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Artificial Intelligence in Big Data Visualization: Advancing Dashboard Technology

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Abstract

The research focuses on five AI-driven systems: AI-based business intelligence, machine learning dashboard systems, cognitive data visualization platforms, smart analytics interfaces, and neural-enhanced business dashboards. The evaluation framework is based on four main criteria: contextual intelligence platforms, adaptive analytics ecosystems, autonomous intelligence generation, and immersive intelligence interfaces. Each criterion was given equal weighting (0.25) in the WSM process to maintain a balanced evaluation of system performance. The methodology involved normalizing data, assigning weights, and calculating preference scores to rank the systems. indings show that machine learning dashboard systems performed best, scoring 0.83926, due to their strong capabilities in immersive interfaces and well-rounded performance across other areas. AI-powered business intelligence systems followed closely with a score of 0.81411, excelling especially in contextual and autonomous intelligence. Smart analytics interfaces placed third (0.74329), with neural-enhanced business dashboards fourth (0.74246), leading in adaptive analytics but weaker in intelligence generation. Cognitive data visualization platforms scored lowest (0.73029), showing moderate performance across all criteria. The results suggest that machine learning dashboards provide a more comprehensive solution for organizations seeking integrated big data analytics tools. This study highlights the distinct advantages of different AI visualization systems and offers valuable guidance for decision-makers choosing suitable AI-powered platforms. Additionally, it demonstrates the utility of the WSM methodology in evaluating complex multi-criteria technology systems, contributing to the expanding knowledge on AI-enhanced business intelligence and data visualization.

Keyword: Machine Learning, Multi-Criteria Decision Making (MCDM), Predictive Analytics, Real-time Analytics, Decision Support Systems

Introduction

Artificial intelligence and big data are reshaping the retail and e-commerce sectors by offering detailed insights into customer behaviour, optimizing inventory management, and enhancing overall operational efficiency. Through the use of advanced algorithms and machine learning, these visualization dashboards provide real-time analytics and predictive intelligence, greatly enhancing both decision-making and customer interaction. [1] The Hybrid AISVF model, as shown in the illustration, integrates artificial intelligence with big data visualization and highlights recall as a crucial metric for detecting significant events and strategic information, including key performance indicators (KPIs) and business insights. [2] Artificial intelligence (AI) equips machines with the ability to solve complex problems, learn from experience, communicate, and adapt similarly to human intelligence. Subfields like machine learning and deep learning utilize big data and statistical techniques to enable continuous improvement in system performance. [3]In the healthcare industry, AI and big data are driving significant advancements, optimizing supply chains and enhancing patient care.

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The increasing complexity of healthcare data has elevated the role of deep learning models in delivering accurate and actionable insights. [4] Various analytical tools including SQL, data mining, clustering, natural language processing (NLP), and AI support big data analytics (BDA), make data processing faster and more efficient. [5]Text analytics, a branch of NLP, analyzes large volumes of text such as emails, customer feedback, and forum discussions, performing sentiment analysis to gauge opinions about brands or products. Originating in the 1950s, text analytics now encompasses tasks like information extraction and named entity recognition, and is considered an essential evolution in big data analytics. [6]This approach holds promise for enhancing decision-making processes by delivering more complete, timely, and accurate information that complements conventional macroeconomic indicators. To support this goal, a range of techniques under the umbrella of big data analytics and artificial intelligence (AI) are being actively developed. [7]This position paper explores the current landscape, potential opportunities, and key challenges related to the use of big data and AI in the education sector. It draws upon insights from experts in education, psychology, data science, AI, and cognitive neuroscience.[8]Big data refers to extremely large and varied datasets that exceed the processing capabilities of traditional analytical tools.

These datasets are commonly encountered in domains like business, marketing, and social media. [9]In the healthcare sector, big data is generated through mobile health applications, wearable monitoring devices, and electronic health records. The integration of AI and natural language processing (NLP) enables the extraction of valuable insights from unstructured medical data. Ongoing advancements in machine learning, NLP, and big data technologies are driving the increasing convergence of AI and business intelligence. [10] For instance, decision support interfaces transform complex analytical outputs into user-

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friendly visuals, aiding efficient decision-making, such as in intelligent water injection control systems. [11]AI and big data analytics also offer promising solutions against cybercrime by utilizing visualization tools, machine learning, and advanced statistics. Visualization techniques from traditional charts to detailed heat maps help stakeholders better understand data. [12]Combining AI with big data enables organizations to analyze large-scale datasets, uncover trends, reduce risks, and seize opportunities. [13]Governments face challenges in leveraging socio-economic big data for policy-making, where visualization plays a key role in simplifying complex information for decision-makers and the public. [14] Effective visualization bridges complex big data and actionable AI-driven insights, empowering stakeholders to make informed decisions. Overall, AI is transforming business intelligence by enhancing predictive analytics, operational efficiency, and customer understanding, making AI implementation essential for competitive advantage. [15]

Material and Method

AI-powered Business Intelligence: I-powered business intelligence combines artificial intelligence techniques with traditional BI systems to enhance data analysis, automate workflows, and deliver deeper, more actionable insights. This fusion enables businesses to react swiftly to market shifts, tailor customer experiences, and optimize operations with greater precision.

Machine Learning Dashboard Systems: Machine learning dashboards visually present key performance metrics and insights, enabling quicker decision-making and real-time monitoring of ML model performance. Designing an effective ML dashboard begins with clearly defining its core purpose.

Cognitive Data Visualization Platforms: These platforms create data visualizations informed by cognitive science principles to make complex data easier to comprehend and process. They aim to improve clarity, reduce mental effort, and increase accuracy in interpreting data.

Smart Analytics Interfaces: Smart analytics interfaces are tools or platforms that empower users to interact with data intelligently, often integrating AI, machine learning, and IoT technologies. They range from simple visualization tools to advanced systems supporting network analysis and AI-driven insights for better decision-making.

Neutrally-Enhanced Business Dashboards: These advanced business dashboards incorporate neural networks and deep learning algorithms directly into their interfaces, enabling features like real-time pattern detection, predictive analytics, and automated intelligence generation.

Contextual Intelligence Platforms: Contextual intelligence involves adapting and applying knowledge or skills appropriately depending on the situation or environment. For example, a word, gesture, or expression may hold different meanings based on cultural or workplace contexts.

Adaptive Analytics Ecosystems: These ecosystems dynamically respond to changing conditions by leveraging data and analytics to inform decisions and update strategies. They are defined by their flexibility, capacity to learn from data, and ability to adjust in real time.

Autonomous Intelligence Generation: This refers to the process of automatically extracting correlations, and trends that help improve understanding and support strategic decisions.

Immersive Intelligence Interfaces: Immersive intelligence interfaces fully engage users' senses, similar to virtual reality, by surrounding them visually and auditory (e.g., through VR headsets) and offering natural, intuitive input methods to create highly engaging user experiences.

WSM method: The Weighted Sum Model (WSM) is commonly applied by first defining evaluation criteria and assigning a weight or score to each. These weights are often normalized to ensure they sum to one. When using scoring systems, a numerical value typically from one to five is assigned to each criterion to reflect its importance. [16] WSM remains one of the most widely used and simplest multi-criteria decision-making (MCDM) methods, allowing for the assessment of various alternatives against defined criteria. [17]However, its use is limited to situations where all input data share the same units or dimensions. This paper aims to review, categorize, and compare several methods using the WSM framework. [18]The process includes selecting relevant criteria, assigning normalized weights, and calculating total scores for each alternative. This analysis helps to identify the strengths and limitations of each evaluated method. In this research, WSM has been applied across all defined criteria and alternatives.[19] Recognized for its ease of use, WSM is frequently adopted in diverse fields, such as robotic data processing. [20]The method operates by multiplying the weight of each criterion by the value of each corresponding alternative, serving as a foundational approach in multi-criteria decision-making. As a decision-making aid, WSM offers a practical and efficient way to assess multiple options based on various criteria. [21]Its straightforward structure and wide applicability make it one of the most trusted tools in the MCDM domain.

In techniques like Simple Additive Weighting (SAW), each criterion is assigned a weight treated as a coefficient that must be normalized to maintain consistency in the evaluation process.[22] Superficial physical indicators for detecting hypoglycaemia were selected using a modified Weighted Sum Model (WSM) and then applied in various machine learning-based feature selection techniques. [23]This study extends prior decades of research on Work System Modelling (WSM), a multidisciplinary framework for systems analysis and design that supports business professionals in visualizing operational workflows and collaborating more effectively with IT teams.[24] The paper offers two primary contributions.

First, it tackles a key challenge overlooked by the DBP model: ranking countries over time while accounting for uncertainty and incorporating investor preferences through weighted criteria. Second, it enhances the traditional WSM approach by introducing Gray numbers to capture temporal variability in evaluation criteria. [25] The conversion of multi-objective optimization problems into single-objective forms known as secularization can be achieved through various methods.

These include weighted sum (WSM), e-constraint, elastic constraints, Benson secularization, compromise programming, cone secularization (CSM), and goal programming. [26]Weighted sum modelling is frequently employed in multi-criteria decision-making to identify optimal suppliers, enabling organizations to enhance productivity, fulfil customer demands, and achieve operational efficiency. The best suppliers are those that consistently deliver the correct product, in the required quantity, at the right time and place. In this research, WSM is used across all defined criteria and alternatives. Its straightforward methodology makes it particularly suitable for use in domains such as robotics and data processing. [27] Additionally, the paper suggests that the fundamental principles of the Work Structure Method (WSM) can be used as a foundational framework to connect business-oriented needs with formal technical specifications. [28]While genetic algorithms (GAs) are often used for multi-objective optimization, their stochastic nature can produce inconsistent results across runs, complicating comparison and reproducibility. In contrast, WSM offers a deterministic alternative by assigning weights to each objective and integrating them into a single evaluative function, delivering consistent outcomes in a single run. [29] Building on earlier research, this study compares two models using a pseudo-fuzzy task. Triplet data (v, a1, a2) was extracted and the dataset was split into 80% training and 20% testing sets. The training portion was used to develop a PLSI model and construct the WSM framework. [30]

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Result and Discussion

Table1.Data visualization Ai and big data				
	Contextual Intelligence Platforms	Adaptive Analytics Ecosystems	Autonomous Insight Generation	Immersive Intelligence Interfaces
AI-Powered Business Intelligence	91.000	120.000	113.000	89.000
Machine Learning Dashboard Systems	67.000	130.000	132.000	49.000
Cognitive Data Visualization Platforms	45.000	150.000	139.000	67.000
Smart Analytics Interfaces	22.000	160.000	143.000	49.000
Neural-Enhanced Business Dashboards	66.000	170.000	181.000	79.000

Table 1 highlights the evaluation of different AI and big data visualization systems using the WSM method across four key areas: contextual intelligence, adaptive analytics, autonomous intelligence, and immersive interfaces. Neural-enhanced business dashboards outperform others in most dimensions, whereas smart analytics interfaces show notably low performance in contextual intelligence, reflecting diverse system strengths.

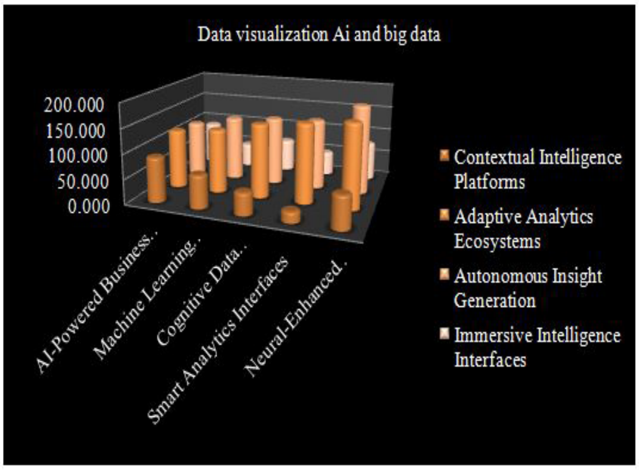

Figure 1: Data visualization Ai and big data

Figure 1 presents the evaluation of AI and big data visualization systems across four key categories using the WSM approach. Neural-enhanced business dashboards show strong overall performance, particularly in autonomous insight generation. Conversely, smart analytics interfaces excel in adaptive analytics but perform poorly in contextual intelligence, highlighting diverse system capabilities

Table 2: presents the normalized results of different AI and big data visualization systems evaluated using the WSM method				
	Normalized			
AI-Powered Business Intelligence:	1.00000	0.70588	1.00000	0.55056
Machine Learning Dashboard Systems	0.73626	0.76471	0.85606	1.00000
Cognitive Data Visualization Platforms	0.49451	0.88235	0.81295	0.73134
Smart Analytics Interfaces	0.24176	0.94118	0.79021	1.00000
Neural-Enhanced Business Dashboards	0.72527	1.00000	0.62431	0.62025

Table 2 presents the normalized results of different AI and big data visualization systems evaluated using the WSM method. AI-powered business intelligence performs strongly in contextual and autonomous intelligence. Machine learning dashboards and smart analytics interfaces excel in immersive interfaces, whereas neural-enhanced dashboards lead in adaptive analytics but fall short in insight generation.

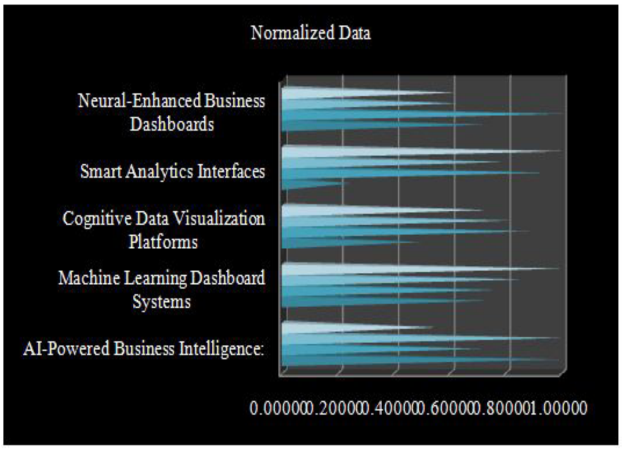

Figure 2: Normalized data

Table 3: presents the performance comparison of AI-driven data visualization systems based on the WSM methodology			
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

Table 3 presents the performance comparison of AI-driven data visualization systems based on the WSM methodology. It highlights that AI-powered business intelligence performs strongly in contextual and autonomous intelligence. Machine learning dashboards and smart analytics interfaces excel in fast, responsive interfaces. Neural-enhanced dashboards lead in adaptive analytics, while cognitive data visualization platforms show steady but moderate performance across all categories.

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Table 4: presents the team evaluation using the WSM approach. AI-powered business intelligence excels in contextual and autonomous intelligence				
	Weighted normalized decision matrix			
AI-Powered Business Intelligence:	0.25000	0.17647	0.25000	0.13764
Machine Learning Dashboard Systems	0.18407	0.19118	0.21402	0.25000
Cognitive Data Visualization Platforms	0.12363	0.22059	0.20324	0.18284
Smart Analytics Interfaces	0.06044	0.23529	0.19755	0.25000
Neural-Enhanced Business Dashboards	0.18132	0.25000	0.15608	0.15506

Table 4 presents the team evaluation using the WSM approach. AI-powered business intelligence excels in contextual and autonomous intelligence. Machine learning dashboards and smart analytics interfaces demonstrate strong performance in high-speed interface capabilities. Neural-enhanced dashboards achieve the highest scores in adaptive analytics, whereas cognitive platforms show consistent but moderate results across all evaluated dimensions.

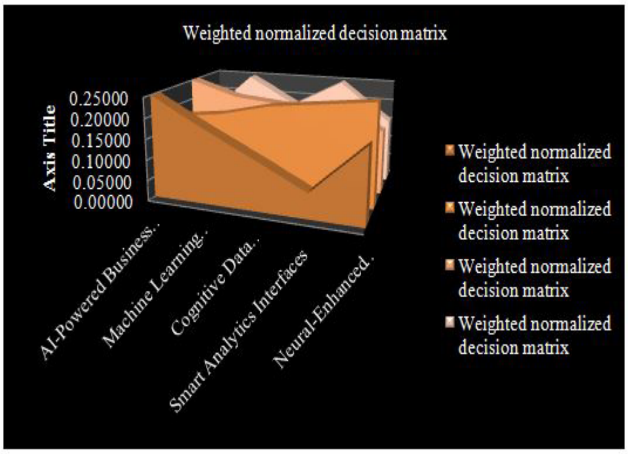

Figure 3: weighted normalized decision matrix

Figure 3 of AI and big data visualization systems evaluated by the WSM method. AI-powered business intelligence performs exceptionally well in contextual and autonomous intelligence. Machine learning and smart analytics interfaces are strong in immersive interfaces, while neural-enhanced dashboards dominate adaptive analytics, with cognitive platforms maintaining moderate, balanced scores throughout.

Table 5: presents the preference scores and rankings of different AI and big data visualization systems based on the WSM method		
	Preference Score	Rank
AI-Powered Business Intelligence:	0.81411	2
Machine Learning Dashboard Systems	0.83926	1
Cognitive Data Visualization Platforms	0.73029	5
Smart Analytics Interfaces	0.74329	3
Neural-Enhanced Business Dashboards	0.74246	4

Table 5 presents the preference scores and rankings of different AI and big data visualization systems based on the WSM method. Machine Learning Dashboard Systems achieve the of 0.83926, AI-Powered Business Intelligence, while Cognitive Data Visualization Platforms receive the lowest ranking, reflecting differences in system performance.

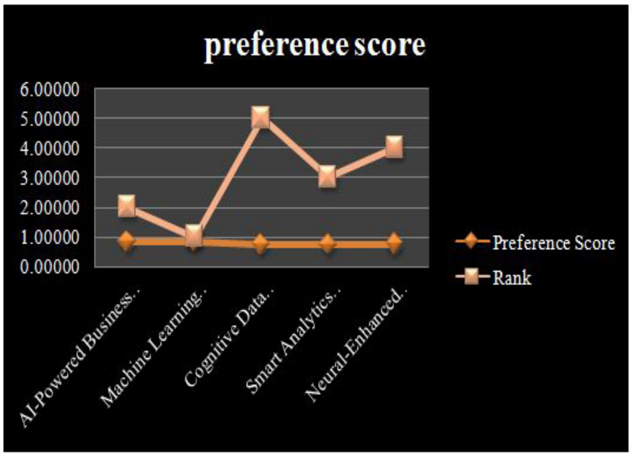

Figure 4: preference score

Figure 4 presents the preference scores and rankings of AI and big data visualization systems based on the WSM method. Machine Learning Dashboard Systems secured first place with a score of 0.83926, followed by AI-Powered Business Intelligence in second. Cognitive Data Visualization Platforms ranked lowest, highlighting differences in system performance.

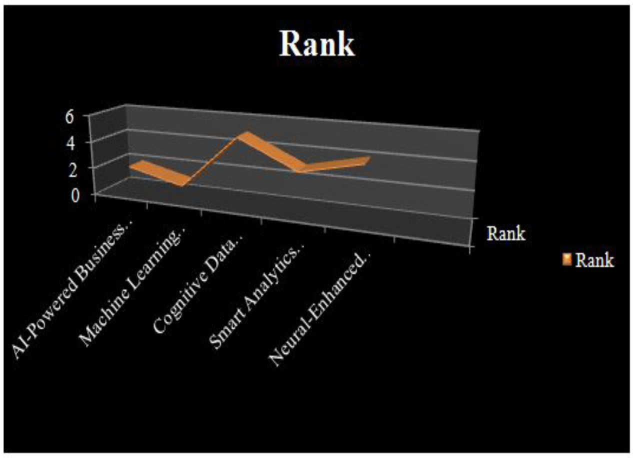

Figure 4: preference score

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Conclusion

The analysis highlights distinct performance variations among the assessed systems across four key dimensions: contextual intelligence platforms, adaptive analytics ecosystems, autonomous intelligence generation, and immersive intelligence interfaces. Machine Learning Dashboard Systems stood out as the highest-ranked solution, achieving a priority score of 0.83926. This system's strength lies in its well-rounded capabilities, especially excelling in immersive interfaces while maintaining strong performance in other areas. Following closely, AI-powered Business Intelligence scored 0.81411, showing notable excellence in contextual and autonomous intelligence, making it particularly well-suited for strategic decision support. The study applied an equal weighting approach (0.25 per criterion) to ensure a fair and unbiased evaluation, giving equal significance to each performance dimension. This balanced method equips organizations with a comprehensive overview of each system's strengths without favouring any particular attribute. Smart analytics interfaces placed third, with neural-enhanced business dashboards fourth and cognitive data visualization platforms ranking lowest. These results underscore the unique advantages and drawbacks of each AI visualization approach, with some excelling in specific criteria but lagging in others. Overall, the findings illustrate how AI-powered business intelligence dashboards are transforming data visualization by enhancing predictive analytics, operational efficiency, and customer insights. The WSM methodology demonstrated its effectiveness for tackling complex multi-criteria decision-making challenges in the AI and big data space. Organizations are encouraged to consider these performance rankings alongside their individual requirements when choosing visualization platforms. Future studies might investigate dynamic weighting schemes and additional criteria to further refine the selection process, thereby enhancing AI integration with big data visualization technologies.

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