive, and prescriptive predictions, and finally to cognitive analytics that automate decision. The advanced analytics maturity path is summarized in Table 1 and shown on Figure 5 (Intel, 2017). Descriptive analytic are valuable for answering questions about what happened in the past and uncovering patterns that offer insight. Such data provide an opportunity for business enterprise to review data to understand the state of affairs of their operations. Business decision makers can drill into specific areas of their business to identify anomalies and root causes of problems or issues.

Table 1: Traditional vs modern analytics

Analytic Workflow Component	Traditional Platform	Modern Platform
Data ingestion and preparation	IT-produced	IT-Enabled
Content authoring	Primarily IT staff-limited usage	Business users-comprehensive governance
Analysis	Predefined, ad hoc reporting, based on predefined model	Free-form exploration
Insight delivery	Distribution and notifications via scheduled reports or portal	Sharing and collaboration, storytelling, open APIs

Descriptive analytics tools include data modeling, reporting, visualization, and regression to collect and store data in an efficient way, to create reports and presentation information, and to find trends in the data. Since data is scattered in large numbers of disparate data sources, analyzing all relevant data can be a challenge for most organizations. Diagnostic analytics are used for discovery.

Table 2: Categories of business analytics

Business Analytics	Questions	Tools	Outcomes	Focus
Descriptive (Hindsight)	• What happened? • What is happening?	• Data modeling • Business reporting • Visualization • Dashboard • Regression	• Well defined business problems or opportunities	• Uncovering patterns that offer insight
Diagnostic (Insight)	• Why did it happen?	• Enterprise data warehouse • Data discovery • Data mining and correlations • Drill-down/roll-up	• Accurate projections of the future conditions and states	• Identify past patterns to predict the future
Predictive (Foresight)	• What is likely to happen? • What will happen? • Why will it happen	• Data mining • Text/media mining • Predictive modeling • Artificial Neural Networks (ANN)	• Accurate projections of the future conditions and states	• Identify past patterns to predict the future
Prescriptive (Automation)	• What should I do? • Why should I do it?	• Decision modeling • Optimization • Simulation • Expert systems	• Optimization-Best possible business decisions	• Focus on decision making and efficiency
Cognitive	• What should I do? • Why should I do it?	• Machine and deep learning • Data lakes • Human thought Simulation	• Better decisions for everyone	• Self-service analytics

They examine data or content to answer the question why did it happen. Diagnostic analytics takes a deeper look at data to attempt to understand the root causes of events and behaviors in an organization. To optimize diagnostic analytics, it needs to be extended to operational employees of the organization. The result of the diagnostic analytics is often an analytic dashboard that is used for discovery or to determine why something happened. Predictive analytics analyze current and historical data to provide insights into what will happen and why will it happen in the future with an acceptable level of reliability. It attempts to accurately project the future condition and states. It uses data, text, media mining, forecasting, and predictive modeling to identify probabilities of potential outcomes and/or likely results of specific operations. Predictive Analytics is an extension of Data Mining technology. Both are based on a huge amount of mathematical theory dating back several decades. Data mining technology helps to examine large amounts of data. One can sift through all the chaotic and repetitive noise in data to discover patterns.

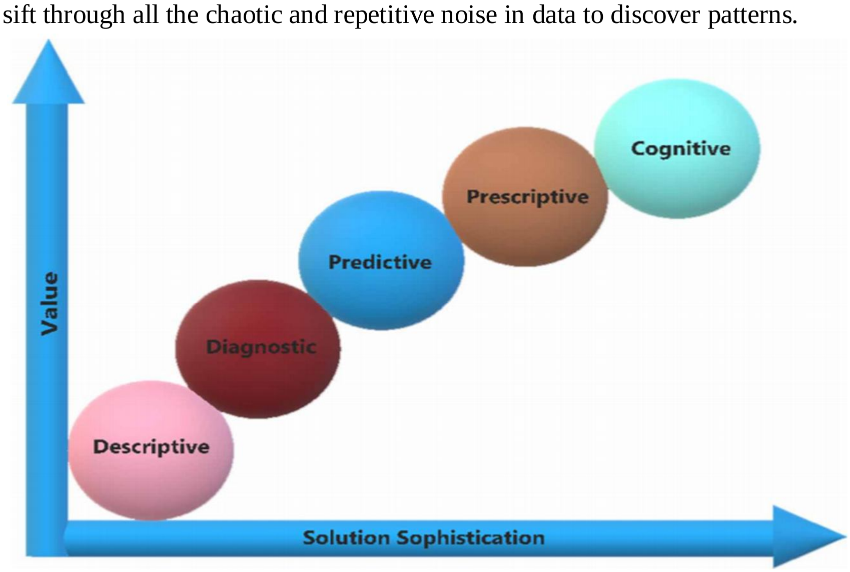


Figure 5: Moving up the analytics value chain

IV. EMBEDDED ANALYTICS VS BUSINESS INTELLIGENCE

Traditional BI is a set of technologies, applications, infrastructure, and best practices that aggregate data from multiple sources, prepare that data for analysis, and then provide reporting and analysis on that data to optimize decisions and performance. These systems are specifically developed to be operated by an organizations' analyst and optimized for supporting managerial decisions that require aggregated views of information from across a department, unit, or entire organization. Traditional BI platforms focus on data preparation and integration and provide analysis via scripting, reports, interactive visualizations, and static dashboards. An important shortcoming of traditional BI is its latency in receiving reports. By the time the decision maker received the reports, it typically is too late to undertake any action. Embedded analytics facilitate dealing and addressing that latency by shifting from reactive analytics to proactive analytics. Embedded analytics inserts intelligence or a set of tightly integrated capabilities inside the everyday systems or applications (such as CRM, ERP, marketing or financial systems) that employees or customers use to improve the analytics experience. This makes users more productive by combining insight and action in the same application. There is no need for users to switch between multiple applications to derive insights and take action. Figure 4 shows the relationship between embedded analytics, traditional BI and business applications (Harris, 2017).

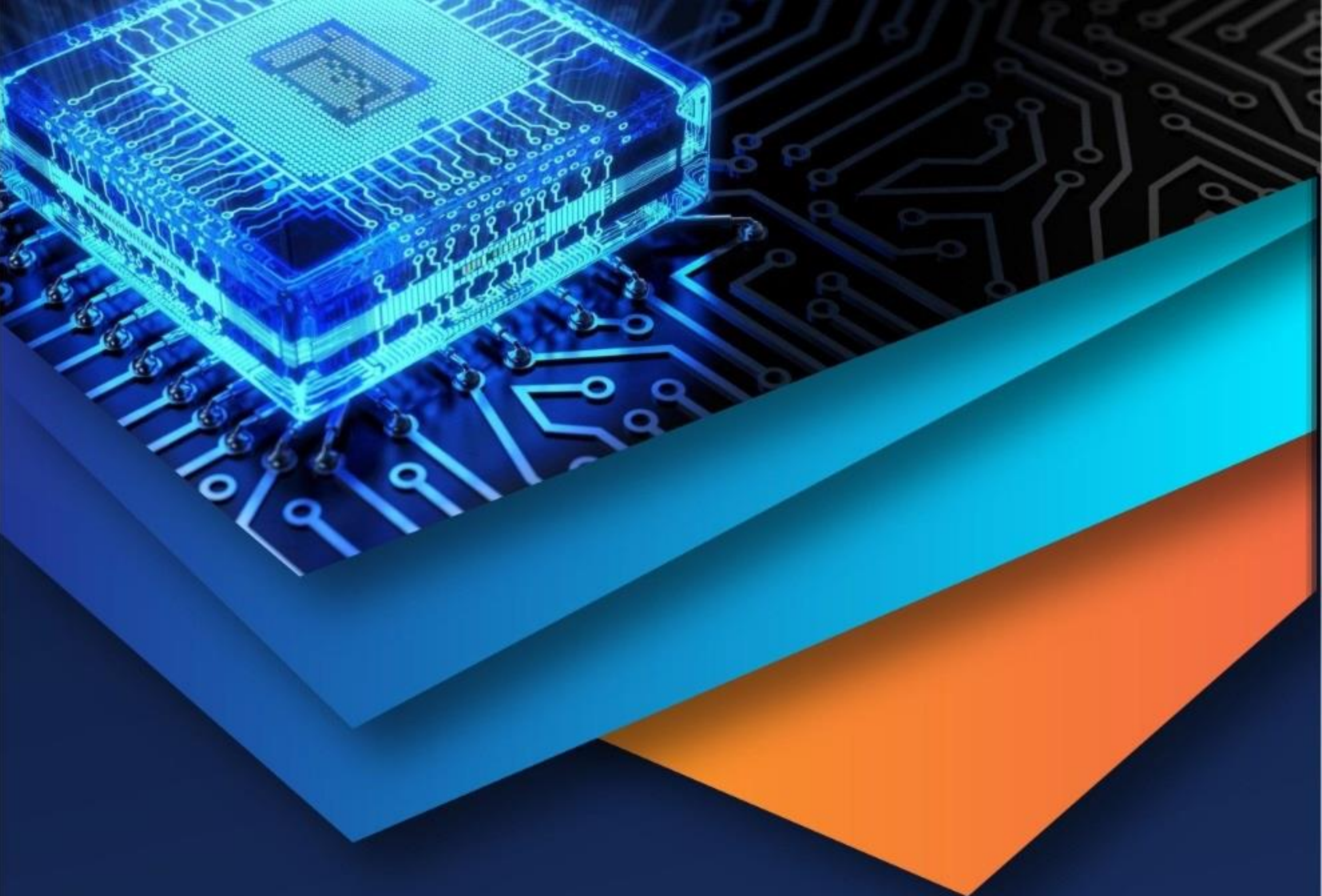
V. CONCLUSION

For decades, business leaders around the world have focused on using analytics techniques to empower decision makers in their organizations and to compete effectively in a digitally driven world. Over the past five years, the sheer volume of data has grown exponentially and new analytics tools have been developed to turn this flood of unstructured, semi-structured, and structured data into insights. Embedded analytics, a term that encompasses a range of algorithmic approaches, or a set of tightly integrated capabilities inserted inside the applications, has rapidly advanced to the forefront of the analytics landscape. Embedded analytics delivers live, interactive and contextual analytical insights from the transactional business applications. Organizations are discovering the power of embedded analytics which accelerate time to insight, deliver greater value for end users, and provide a greater strategic value for the organization. As highlighted in this paper, there are several factorsfueling the evolution of embedded analytics. Advances in data collection, analytics solutions, hardware and software, and computational power have revolutionized the field. Additionally, business users within organizations need more than personal productivity tools, and more than analytic engines understood only by expert data scientists. They demand, more than ever, autonomy, agility, and self-service analytic capabilities. They need a thoughtfully designed analytics platform that empowers everyone within these organizations to make data an integral part of their day-to-day processes and decisions.

VI. REFERENCES

[1] Adelman, S. (2015). Why Big Data Means Big Opportunity for the Travel Industry. Forbes, 9(July). Retrieved from https://www.forbes.com/sites/ibm/2015/07/09/ why-big-data-means-big-opportunity-for-the travelindustry/#5528576b21a5 Analyticsvidhya. (2015, September 21).
[2] Amazing Applications/Uses of data Science Today. Retrieved from https://www.analyticsvidhya.com/blog/2015/09/applications-data-science/
[3] Asllani, A. (2015). Business Analytics with Management Science Models and Methods (p. 07458). Upper Sadler River, NJ: Pearson Education, Inc.
[4] Bughin, J. (2016). Big Data, Big Bang? Journal of Big Data, 3(2). Bughin, J. (2016). Big Data: Getting a Better Read on Performance. McKinsey Quarterly, February. Retrieved from https://www.mckinsey.com/industries/high-tech/our-insights/big-data-getting-a-better-read-on-performance
[5] Bulygo, Z. (2015, September 13). How Netflix Uses Analytics To Select Movies, Create Content, and Make Multimillion Dollar Decisions. Kiss Metrics. Retrieved from https://blog.kissmetrics.com/how-netflix-usesanalytics/
[6] Butler, C. (2017). 2017 State of Embedded Analytics Report. Logi Analytics. Retrieved from http:// go.logianalytics.com/rs/793-ECD-841/images/2017%20State%20of%20Embedded%20Analytics_Logi_final.pdf Gomez-Uribe,
[7] C. A., & Hunt, N. (2016). The Netflix recommender system: Algorithms, business value, and innovation. ACM Transactions on Management Information Systems, 6(4).
[8] Davenport, T. (2013). Analytics 3.0. Harvard Business Review, (December), 13. Decker, J. (2017). Embedded Analytics for Dummies. John Wiley & Sons, Inc.
[9] Diebold, F. X. (2012). On the Origin(s) and Development of the Term "Big Data" (PIER Working Paper 12- 037). Penn Institute for Economic Research, Department of Economics, University of Pennsylvania. Retrieved from https://economics.sas.upenn.edu/sites/economics.sas.upenn.edu/files/12-037.pdf
[10] Evelson, B., & Bennett, M. (2015). Quantify Tangible Business Value of BI. Forrester. Retrieved from http:// www.lavastorm.com/assets/2015-Forrester-Quantify-Tangible-Business-Value-of-BI.pdf
[11] Feki, M., Boughzala, I., & Wamba, S. F. (2016). Big Data Analytics-enabled Supply Chain Transformation: A Literature Review. In 49th Hawaii International Conference on System Sciences.
[12] Gartner. (2018). IT Glossary. Embedded Analytics. Retrieved from https://www.gartner.com/it-glossary/ embedded-analytics
[13] Gartner. (2015). Gartner Survey Shows More Than 75 Percent of Companies Are Investing or Planning to Invest in Big Data in the Next Two Years. Retrieved from http://www.gartner.com/newsroom/id/3130817

[14] Gaitho, M. (2017, August 8). How Applications of Big Data Drive Industries. SimpliLearn. Retrieved from https://www.simplilearn.com/big-data-applications-in-industries-article
[15] Marr, B. (2015). Big Data: 20 Mind-Boggling Facts Everyone Must Read. Forbes, 30(September). Retrieved from https://www.forbes.com/sites/bernardmarr/2015/09/30/big-data-20-mind-boggling-facts-everyone
[16] McAfee, A., & Brynjolfsson, E. (2012). “Big Data: The Management Revolution.” Harvard Business Review. Retrieved from https://hbr.org/2012/10/big-data-the-management-revolution
[17] McNeill, D. (2014). Analytics in Healthcare and the Life Sciences: Strategies, Implementation Methods and Best Practices. Upper Saddle River, NJ: International Institute for Analytics.
[18] Minelli, M., Chambers, M., & Dhiraj, A. (2013). Big Data, Big Analytics: Emerging Business Intelligence and Analytic Trends for Today’s Businesses. Hoboken: John Wiley & Sons. doi:10.1002/9781118562260
[19] Perrin, A. (2015). One-fifth of Americans report going online-almost constantly. Pew Research Center. Phillips,J. (2014). Analytics 3.0: The Era of Impact. International Institute for Analytics. Retrieved from https:// www.sas.com/content/dam/SAS/en_us/doc/event/The-Era-of-Impact-127837.pdf
[20] Riabacke, M., Danielson, M., & Love, E. (2012). State-of-the-Art Prescriptive Criteria Weight Elicitation. Advances in Decision Sciences. doi:10.1155/2012/276584
[21] Rosenbush, S., & Stevens, L. (2015, February 16). At UPS the Algorithm is the Driver. The Wall Street Journal. Retrieved from https://www.wsj.com/articles/at-ups-the-algorithm-is-the-driver-1424136536
[22] Strickland,J. (2015, September 16). Analytics: isit more than a buzzword? Bicorner.com. Retrieved from https:// bicorner.com/2015/09/16/analytics-is-it-more-than-a-buzzword/
[23] Taylor, P. (2012, June 19). Crunch Time for Big Data. The Financial Times.
[24] Weiss, S.M.,&Indurkhya,N.(1998).Predictive Data Mining: A Practical Guide.MorganKaufmann Publishers,Inc.
[25] Wetherbee, C. (2014). Optimizing Your Agency’s Business Processes through Analytics. Retrieved from http:// slideplayer.com/slide/1606960/
[26] Wong, A. (2013, October 1). What is Embedded Analytics? Logi Analytics. Retrieved from https://www. logianalytics.com/bi-trends/what-is-embedded-analytics/



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL
IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY