Emerging Concept of *Tech-Business-Analytics* an Intersection of IoT & Data Analytics and its Applications on Predictive Business Decisions

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ABSTRACT

This study examines the emerging fields of data analytics and decision prediction using data collected across different systems using Internet of Things technology. The Internet of Things (IoT) is a collection of interrelated computing devices, mechanical and digital machines, objects, animals, or people that are provided with unique identifiers and the ability to transmit data across a network without needing human-to-human or human-to-computer interaction. A specified aim of predicting the future, along with the explanation of the problem using another high-tech system and model should be used to process the enormous and continuous data produced. The possibility of realizing (design and development) such systems for so-called Tech-Business-Analytics for different real-world applications of predictive business decisions has been addressed in this paper.

Keywords: ICCT, Internet of Things, IoT, Data analytics, Tech-Business-Analytics, Predictive business decisions

1. INTRODUCTION:

Big data and the Internet of things (IoT) are underlying technologies of Information Communication and Computation technology (ICCT) [1-2] and have developed over time. This explores ways in which the study of the supply chain and related fields such as tech-business analytics differ when responding to predictive changes and managing them. Big data analytics and IOT were divided between two periods of time, with work showing steady growth by 2015 and rapid growth subsequently. This is because the integration of the network, processes, and quality of customer care, support, and supply chain is a key concern in recent big data [3]. The internet of things (IoT) envisages an interconnected network of smart physical things around the world. Such physical entities generate huge quantities of data in operation and the total scale of those data appears to be bound to continue to grow with the IoT gaining momentum in implementation. Increasingly, IoT criteria include analytics. The method of deriving knowledge from data is data Analytics, which derives meaning from it as actionable insights. From their usefulness in creating efficient, effective, and innovative applications and services across a broad range of fields, this article reviews IoT and big data analytics research. They discuss the IoT's broad vision as it is established in different cultures, explore the application of data analytics through IoT contexts, categorize analytical approaches, and propose an IoT data organized taxonomy for research because of the adequacy of analytical approaches, this taxonomy provides us with, in turn, a survey of supporting technologies and IoT analytics infrastructure. Lastly, we look at some trade-offs in IoT and analytics that can affect future research [4]. The internet of things (IoT) is a new phenomenon that has transformed the traditional way of life into a high-tech lifestyle. These IoT related transitions include smart cities, smart homes, emissions

control, energy efficiency, smart transport, and smart manufacturing. A lot of important research studies and investigations were conducted to strengthen technology through IoT. Nevertheless, there are still a lot of hurdles and challenges that need to be solved to achieve the full potential of the IoT. these issues and concerns need to be discussed in different fields of IoT, such as applications, risks, funding for technology, social and environmental impacts, etc. The main purpose of this review article is to provide a concise overview of both a technological and social perspective. Here is a discussion of different problems and main issues related to the fields of IoT, architecture, and critical technology. It also sheds light on existing literature and describes their involvement in various aspects of the IoT. Furthermore, the importance of big data and its IoT analysis has been discussed. This will help readers and researchers understand the real world of IoT and how it applies to it [5].

2. OBJECTIVES OF THE STUDY:

(1) An overview of the Internet of Things (IoT).
(2) An overview of Data & Business Analytics
(3) Possible Integration of IoT and Business Analytics
(4) Prediction on the Emergence of the new concept of "Tech-Business Analytics". This is based on data analytics and decision prediction using data collected from many devices interconnected using IoT.
(5) Design and development of Tech-Business Analytics and applications on Predictive Business Decisions.
(6) Further Research Directions in this new field.

3. OVERVIEW OF DATA & BUSINESS ANALYTICS:

3.1 Overview on Data Science & Big data:

Big data was first reported as a concern by NASA scientists in 1997 when they faced major difficulties in designing and storing massive datasets for computer systems. The rapid development of technology over the past decade has enabled business communities to take on the challenges of recording, processing, analyzing, handling, exchanging, and transmitting vast and complex digital resources. Today, data is rising at nearly 50,000 GB a second compared to a peak of 100 GB a day 25 years ago. While the debate on how to define big data in industry and academia is still ongoing, the volume of the five vs is the general characteristics described in :
(a.) Volume – a large amount of produced and stored data. The scale of the data determines the possible benefit and perspective.
(b.) Diversity – data comes in a wide range of formats including standardized, conventional database numerical data, and unstructured data such as text, video, and audio. Data are often created from various sources, making the transformation and integration of data across systems difficult.
(c.) Velocity – The data stream must be produced and processed in a timely fashion. Highly variable can be the speed at which the data is produced and processed to meet demands. It can be difficult to accommodate regular, seasonal, and event-triggered peak data loads.
(d.) Veracity – the inherent unpredictability of certain data involves analyzing big data in order to achieve an accurate forecast.
(e.) Value- what degree big data generate economically viable insights and or profits through extraction and transformation [3, 6-7]. Big data based Data Science has many applications in business related industries [8-9].

3.2 Overview on Business Analytics:

Business data analytics is a methodology that uses a particular collection of methods, competencies, and procedures to continually explore, iterate and examine past and current business data in order to gain insights into an organization that can contribute to better decision-making.
Market Data Analytics comprises 6 areas of practice:
(a) Decide the study questions
(b) Source data
(c) Evaluating data
(d) Data interpreting and reporting
(e) Using outcomes to influence decision making
(f) Guide to Enterprise Data Analytics Approach at Organization level

Business Data Analytics offers a basic understanding of the principles of business data analytics, including how to build a system, main techniques, and implementation, how to define, communicate and incorporate outcomes, and more [10-11].

4. OVERVIEW OF INTERNET OF THINGS (IoT):

4.1 IoT as ICCT underlying Technology:

The Internet of Things (IoT) is a collection of interrelated computer equipment, mechanical and digital devices equipped with unique identifiers and the ability to transfer data through a network without the need for contact between humans and computers. IoT is one of the ICCT (Information Communication and Computation Technology [12-13) underlying technology with many industry applications [14-19]. Kevin Ashton and some other researchers first presented the IoT to the Massachusetts Institute of Technology in 1999. The IoT has gained widespread attention because of its ability to offer convenience, productivity, and competitive benefits to the business world. The IoT connects independently identified objects, machines, and individuals, similar to how the Internet connects individual computers, to provide personalized solutions through sensor devices, data storage and analysis equipment, and decision-making tools. Gartner Research expects the IoT will grow to around 52 billion connected devices by 2030, and Cisco forecasts the IoT's market size to be $40 trillion. Many local organizations and their representatives of the supply chain have begun investing in IoT to improve their supply chain processes. For example, United Parcel Service (UPS) successfully reduced idling time and maintenance costs and improved performance and safety by using the IoT technologies in their trucks. Freestyle beverage machine from Coca Cola will record receipts designed by customers and recognize the desired tastes of customers for their future product design. Disney uses Magic Band, a wristband that is powered by IoT to reduce waiting times and boost customer satisfaction [3]. There is a huge opportunity for the Internet of Things (IoT) to provide revolutionary innovations and applications in many fields, and the momentum it has built along with its wide ambitions makes it an ideal frontier to drive technical progress forward. This has shown that analytics plays a role in many applications across many IoT-built domains, and will be much more necessary in the future as it becomes truly omnipresent to enable devices to be deployed in restructured envelopes and scales. We also tackled the problem of analytics comprehension as it creates a thorough overview of IoT analytics applications. It results in a layered taxonomy that defines and classifies analytics for analysis and implementation roadmaps according to their strengths and application potential. It then analyses the supporting structure and discusses methodological approaches from various stages of the data flow. Finally, it looks at some trade-offs in IoT analysis that can form the direction of future research [20-22].

4.2 IoT as Industry 4.0 Technology:

When applied to the manufacturing sector, the Industrial Internet of Things (IoT), also known as Industry 4.0, is a philosophy of combining smart manufacturing machinery, AI-powered automation, and advanced analytics to help make every worker and every factory more productive [14-19]. The IoT would revolutionize production by allowing even greater quantities of information to be obtained and accessed both faster and more effectively than ever before. By leveraging intelligent, wired devices within their factories, warehouses, and labs, several manufacturers have already begun to introduce IIoT devices and procedures. In most instances, businesses deploy IoT devices and machinery linked by communication technologies that help industries gather, monitor, evaluate, and provide useful insights like never before. The precise mechanics of how this technology is applied vary from business to business, but the aim is often the same; analytics, automation, and networking to boost operational performance. For example, businesses may gather advanced analytical information and gain insights into warehouse productivity by equipping warehouse staff with wearable technology. These useful insights will assist manufacturing companies to make decisions that are quicker and better educated. Systems can be trained to recognize possible trends that may lead to a future failure by using machine learning; and if the findings are concerned, it can be reported for further review automatically. These applications can help save millions, or even billions of dollars, for businesses. By continuously gathering, analyzing, and acting on data, IoT is to make machines smarter and more effective than human counterparts. To obtain a deeper understanding of how devices and production lines work, the retrieved data can be combined with real-time predictive analytics, artificial intelligence, and machine learning with businesses currently developing cutting-edge sensory technology to collect data [23].

5. POSSIBLE INTEGRATION OF IoT & BUSINESS ANALYTICS:

IoT data analytics will offer benefits in many business fields, such as reducing maintenance costs, preventing equipment failures, and increasing customer service and human productivity. But despite the proven advantages of applying IoT data, many organizations simply don't derive value from their data assets because they don't know what to do with it. Workers often get frustrated by the volume of data that comes in, stopping them from sorting through it all, and finding successful ways to use it. For multiple sensors supplying information as often as every 30 seconds, if the correct ones are not used, this may lead to data overload for the staff or computers. Many potential obstacles to the adoption of IoT data analytics include security concerns and high costs. As it needs numerous machines and devices that work together and share information, it could spread to all systems if one system were exposed to a security breach. Also, as IoT data analytics is still relatively recent, the cost of implementing them can be high. It can discourage business owners from embracing it, particularly when the long-term benefits of investing are difficult to see. According to Mordor Intelligence 2019 projections, the IoT market is projected to hit a size of $6.1 billion by 2024 at a CAGR of 31.8 percent. The global market favors the advancement of IoT and its ability to offer significant economic benefits. The combination of IoT and big data — IoT data analytics is one aspect of growth in the IoT sector. IoT data analysis is the study of the enormous quantities of data produced by connected devices. Organizations can derive many benefits from this: optimizing operations, automatically controlling processes, engaging more customers, and empowering staff. In retail, healthcare, telematics, manufacturing, and smart cities, the combination of IoT and data analytics has already proved beneficial. Yet its true value for organizations still needs to be fully realized. Analyzing massive volumes of information provided by a variety of connected devices was extremely difficult and expensive at least a decade ago. As time goes on, data storage costs are falling, and the analytics capabilities are making huge leaps forward. This creates favorable conditions for organizations to begin investing in IoT data analytics and implementing it. As IoT data analytics becomes more available, more and more companies are seeing the benefits of using it. Widespread businesses like Microsoft, GE, Amazon, SAP, and Salesforce have already begun integrating IoT data analytics into their everyday processes. Each company aims to create a greater and more customized customer experience, whether it's a retail shop or a healthcare center. Implementing data analytics from IoT will help with this onerous mission. IoT data shows a wealth of customer habits and desires that can be analyzed and used to forecast the needs of the client. Once a customer enters a store, for example, the IoT data analytics system will direct the shopper to the jeans they looked at online. This can even give them a customized voucher to make the day's purchase instore. Furthermore, supermarkets, restaurant chains, and consumer goods manufacturers may use IoT data for targeted ads and promotions. Hospitals can use IoT data analytics in real-time to manage increased patient traffic and improve overall operational efficiency in healthcare. Both parties benefit from this; consumers gain greater value through convenience and time savings, while organizations increase their revenue and remain more attractive to customers [23-25].

6. EMERGENCE OF THE NEW CONCEPT OF *TECH-BUSINESS-ANALYTICS (*TBA):

Business Analytics is the mechanism by which organizations use statistical tools and technology to analyze historical data to obtain new insights and enhance strategic decision-making. The concentration of Business Analytics and Technology aims to grow this managerial expertise through a series of courses covering methods for critical and analytical thought, information technologies, and techniques for applying those methods, and business applications that use these methods and technologies heavily. Departing from the old approach of being TBA education's "quant skills" aspect, this area is built around a crucial balance between general analytical thought, technology, and applications. Thanks to new information technology – the Web, omnipresent networking, digitized data collection systems, weblogs, wireless sensors, miniaturized devices – companies have captured, stored, and transported vast quantities of consumer data, inventories, business processes, product results, costs, sales, promotional campaigns, personnel, supply chain, and so on. It requires managerial skill that incorporates business experience, needs to identify market value opportunities, or recognize issues, with a strong understanding of analytical approaches required to align technical talent with functional managers that can drive business change. Here, we have proposed a new model industry 4.0 technology based business analytics using a recently developed analysis framework called predictive analysis [26]. A Tech-Business-Analytics (TBA) core component:

• Data aggregation: data must first be collected, organized, and filtered, either via voluntary data or transactional records, before analysis.

• Data mining: data mining for business analytics tries to identify trends and establish relationships through large datasets using databases, statistics, and machine learning. Relationship and sequence Detection: Detection of predetermined actions carried out in combination with certain actions or sequence Text Mining: examines and organizes comprehensive, unstructured text databases for qualitative and quantitative research

• Forecasting: analyses historical data from a given timeframe to provide educated predictions indicative of potential events or behaviors [27-29].

• Predictive analytics: predictive business analytics utilizes several statistical techniques to construct predictive models that extract data from databases, detect trends, and include a predictive score for a range of organizational outcomes.

• Optimisation: once patterns have been established and forecasts made, companies can use simulation techniques to evaluate best-case scenarios

• Data visualization: offers visual representations for simple and fast data analysis, such as charts and graphs.

*Tech-business analytics is a predictive analysis model used in business analytics by utilising the data obtained from many interconnected devices using IoT.

For example, Tech-market analytics is typically defined as descriptive analytics using IoT integrated systems data that analyzes data obtained from various marketing related data capturing systems interconnected using IoT to determine how a unit responds to a variable collection of marketing data to measure the likelihood of particular future results. A mixture of a descriptive-analytical process that provides insight into what happened and a predictive analytical process that provides insight into what might happen, a process that helps users to predict what is going to happen, when it is going to happen and why [30-32].

7. APPLICATIONS TBA ON PREDICTIVE BUSINESS DECISIONS:

Predictive analytics extracts information from data sets to recognize relationships, acknowledge patterns, predict trends, find correlations, etc and communicates/exchanges these information between various industrial devices for their operation and control using Internet of Things (IoT). It helps one to predict the future and to make the right decisions.

(a) The method of dividing a client base into groups of similar individuals in various marketing-related ways, such as age, gender, interests, and purchase habits, is consumer targeting. This enables advertisers to tailor targeted advertisement campaigns directly to customers who are most likely to buy their products. Predictive analytics are much better able to classify future clients than conventional techniques [31-33].

(b) Churn avoidance seeks to anticipate which clients, when and why they will end their partnership with our business. This trend can be costly because the cost of maintaining a current customer is much smaller than that of obtaining a new. By harnessing the power of large consumer data sets, businesses can build predictive models that allow for proactive action before it's too late.

(c) Sales forecasting analyses the historical experience, seasonality, market-moving events, etc. to generate a reasonable estimate of a product or service demand. It can be applied to short, medium, or long-term forecasting. By looking at all aspects, predictive analytics will foresee consumer reaction and shift perceptions in this regard.

(d) Quality Management Market survey research helps businesses meet consumer needs, increase their income, and decrease the rate of attrition. When the predictive model is developed, it may be used by the business to look for certain attributes that suit the preferences of customers.

(e) Risk evaluation helps businesses to evaluate possible issues associated with a particular business. Predictive analytics aims to create decision support systems that can measure the successful operations for the company with accuracy and that are not. Risk evaluation is a common term for different people,

meaning different items. In reality, we may want to assess a client's risk, a business, etc [34- 36].

(f) Financial modeling is about translating a set of market behavior hypotheses or agents into numerical predictions. These predictive models are used to support firms in investment or return decision-making processes. An example is to predict stock market trends from internal and external variables [37-38].

8. DESIGN AND DEVELOPMENT OF TECH-BUSINESS ANALYTICS AND APPLICATIONS ON PREDICTIVE BUSINESS DECISIONS:

As already stated, a Tech-business analytics conceptual model is a predictive analysis model used in business analytics to provide futuristic information as output by utilizing the data obtained from many interconnected devices using IoT. The futuristic information output can be used for future predictive business decisions by managers. The concept is explained using the block diagram depicted in Figure 1.

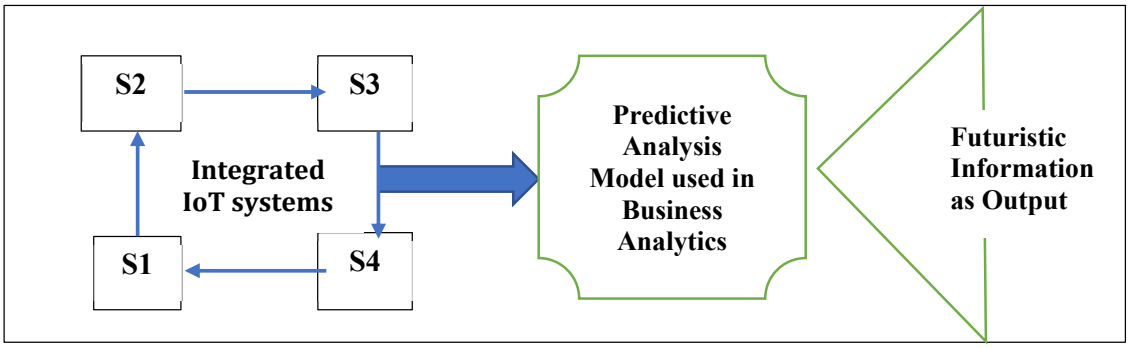

Fig. 1 : Block diagram that represents Tech-Business Analytics System based on Predictive analysis

Some of the applications of this newly introduced concept of tech-business analytics include the following areas :

Bayesian analysis. Bayesian methods consider parameters as random variables and describe probability as "degrees of belief" (i.e., the likelihood of an event is the degree to which you assume the event is true). You start with a prior belief regarding the probability distribution of an unknown parameter when conducting a Bayesian analysis. You have modified or revised your belief about the unknown parameter after you have learned knowledge from data.

Ensemble models. Ensemble models are developed by training many similar models and combining their results to increase accuracy, decrease bias, decrease variance, and determine the best model for new data to be used.

Gradient boosting. This is a boosting technique that resamples the data set many times to yield results that form a resampled data set weighted average. Boosting does not make any assumptions about the distribution of the data, including decision trees. Boosting is less likely than a single decision tree to overfit the data, and if a decision tree fits the data fairly well, then boosting often increases the fit. (data overfitting means that too many variables are used and the model is too complex. Underfitting means the opposite, not enough variables, and the model is too simple. Both decrease the accuracy of prediction.) Incremental response (also called net lift or uplift models). Such a model the shift in probability induced by an event. They are commonly used to minimize turnover and to discover the impacts of various programs of marketing.

K-nearest neighbor (knn): This is a non-parametric classification and regression method that, based on the k-closest training examples, forecasts the values or class memberships of an entity.

Memory-based reasoning. Memory-based logic for categorizing or predicting findings is the k-nearest neighbor technique.

Partial least squares: Data of any type can be added to this versatile statistical technique.

And when the inputs are correlated and noisy, there are many outputs or there are more inputs than observations, it models interactions between inputs and outputs.

The method of partial least squares looks for variables that describe both the variations of answer and predictor.

Principal component analysis. The main component analysis aims to extract from a set of variables a

small number of independent linear combinations (primary components) that preserve as much of the information as possible in the original variables.

Support vector machine. To evaluate knowledge and identify patterns, this supervised machine learning technique uses associated learning algorithms. Both classification and regression can be used for it.

Time series of data mining: Time series information is time-stamped and obtained at a fixed period over time (sales in a month, calls per day, hourly site visits, etc.). Time series information mining incorporates conventional

Methods of data mining and forecasting: Data mining techniques such as sampling, clustering, and decision trees are applied to data collected over time to improve predictions. Market analysts, investment officers, liquidity managers, and corporate leaders all regard big data predictive analytics and multicriteria modeling as the differentiating capabilities of their own financial institutions' governance systems.

Indeed, in today's most financial market decision-making, the evolved analytical modeling method as well as the conventional means of predictive analytics are the main requirement for success. Indeed, in most areas of the financial industry, financial institutions rely heavily on quantitative analysis and models.in several strategies, product and operational corners of the business, predictive analytics for big data and modeling functions are further found, e.g. Healthcare, transport, risk management, e-commerce, marketing, social networks, retail credit capability strategy, pricing strategies, customer behavior prediction, market strategy modeling, investment portfolios, risk assessment, financial fraud investigation, advertisement, and target market campaign optimization, innovation policies, business strategies, growth, economics and financial policies [37-38].

9. FURTHER RESEARCH DIRECTIONS IN THIS NEW FIELD:

To help address tough challenges and discover new opportunities, companies are turning to predictive analytics. Popular uses include:

Detecting fraud. Combining different methods of analytics will enhance pattern detection and avoid criminal activity. High-performance behavioral analytics analyses all activities on a network in real-time to identify anomalies that may signify fraud, zero-day vulnerabilities and advanced persistent threats as cybersecurity becomes an increasing concern.

Optimizing marketing campaigns. To evaluate consumer reactions or transactions, predictive analytics are used as well as facilitate cross-selling possibilities. Predictive models help organizations attract their most profitable clients, maintain them, and expand them.

Improving operations. Predictive models are used by many businesses to predict inventory and control capital. To set ticket prices, airlines use predictive analytics. To maximize occupancy and raise sales, hotels aim to predict the number of guests for any given night. Predictive analytics allows companies to operate more effectively.

Reducing risk. Credit scores are used to measure the probability of default for transactions by a customer and are a well-known predictive analytical example. A credit score is a number generated by a predictive model that integrates all information related to the creditworthiness of an individual. Insurance claims and collections provide several risk-related applications.

Natural language conversational data analysis. To democratize data processing, Natural language is a perfect solution. It will significantly enhance ordinary users' ability to perform data discovery and analysis rapidly and efficiently. With rapid developments in natural language processing and artificial intelligence technologies in re-enters, the use of natural language to query and analyze data has become possible Intelligent data analysis. In data intelligence, data interpretation plays a central role. Descriptive analysis, explanatory analysis, predictive analysis, and prescriptive analysis are typically included. These kinds of analyses provide various levels of perspectives, with growing levels of values and technological challenges.

Data visualization. To interpret and communicate data, data visualization is important. It is a multidisciplinary area involving interaction between humans and computers, graphics, perception, and more. Visualization of data has increased in significance in the age of big data and is now an integral part of data intelligence.

Privacy-preserving data analytics. Data privacy has become a subject of concern in recent years and applicable data privacy regulations, such as the general data protection regulation (GDP), have been

implemented. As a result, researchers have been actively developing data analysis techniques for privacy protection that allow data collection and processing, while also preserving data privacy [39-41].

10. CONCLUSION:

Predictive business decisions pursue the same cycle of growth as web technologies. It has been the subject of numerous research disciplines, such as computer science, management science, and information systems. Tech-Business Analytics aims to conduct a systematic analysis over the past 20 years of predictive technology, especially big data and IoT literature. The latest advances in IoT have attracted interest from researchers around the world and developers. To extend large-scale technology and help society to the highest degree possible, IoT developers and scientists work together. However, modifications are only possible if we look at the various problems and vulnerabilities in the current technical approaches. IoT developers need to take care of it to create a better model. It also deals with related areas of IoT technology in which IoT developers and researchers are involved. As IoT not only offers services, a large amount of data is also generated. The importance of big data analytics that can provide reliable decisions that could be used to create an enhanced IoT system is therefore also discussed. Predictive analytics can be used in a wide variety of sectors and are a perfect way to boost performance and to predict potential events. Neural Designer is a platform for data science and machine learning, specialized in making predictive models simple. This method has been implemented successfully in numerous industries such as commerce, finance, insurance, telecommunications, and oil.

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