

ROLE OF AI IN DATA SCIENCE: PREDICTIVE ANALYSIS AND DECISION-MAKING

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Abstract:

The impact of AI in data science is beneficial through its sophisticated prediction and decision-making systems. These systems enable organizations to analyze vast amounts of data more reliably and faster, they may also deliver complex tasks with less human involvement. This lets firms spend more time on the strategic intent, while then letting automated algorithms handle any data-heavy processes. AI-based decision-making typically fuses multiple sources of information, ranging from structured data, such as databases, to terabytes of unstructured text. The organizations use the AI along with the analytic tools to generate the actionable results. Encoding-Models minimizes the amount of errors / faults of interpreting the data. Predictive Algorithms allow companies to get insights into consumer behavior, market changes, and interruptions in the supply chain. Socioeconomic factors influence AI adoption in forecasting and decision-making. Large firms with resources build sophisticated actual AI systems, small don't know much, so they iterate to make their models better. Businesses leverage AI models to increase customer personalization, optimize resources, and enhance service. AI-powered systems are also working towards waste reduction and process optimization across sectors. Similar economic considerations come into play when devising the role of AI within data science. Corporations pursuing aggressive growth heavily invest in artificial intelligence powered technologies, favoring implementations with a higher price tag, but smaller businesses are taking a more tempered approach with more cost-effective implementations. Data-based scalable solutions make AI-driven decision-making possible which enhances industry-wide competitiveness. Fast-paced, data-hungry world Organization is developing advance forecasting methodologies, optimize risk management and decision making to keep up with competition. 201 people from data science sector were surveyed to know different roles of AI in data science: predictive analysis and decision making and concludes that AI plays significant role in data science: predictive analysis and decision making.

Keywords -AI in Data Science, Predictive Analysis, Decision-Making, Machine Learning, Business Intelligence, Data-Driven Insights.

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Introduction:

AI is Shaping Data Science, From AI-Powered Predictive Analytics to Useful Insights for Decision-Making AI, will put an end to so-so general predictions and replace them by data driven insights based on contemporary

market tactics and dynamic competition mapping through a historical and a real time data-set. Machine learning algorithms are trained on large datasets that enable them to perform learning without human intervention, and help organizations to derive significant insights from that data. **As per research by** Sarker (2021), Indeed, statistical-based traditional frameworks have been adapted to realise AI-based predictive models, like in financial forecasting, where figures can be much more precise before being recorded in spreadsheets. AI tools are embedded within analytical workflows, enabling strategic planners to discern trends and evaluate risks.

Predictive analytics makes it increasingly easier for businesses to identify consumer demand, optimize processes and ensure successful competitiveness. AI reduces human errors, quicker decision-making, and higher success rates. Industries. Adept AI Driven Predictive Models are now in business solutions which are already being adopted commercially for heavy sectors. **According to** Lopez (2023), AI-powered approaches help businesses predict consumer behaviour in geographic regions, enhancing financial forecast models. AI algorithms then analyze historical data to uncover trends that allow businesses to respond to market changes with flexibility. Automated forecasting simplifies decision-making, whether it relates to demand planning, inventory control, or financial analysis.

AI-driven insights enables enterprises to align business strategies with prevailing market condition. These systems enhance service provision and smooth risk management to minimize potential threats. Building on massive databases, machine learning algorithms are trained to discover patterns, facilitating extracting valuable insights for organizations. **As per findings by** Subrahmanya et al. (2022) More conventional statistical frameworks have been combined to include AI-based forecasting methods, such as financial forecasts, in which numbers can be much more accurate even before being recorded in spreadsheets. AI tools are integrated into analytical workflows to help strategic planners identify trends and assess risks. Predictive analysis makes it easier for businesses to see consumer demands, refine their procedures, and promote successful competitiveness. AI minimizes human errors and leads to faster decision-making and higher success rates. Industries use scalable business solutions powered by AI-driven predictive models, leading to widespread adoption in large-scale sectors.

According to the study by Kagalwala et al. (2025), Businesses use AI-powered approaches to anticipate regional consumer behavior, improving financial forecast models. By analyzing historical data, AI algorithms discover trends that aid businesses in flexibly responding to market shifts. Automated forecasting makes it easier to make decisions concerning demand planning, inventory management, or financial analysis. AI-powered insights enable enterprises to match business strategies with actual market conditions. These systems improve service delivery and streamline risk management to minimize potential threats. Corporate Decision-Making Transformed by AI-Driven Decision-Support Systems Its role and impact are influenced by sector and organizational dynamics, molding applied leadership in the organizations within the corporate structure.

As highlighted by Karo et al. (2024), In addition, AI applications in resource allocation, cost management, and workforce planning help improve operational management efficiency. Specifically, AI-based prediction models are very popular in audience behavior forecasts, allowing businesses to optimize customer engagement. Retailers

also use AI to study purchasing behavior, tailor product offerings, and manage stocks effectively. Data analysis and interpretation are being enhanced with AI, as it helps predict behavior patterns of online consumers; this even further fine-tunes targeted marketing. Recommendation engines guide users by recommending relevant content, products, or services. Businesses use AI-driven analysis platforms to evaluate financial situations, forecast economic trends, and optimize money strategies.

Literature review:

AI predictive analytics uses machine learning algorithms to identify patterns in data and make informed forecasts. AI models based on ML algorithms are used in predictive analytics today. Business managers can actually put their fingers on how long a product has lasted and whether or not there will be any significant changes in its future longevity from demand-side shifts. , financial institutions and businesses integrate AI-driven predictive models into their operations in order to improve strategies, boost efficiency, and manage risk. **As per research conducted by Chenna (2024)** through predictive analytics that raw data is refined into actionable intelligence, enabling enterprises to predict changes in the market, anticipate operating challenges, and understand shifts in consumer behavior. AI predictive analytics based on three essential components: data, algorithms, and predictions.

All participate in changing raw information into useful insights. Recognition of the importance of convincing evidence requires first, that the quality data be adequate; next comes selection of appropriate algorithm; lastly it is essential to produce a successful prediction. The cyclic dependence between input and output-the question of whether we can attribute incorrect effects to predicted causes that do not exist in the real world-makes this determination difficult. **According to the analysis of Chmait and Westerbeek (2021)**, whether selection of appropriate algorithms, quality data intake, or producing an accurate prediction are of paramount importance in forecasting for AI predictive models. Algorithm Selection--and the Ability to Generate Accurate Forecasts. The effectiveness of predictive models depends largely on data quality, algorithm selection, and the ability to generate accurate forecasts.

As observed by Sheng et al. (2021) data serves as the foundation of AI predictive analytics. Until predictions can be tested on a new instance or the known values for 'answers' (which are provided in addition to inputs), predictive models must be based on structured or unstructured data. Data comes from a multitude of sources: examples include transactions, consumer interactions, medical records and industrial processes. Structured data is composed of numerical values and divisions, while unstructured data includes texts, images and output from sensors. AI models need high-quality data in order to be effective. This involves preparing data so that it can be used in algorithms by cleaning (removing errors) and preprocessing (shaping for algorithm manipulation). Data quality and relevance have to be considered as well as quantity, as all three affect the reliability of predictions generated by AI.

Algorithms process data and identify patterns that inform predictions. These mathematical models range from simple regression formulas to complex deep learning networks. Supervised learning algorithms train on labeled data sets, while unsupervised learning models detect hidden patterns without predefined classes. Reinforcement

learning adapts decision making through trial and error ways. **According to research by** Ravichandran et al. (2022) algorithms continuously improve predictions by adjusting parameters in response to new data. Average Reference Length Selecting the right algorithm has a significant effect on how precise and reliable predictive insights are expected to be. Predictions are the result of bringing AI algorithms in contact with data. Models driven by AI forecast trends, classify data state changes and detect anomalies. Predictive Analytics Benefits Businesses. Time taken becomes predictable (and is therefore budgeted as part of production schedules). In choosing the best AI algorithms to produce valuable insights and forecasts, we can seldom make any distinction between precision and reliability of conclusion itself. Financial institutions use AI to predict stock market movements, detect fraudulent transactions and evaluate credit risk.

As per the study by Hariri et al. (2019) predictions guide decision-makers by providing probability-based insights into future scenarios. Healthcare providers use forecasting models to help anticipate patient outcomes, thus supporting their preventive care strategies. Predictions provide decision-makers with a view of the future that is based on probabilistic scenarios. Predictive AI utilizes a variety of machine learning algorithms to process data and generate precise predictions. Algorithms used are determined by the type of prediction that needs to be made and the nature of the data. Each algorithm contributes to predictive analytics in its own way, whether it is identifying trends, classifying data or discovering anomalies. Neural networks process large data sets by identifying intricate patterns and relationships. **According to the work of** Farayola et al. (2024) these models are multi-layered, each layer changes the raw inputs into more meaningful representations of the world as it is perceived through connections accrued over time. Deep learning techniques can increase predictive accuracy by enabling neural networks themselves to adjust their inner parameters thanks to feedback.

As such, organizations use neural networks to crunch unstructured data - like text, images and sound - and apply deep learning in areas such as fraud detection, customer behavior analysis or medical diagnostics. Linear regression estimates relationships between variables, which makes it ideal for trend analysis and forecasting. Projections of sales behavior, demand patterns and pricing strategy can be studied using linear regression. Logistic regression is a classification algorithm that predicts categorical outcomes given input variables. Organizations employ logistic regression for jobs like customer segmentation, credit risk evaluation and medical diagnosis classification. Both of these methods support predictive analytics by creating equations that represent the relationships between input factors and expected outputs. **As highlighted in the research by** Bharadiya (2023) Support vector machines classify data points by finding the best line or plane that can divide them into two groups. These models go looking for patterns separating well defined sets, meaning they perform well on image recognition, fraud detection and financial risk analysis. If the dataset contains clear branch points, SVMs work fine; this is when organizations should use them for structured data classification tasks. Decision trees model all the different results which could happen by taking pieces of data and carving them up into segments. Through automating predictive analysis and improving decision-making, AI has transformed data science. AIs in operation by putting remarks to processes: kinds of trends. More often than not, it is difficult for us to find the correlations between unwound data and explore potential measures as a guide to this overlooked disorder.

Handling large datasets can also lead to minimizing uncertainty and improving real-time insights--all made possible by the AI in making intelligent judgments kind of method. Data-driven decision making gets a lift from AI by providing accurate forecasts, improving risk assessments, and optimizing business strategies. AI can handle data-processing chores, such as preprocessing, cleaning and transforming, in a programmed way. Historically speaking, these necessary jobs were done by human operators. AI can automatically simplify repetitive tasks: data preprocessing, cleaning and transformation. These traditional jobs are normally done manually by engineers who have prepared the data for analysis. In practice, automation means that the time required for each operating step is much shorter, and so freed up data analysts can get on with pursuing strategic goals. Machine learning algorithms handle raw data, check on fault conditions, then apply transformations to the optimal structure. AI predictive analytics refines business strategies, optimizes processes, and raises profits of industries.

Organisations put AI models into action to anticipate process optimization, set the challenges that pose greatest difficulties, and seek out paths for innovation. AI-driven analysis brings customer information into sharper focus. Predictive models tell the future buying behavior of customers and further develop marketing strategies. By putting advanced models into action, organizations can personalize recommendations based on customer preferences and optimize the entire purchasing process. AI-driven customer insights are able to heighten retention strategies. They pinpoint the factors which produce satisfaction or determinant purchasing decisions. Machine Learning models can assign an abuse probability to financial transactions in fraud detection. To detect abnormalities within transactions, find threats to your cybersecurity and check for abuses of regulations, AI is used by compliance management systems. Fraud detection systems use AI to analyze transaction patterns, identify anomalies, and prevent unauthorized activities. AI-based risk management frameworks evaluate investment risks, credit qualification and regulatory compliance. AI's Regression Mining face a trio of challenges: data quality, model-transparency, and ethical concerns. Companies have to make sure AI models lead to efficient, fair predictions by training them on a wide base of data samples. AI's embrace in organisations is moulded by compliance frameworks that set the principles of data governance, and obligatory accountability for algorithms. In AI models, Explainability enhances trust and conforms to regulations by clarifying decision-making processes.

Each decision node in the tree stands for a variable, and the branches leading out are possible choices. Business employ decision trees to calculate customer churn prediction, credit scoring and equipment failure recognition: these models learn from classification of complex decisions in stepwise detail. K-means clustering groups points into patterns based on their similarity. This technology detects underlying structures in data sets that cannot be labeled before hand. Clustering is used by businesses for customer segmentation, product recommendations and detection of anomalies. It is because of K-means clustering that predictive analytics can now be applied to unstructured data, with the information classified into meaningful groups to inform decision-making based on individual cases.

According to the findings of Debbadi and Boateng (2025), through automating predictive analysis and improving decision-making, AI has transformed data science. AIs in operation by putting remarks to processes:

kinds of trends. More often than not, it is difficult for us to find the correlations between unwound data and explore potential measures as a guide to this overlooked disorder. Handling large datasets can also lead to minimizing uncertainty and improving real-time insights--all made possible by the AI in making intelligent judgments kind of method. Data-driven decision making gets a lift from AI by providing accurate forecasts, improving risk assessments, and optimizing business strategies. AI can handle data-processing chores, such as preprocessing, cleaning and transforming, in a programmed way. Historically speaking, these necessary jobs were done by human operators. AI can automatically simplify repetitive tasks: data preprocessing, cleaning and transformation. These traditional jobs are normally done manually by engineers who have prepared the data for analysis.

As noted by Sousa et al. (2019), automation means that the time required for each operating step is much shorter, and so freed up data analysts can get on with pursuing strategic goals. Machine learning algorithms handle raw data, check on fault conditions, then apply transformations to the optimal structure. AI predictive analytics refines business strategies, optimizes processes, and raises profits of industries.

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AI models must be able to provide transparent reasoning behind their predictions, especially in areas like finance, healthcare, and law enforcement. To enhance accountability and validate model accuracy, organisations have put in place Explainable AI frameworks that conform to ethical guidelines. Bias in training data influences the predictions of AI agents, damaging their reliability and fairness. Organisations have cut bias by broadening out training sets, monitoring the performance of miniature models, and perfecting the processes of feature selection. To keep discrimination out of ethical consideration in AI decision logic requires continuous introspection and the improvement of model generalisation. Model adaptability has emerged as a strong point of future progress for this kind technology, real-time forecasting soberly maintained and decision automation detail developed fully. Consequently AI models will integrate with quantum computing and emerging technologies like edge AI to increase processing efficiency. Organisations will apply AI-driven predictive analytics to job outcome improving operation efficiency gains in competitive edge warmly.

Objective: To know different roles of AI in data science: predictive analysis and decision making

Methodology: Study survey was conducted among 201 people from data science to know different roles of AI in data science: predictive analysis and decision making. “Random sampling method” along with “T-test” were used to collect and analyse the data.

Data Analysis: In the total population of study survey males are 56.2% and females are 43.8%. 29.3% of them are below 27 years, 39.3% comes under the age group of 27-35 years and rest 31.4% are above 35 years of age. 25.4% are data scientists, 23.4% are data analysts, 30.8% are data engineers, and rest 20.4% are working on other positions.

“Table 1 General Details”

“Variables”	“Respondents”	“Percentage”
Male	113	56.2
Female	88	43.8
Total	201	100
Age (years)		
Below 27	59	29.3
27-35	79	39.3
Above 35	63	31.4
Total	201	100
Types of jobs		
Data scientists	51	25.4
Data analysts	47	23.4
Data engineer	62	30.8
Others	41	20.4
Total	201	100

Table 2 Roles of AI in data science: predictive analysis and decision making

“S. No.”	“Statements”	“Mean Value”	“t value”	“Sig.”
1.	AI models help to identify patterns and trends	3.12	1.731	0.042
2.	Used by marketers to forecast sales	3.18	2.758	0.005
3.	Helps to predict customer behavior	3.14	2.065	0.020
4.	AI models in data science are used in detecting fraud	3.13	1.879	0.031
5.	AI is used to identify complex patterns in data for medical diagnosis	3.19	2.644	0.003
6.	AI is used in optimizing decision making process	3.15	2.166	0.016
7.	AI models are used in automating strategic choices	3.16	2.332	0.010
8.	Helps to make real time decisions	3.17	2.489	0.007
9.	AI in data science is used in risk assessment	3.12	1.736	0.042
10.	AI provides quick recommendations	3.14	2.061	0.020

Table 2 is showing different roles of AI in data science: predictive analysis and decision making. The respondent says that AI is used to identify complex patterns in data for medical diagnosis with mean value 3.19, Used by marketers to forecast sales (3.18), Helps to make real time decisions (3.17) and AI models are used in automating

strategic choices with mean value 3.16. The respondent also says that AI is used in optimizing decision making process with mean value 3.15, Helps to predict customer behaviour (3.14), AI provides quick recommendations (3.14), AI models in data science are used in detecting fraud (3.13), AI models help to identify patterns and trends (3.12), and AI in data science is used in risk assessment with mean value 3.12. All statements pertaining to different roles of AI in data science exhibit statistical significance, with p-values below 0.05 following the application of a t-test.

Conclusion:

As AI takes root in data science, predictive and decisive data-based intelligence bring about a great change. Machine learning models search for regular patterns, anticipate trends, and modernise business strategy. AI thus enables organisations to process vast amounts of data with a reduced margin of error and quick response times. More time is left for strategic goals with fewer interventions by auto algorithms. Decisive intelligence built around high-risk assessment, the discovery of abnormal market behaviour and other features that precede malformations AI-driven decision-making begins with data of all types, from structured records to mountains of unformatted text. Organizations take actionable insights out of their data by hitching AI into analysis tools. At the same time an enterprise is forced to adapt in large part to the requirements of its particular field and must also comply with local ordinances wherever it operates. Businesses use AI models to adapt customer experiences, making customers more satisfied with the company as a result. AI-powered systems help industries to optimize resource allocation, eliminate waste, and improve service. Economics also affect how AI docks itself in data science. A corporation seeking rapid development pours large amounts of capital into AI, while smaller companies aim at lean implementations. AI-driven decision-making will lift the competitive edge of the whole industry, since it can provide a scalable, data-centered solution. With its capabilities, organization as a whole caves in on itself to perfect forecast strategies, improve risk control and even streamline decision-making processes.

The study aims to know different roles of AI in data science: predictive analysis and decision making and found that AI is used to identify complex patterns in data for medical diagnosis, used by marketers to forecast sales, helps to make real time decisions and AI models are used in automating strategic choices.

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