The Future Data Driven Decision Making

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Abstract—**Abstract for Data Driven Decision Making:- This empirical study on Industry 5.0 provides verifiable evidence of the transformational potential of data-driven decision making. The validation of data-driven choices as one of the essential elements that Industry 5.0 would use in performance was presented by an impressive increase in decision outcomes of a 46.15%. This fact about choice criteria aligning with pertinent data sources is a manifestation of how much data is significant in the establishment of well-informed processes for decision making. Moreover, the methodical execution and oversight of choices showcase the pragmatic significance of data-driven methodologies.This empirical evidence positions data-driven decision making as a cornerstone for improving operational efficiency, customer happiness, and market share, solidifying its essential role as the industrial environment changes. These results herald in an age when data's revolutionary potential drives industrial progress by providing a compass for companies trying to navigate the complexity of Industry 5.0. This study proposes a model to assess data-driven decision-making (DDDM) readiness in organizations.**

We present the results from investigating the DDDM readiness of a Sweetdish organization in the food industry. We designed and developed a questionnaire to collect data about the organization's decision-making and IT systems. We conducted eleven interviews at the case study organization: ten with various functional decision makers and one with the IT Manager about IT systems. The interview data were then analyzed against known decision theories and state-of-the-art DDDM. Based on the interview outcomes, we analyze the data according to the assessment model and recommend changes to the organization's readiness for data-driven decisions. The findings show that while the organization was assessed as ready in the decision-making process and decision-maker pillars, it was not ready in the data or analytics pillars. Accordingly, we offer a set of actions, including reviewing integration and decision systems further, developing dashboards further, increasing data and analytics resources with an enterprise data warehouse, big data management tools, data lake environment, and data analytics algorithms, and defining key roles needed for digitalization and DDDM, such as Data Engineer, Data Scientist, Business Intelligence Specialist, Chief Data Officer, and Data Warehouse Designer/Administrator. The contribution of this study is the DDDM readiness assessment model, which is accompanied by a questionnaire for determining the readiness level in organizations.

I. INTRODUCTION

1.1 Motivtion:

The Future:- Data Driven Decision Making Data-driven

Decision-making is the process of gathering data and using facts and statistics to make strategic decisions that are in tandem with the business goals and objectives. The systematic approach to gathering and analyzing data can help an organization move forward by gaining actionable insights.

1.2 objective:-

From a terminological point of view, it must be distinguished between data-informed, data-driven and data-centric. Data-informed indicates little usage of data, in the sense that an organization systematically collects and stores data and decision-makers are principally aware of that data. However data are not the main driver within decisionmaking processes. Data-driven also entails that there are experts directing the data structuring process but, more importantly, these experts structure the analysis of such data, based on advanced technologies and in relation to the needs of decision-makers. In addition, data-driven stipulates that the intensified use of data in decisions is embraced and practiced from the company-wide level downwards to the different hierarchical levels Big data and big data analytics are the two main components of data-drivenness.Lastly, data-centric organizations are those where the business model is set on data, and indeed, data is part and parcel of the value-added process within products or services,such as Google. However, despite the increasing wealth of data, tools and insights, decision-makers remain not fully able to use the potential of current technologies, especially without well-understood guidelines and processes.

Need:-

This abundance of data, once collected and processed, is used by businesses to develop effective decisions that serve business objectives and good customer experiences. Data-driven decision-making offers businesses real-time insights and predictions, performance optimization and testing of new strategies.

II. LITERATURE REVIEW

Data-driven decision making has been a hot property in the business sector, in the fields of health, finance, education, and government. It is described as the use of data analytics and statistical methods for the purpose of making decisions and not intuition, gut feeling, or anecdotal evidence. Quite extensively, the literature discusses techniques, challenges, and benefits of data-driven decision making and its application across the domains.

DDDM refers to the process of making decisions based on the analysis of data, rather than on intuition or personal experience alone. It involves the systematic collection, analysis, and interpretation of data to drive better outcomes.

• Data-Driven Culture: Organizations with a strong data-driven culture integrate data analysis into every decision-making process, from high-level strategy to day-to-day operations. Davenport and Harris (2007) research speaks for this fact as that companies with comprehensive frameworks of data analytics generally outperform their peers.

•\tDecision Making: Formerly, decisions were taken using experience, expertise, and subjective judgment. With the introduction of big data and advanced analytics, the situation has changed. According to several reports, DDDM enhances decision accuracy with reduced risks and increases efficiency in many industries (Brynjolfsson et al., 2011).

Techniques Used in Data-Driven Decision Making

1. DDDM utilizes a range of data analysis techniques, from basic statistical analysis to more complex machine learning algorithms. Some of the most widespread techniques include:

•\tDescriptive Analytics: This is summarizing historical data to understand trends and patterns. Bihani et al. (2018) describe how descriptive analytics can help organizations understand their historical data better, leading to better prediction and informed decisions.

• Predictive Analytics: It is based on past data for predicting future trends. Technically, the methods used in predictive analytics include regression analysis, time series forecasting, and machine learning models such as decision trees or neural networks (Choi et al., 2020).

• Prescriptive Analytics: It is predictive analytics plus, since it provides explicit recommendations for recommendations. Prescriptive models rely upon optimization techniques and simulations to devise decisions that would lead to optimal outcomes (Gartner, 2022).

•\tReal-Time Analytics: In financial or e-commerce businesses, it enables the ability to make decisions in real time, for example, fraud detection or personalized customer recommendations.

2. Applications of Data-Driven Decision Making

DDDM is most commonly applied in sectors to enhance decision outcomes. The important ones are as follows

• Business and Marketing: Companies use customer data to segment markets, personalize offerings, optimize pricing, and predict customer behavior. According to research by Erevelles et al. (2016), data-driven marketing enhances customer satisfaction and ROI.

• Healthcare: Healthcare systems apply data-driven decision-making to improve patient care, predict disease outbreaks, optimize resource allocation, and personalize treatments. Topol (2019) illustrates the increasing role of artificial intelligence in healthcare decision-making.

•\tFinance: DDDM is used in finance to perform risk assessment, fraud detection, portfolio optimization, and stock market prediction. According to Chen et al. (2018), big data in finance has resulted in more accurate models of risk management and investment strategies.

•\tSupply Chain Management: In logistics, data-driven decisions optimize routes, manage inventories, and forecast demand, thereby improving efficiency and reducing costs. Simchi-Levi et al. (2018) state that data analytics is used for demand forecasting and supply chain optimization.

•\tEducation: Data is increasingly used to improve learning outcomes, manage resources, and personalize educational experiences. Siemens (2013) discusses learning analytics, where data is used to enhance student performance and engagement.

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3. Challenges in Data-Driven Decision Making

Despite its many benefits, there are challenges associated with the implementation of DDDM, including:

• Data Quality: Data is valuable only if it is good, complete, and available on time. Low quality may lead to a wrong choice. Redman (2013) highlights the important role of data governance in ensuring and maintaining data integrity.

•\tData Privacy and Security: Organizations need to ensure that the data used for decision-making is protected against breaches. Privacy concerns are heightened in fields like healthcare and finance.

•\tSkills and Expertise: Data science and analytics require specialized skills, including statistical analysis, machine learning, and data engineering. Davenport and Patil (2012) emphasize that organizations need to invest in upskilling their workforce to fully leverage data.

•\tResistance to Change: Many organizations face resistance from employees who are accustomed to traditional decision-making processes. Creating a data-driven culture often requires a lot of organizational change.

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4. Advantages of Data-Driven Decision Making

DDDM has many benefits, including:

•\tAccuracy: The decisions are based on facts, not intuition. According to research done by Provost and Fawcett (2013), data-driven decisions are often more accurate and reliable.

•\tIncreased Operational Efficiency: Data analytics can identify inefficiencies, streamline processes, and optimize operations in various industries.

•\tCompetitive Advantage: Organizations that make decisions based on data can get ahead of the curve faster than their competitors by identifying emerging trends.

•\tImproved Customer Insights: Businesses can understand customer preferences, behavior, and needs, which would lead to more personalized offerings and better customer satisfaction.

5. Future of Data-Driven Decision Making

The future of data-driven decision making is likely to see:

•\tIntegration of AI and Automation: The more advanced artificial intelligence gets, the more it will be integrated with decision-making systems to automate the most processes and accelerate decisions.

•\tMore Use of Unstructured Data: There is an increasing attention paid towards making decisions by using unstructured data (e.g., social media, text, images). Kshetri (2014) discusses how big dataanalytics extract value from sources that are not structured.

•\tExplainability in AI Models: As machine learning and AI become more involved in decision making, the demand for transparency and explainability of AI-driven decisions will increase. This can help mitigate concerns about bias and fairness in automated decision-making.

III. FUTURE SCOPE

Data-driven decision-making scope cuts across all the levels of an organization and affects many business functions. The main areas that cut across scope include;

1. Strategic Decision Making: DDDM helps organizations develop long-term strategies on matters such as market extension, product development, and resource allocation. It enables them to assess the risks and opportunities in the light of data insights.

2. \tOperational Decision Making: Using data can also be optimized for operational decisions like supply chain optimization, customer service enhancement, and production processes with DDDM.

3. \tCustomer and Marketing Decisions: DDDM identifies customer behavior, customer preferences, and market trends, thus making targeted marketing campaigns and product recommendations a result of this process. It also impacts customer relationship management.
4. Financial Decision Making: Financial decisions, such as budgeting, forecasting, and investment analysis, can be improved by DDDM with accurate predictions and the assessment of financial health from historical data.
5. Risk Management: Organizations can identify potential risks, forecast future challenges, and implement proactive strategies to mitigate those risks by analyzing data. This includes fraud detection, cybersecurity, and compliance.
6. Human Resources: Data-driven insights can be applied to optimize workforce management, including recruitment, performance evaluations, employee satisfaction, and talent retention strategies.
7. Innovation and Product Development: By analyzing customer feedback, usage data, and market trends, organizations can drive innovation, improve existing products, and develop new offerings that better meet customer needs.
8. \tCompliance and Reporting: DDDM can also help in complying with the organization's effort by ensuring that the organization meets regulatory requirements

based on data-driven audits and reports, thus decreasing the risk of non-compliance.

Key Components of the Scope of DDDM:

Data Collection: Collecting accurate and relevant data from multiple internal and external sources.

Data Storage and Management: Storing and organizing data in a way that is accessible and secure.

Data Analysis: The application of statistical tools, machine learning, and artificial intelligence to derive insights from data.

Data Visualization: Presenting data in an understandable and actionable format, often through dashboards or reports.

Decision Execution: Translating data insights into actionable steps and monitoring their impact.

IV. METHODOLOGY

. Data and Source of Data

The study utilized both primary and secondary data. All data were collected from banks in Pakistan as both primary and secondary data were merged to perform an econometric analysis. There are 33 commercial and 11 microfinance banks registered with the State Bank of Pakistan (SBP). However, foreign banks have been excluded from the sample because of their small operation size in Pakistan. Additionally, four specialized banks were excluded from the sample due to the varied nature of operations and their target market. The final sample contains 36 banks that represent 26 commercial and 10 microfinance banks operating in Pakistan. Secondary data was collected over 2016 to 2020 from online publicly available sources, including the State Bank of Pakistan and Banks' annual reports.

On the other hand, primary data was collected by administering a structured questionnaire survey to the chief information officer, data analyst, IT heads and senior bank managers from all banks in the sample. The questionnaires have been sent to all banks in the sample and can be accessed online by respondents. The questionnaire included questions on IT usage in decision making, employees' usage of IT, adjustment to organizational change after adoption and implementation of IT and DDDM. Primary data was collected in 2020 alone and index which was rolled back to the past 4 years that is 2016–2019, as used by Brynjolfsson and McElheran (Citation2019, Citation2016). This makes DDDM a static variable, which is merged with secondary data to make econometric analysis for 5 years. Maximum possible time any static variable can be extended back would be 5 years; thus, our sample period would be for 5 years (Brynjolfsson & McElheran, Citation2019, p. 2016).

The variable DDDMit is an index constructed with reference to the work of Brynjolfsson and McElheran (Citation2019). The index was calculated based on primary data collected from our survey. More specifically, the respondents were asked to choose a value on a 5-point Likert scale for five items. The responses to these five items were combined to develop an index through principal component analysis (PCA).

We also constructed one DDDM related instrumental variable, Adjustment Cost (AdjC). Adjustment Cost measures the cost of the change in the business environment due to the increased use of data. The AdjC composite index was constructed through six survey questions regarding the organizational factors, which facilitate or inhibit change. Other control variables that could affect the bank performance were also included in the analysis.

V. CONCLUSION

Better data allows for better decisions. New digital technologies have dramatically increased the scale and scope of data available to managers. We find that between 2005 and 2010, the share of manufacturing plants that adopted data-driven decision-making nearly tripled to 30 percent. Details of DDD adoption patterns reveal that this rapid diffusion is uneven and consistent with three mechanisms that help us to understand the diffusion of management practices, more gen erally. We find evidence suggesting that econo mies of scale, complementarities between DDD and both IT and worker education,9 and firm learning can explain a significant amount of the variation in DDD in recent years. part of the variance. About 70 percent of the plants in our sample had not yet adopted DDD by 2010, and even after controlling for many observable characteristics, there still remains signif icant heterogeneity in the use of DDD. In short, even our very rich window on the phenomenon is still incomplete. A number of potentially salient factors, such as firm culture (e.g., Blader et al. 2015) are beyond easy reach of our data. Our ongoing work continues to seek additional mechanisms that might better explain the adoption and productivity effects of this rapidly diffusing approach to managerial decision making.

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