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Big Data and Strategic Decision-Making: Towards a Deep Learning-Based Approach

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Abstract

The explosion in the volume of digital data generated by organisations, social media, connected devices and information systems has profoundly transformed decision-making processes. Big Data is now a strategic resource enabling businesses and institutions to develop more effective and responsive decision-support systems. However, the complexity, diversity and velocity of the data require the use of advanced analytical techniques capable of efficiently extracting relevant insights from vast datasets.

In this context, deep learning – an advanced branch of artificial intelligence based on deep neural networks – is emerging as a key technology for harnessing big data. According to Hou et al. (2024), deep learning models offer remarkable capabilities for machine learning and the identification of complex patterns, enabling significant improvements in the performance of decision-making systems. Similarly, Kokol (2024) emphasises that the integration of artificial intelligence into analytical processes helps to increase the accuracy of predictions and optimise decision-making across various sectors.

This article analyses the interactions between big data and the decision-making process, focusing on the contributions of deep learning to decision intelligence. It presents the main architectures used, notably artificial neural networks (ANNs), convolutional neural networks (CNNs), recurrent neural networks (RNNs) and Transformer models, as well as their applications in the fields of healthcare, finance, telecommunications, e-commerce and public administration. The study also examines the challenges relating to data quality, information governance, data security and the computational requirements associated with deep learning models.

The analyses show that integrating deep learning into big data environments can significantly improve the speed, reliability and relevance of strategic and operational decisions. However, several challenges remain, particularly regarding model interpretability, the protection of personal data and the availability of suitable technological infrastructure. Deep

learning therefore emerges as a key driver of transformation in modern decision-making systems and offers a promising avenue for the development of advanced decision intelligence in the digital age.

Keywords: Big Data; Decision-making process; Deep Learning; Artificial intelligence; Predictive analytics; Decision support; Neural networks; Decision intelligence; Data science; Digital transformation.

1. Introduction

The advent of digital transformation has profoundly changed the way organisations produce, store, analyse and utilise data. Over the past few decades, advances in information and communication technologies have fuelled exponential growth in the volumes of data generated worldwide. This trend is primarily driven by the widespread adoption of the internet, the development of social media, the rise of connected devices (the Internet of Things – IoT), the widespread use of smartphones, and the increasing digitisation of economic and administrative activities.

According to the International Data Corporation (IDC), the global volume of digital data is growing at an unprecedented rate and is expected to exceed several hundred zettabytes in the coming years. This spectacular growth has given rise to the concept of 'Big Data', which refers to data sets characterised by their volume, variety, velocity, veracity and value (Kelleher & Tierney, 2024). Modern organisations now have access to a vast amount of information from multiple and diverse sources such as social media, transactional systems, e-commerce platforms, smart sensors, mobile applications, ERP (Enterprise Resource Planning) systems and CRM (Customer Relationship Management) systems.

In this context, data has become a strategic resource on a par with financial assets or human resources. Effective use of data enables businesses to better understand their environment, anticipate market developments, identify consumer behaviour and improve their operational performance. As Sharda, Delen and Turban (2024) point out, organisations that make effective use of their data enjoy a significant competitive advantage thanks to their improved ability to analyse and anticipate trends.

However, an abundance of data does not automatically guarantee the generation of knowledge useful for decision-making. The increasing complexity of the available information often makes it difficult to process using traditional methods of statistical analysis. Decision-makers face several challenges, including managing massive volumes of data, the diversity of formats, the quality of the information collected, and the need to obtain results in real time. These constraints require the use of advanced technologies capable of transforming raw data into actionable insights to support strategic decision-making processes.

In light of these challenges, artificial intelligence (AI) is emerging as a key driver for harnessing the value of Big Data. Among the various branches of AI, deep learning plays a central role thanks to its ability to automatically learn complex representations from large quantities of data. Based on multi-layer artificial neural networks, deep learning enables the detection of hidden relationships, the making of accurate predictions and the automation of complex analytical tasks that often exceed the capabilities of conventional approaches (Aggarwal, 2023).

Furthermore, the recent emergence of generative artificial intelligence models and large language models (LLMs) is opening up new possibilities for decision-making analysis. According to Hou et al. (2024), these technologies significantly improve the interpretation of complex data and enhance decision-support capabilities in modern digital environments. Similarly, Kokol (2024) emphasises that the growing integration of artificial intelligence into information systems helps to improve the quality, speed and relevance of organisational decisions.

Against this backdrop, this study examines the role of Big Data in strategic decision-making processes, with a focus on the contributions of deep learning. The main objective is to analyse the mechanisms through which deep learning technologies enable the effective utilisation of big data to improve organisations' decision-making performance. The article also examines the main technical, organisational and ethical challenges associated with the use of Big Data, as well as future prospects linked to the evolution of artificial intelligence technologies.

Thus, at a time when organisations are seeking to develop ever more effective decision-making capabilities, the combination of big data and deep learning appears to be an essential approach for transforming data into strategic insights and supporting decision-making in an increasingly complex and competitive economic environment. Companies now collect data from multiple sources:

- Social media;
- Connected devices;
- Financial transactions;

- Mobile apps;
- E-commerce platforms;
- ERP and CRM systems.

Faced with this explosion of information, decision-makers need tools capable of transforming raw data into actionable insights.

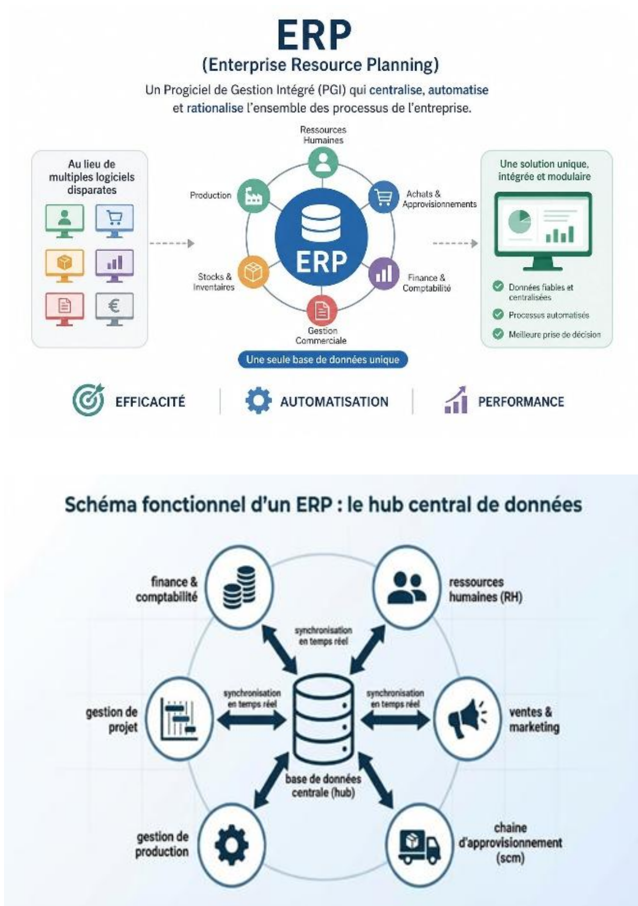

Figure 1: Growth in global data volume

2. Background

According to Sharda, Delen and Turban (2024), data now represents a strategic asset enabling organisations to improve their competitiveness, optimise their performance and support their decision-making processes. However, the mere availability of large quantities of data does not automatically guarantee the production of relevant insights or an improvement in the quality of decisions. On the contrary, the exponential growth of data raises new technological, organisational and methodological challenges that complicate its effective utilisation. One of the primary challenges concerns the **storage of massive amounts of data**. Traditional relational database management infrastructures often reach their limits when faced with the growing volumes of information generated on a daily basis.

According to Kelleher and Tierney (2024), the effective management of Big Data requires distributed architectures capable of processing petabytes, or even exabytes, of data whilst ensuring its availability and accessibility. A second challenge relates to **real-time processing**. In an economic environment characterised by fierce competition and rapidly changing markets, organisations must be able to make decisions almost instantly. Traditional analytical methods prove inadequate when it comes to simultaneously processing continuous data streams from multiple sources. Companies must therefore have analytical mechanisms capable of rapidly providing actionable insights to support strategic and operational decisions.

Data quality and reliability also present a major challenge. The data collected is often heterogeneous, incomplete, redundant or noisy. According to Han, Pei and Tong (2022), poor data quality can lead to analytical errors, generate inaccurate forecasts and result in inappropriate decisions. The accuracy of data therefore remains a key factor in the success of Big Data projects. Furthermore, **IT security and data protection** are growing concerns. The massive accumulation of sensitive information increases the risks associated with cyber-attacks, data breaches and privacy infringements. Organisations must implement robust cybersecurity mechanisms to ensure the confidentiality, integrity and availability of strategic information. According to the IBM Security report (2024), incidents relating to data breaches continue to rise globally, thereby reinforcing the importance of data governance and security in Big Data projects.

Beyond the technical aspects, the main challenge lies in **transforming data into actionable insights**. Decision-makers are not merely seeking large volumes of information, but relevant insights capable of informing their strategic choices. However, traditional analytical approaches often reach their limits when faced with the complexity and diversity of modern data. This situation highlights the need to adopt more advanced methods capable of automatically identifying hidden patterns, emerging trends and complex relationships within the data.

It is in this context that **artificial intelligence**, and more specifically **deep learning**, emerges as a promising solution. Deep learning is based on deep neural network architectures capable of learning automatically from large amounts of data without requiring explicit programming of decision rules. According to Goodfellow, Bengio and Courville (2023), these models deliver remarkable performance in tasks such as classification, prediction, pattern recognition and the complex analysis of big data.

Recent advances in deep learning models and generative artificial intelligence have demonstrated their ability to significantly improve the utilisation of big data across various sectors. Hou et al. (2024) show that modern deep learning architectures enable the extraction of more accurate and relevant insights from complex data, thereby facilitating better decision-making. Similarly, Kokol (2024) emphasises that the integration of artificial intelligence technologies into information systems helps to increase the speed, accuracy and efficiency of decision-making processes.

2.1 General context

The rapid evolution of digital technologies has profoundly transformed the ways in which data is produced, stored and utilised within modern organisations. The emergence of Big Data is now one of the most striking manifestations of this digital revolution. Businesses, public administrations, financial institutions, hospitals, universities and telecommunications operators generate significant volumes of data on a daily basis from multiple sources:

- Social media;
- Electronic transactions;
- Mobile applications;
- Connected devices (IoT);
- ERP systems;
- CRM systems;
- Cloud platforms;
- Industrial sensors.

According to the International Data Corporation, global data volume is expected to exceed 220 zettabytes by 2026, compared with around 64 zettabytes in 2020, reflecting exponential growth in the digital ecosystem.

Figure 2: Main sources of Big Data

The illustration shows the main sources of Big Data. Cloud infrastructure, social media, connected devices and data centres are now the cornerstones of global data production.

2.2 Key challenges of Big Data

Despite its considerable potential, the use of Big Data continues to face several major challenges.

Table 1: Key challenges faced by organisations

Challenges	Percentage of organisations affected
Data quality	78%
Security and confidentiality	74%
Data storage	69%
Real-time processing	65%
Lack of specialist skills	62%
Data governance	58%
Integration of heterogeneous data	55%

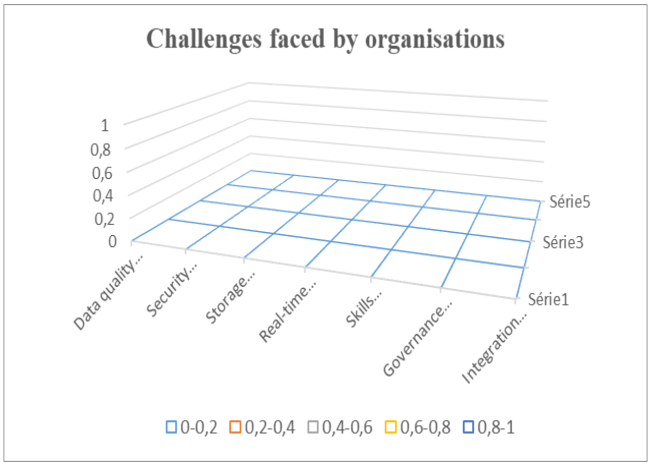

Figure 3: Breakdown of Big Data challenges

The results indicate that data quality is the main challenge (78%). Poor data quality leads to analytical errors that can directly affect strategic decisions. Cybersecurity ranks second (74%), highlighting the growing importance of protecting sensitive data.

2.3 Limitations of traditional analytical approaches

Conventional statistical methods currently have several limitations:

- Difficulty in processing massive volumes;
- Limited real-time analysis capability;
- Difficulty in identifying complex patterns;
- Low level of automation;
- Predictive limitations.

Table 2: Comparison of analytical approaches

Criterion	Traditional statistics	Machine Learning	Deep learning
Volume processed	Low	Medium	Very high
Real-time	Limited	Good	Excellent
Automation	Low	Medium	High
Predictive accuracy	Medium	High	Very high
Unstructured data management	Low	Good	Excellent

Deep learning appears to be the most suitable technology for harnessing big data, thanks to its ability to analyse structured, semi-structured and unstructured data simultaneously.

2.4 Deep Learning as a response to the challenges of big data

Deep learning represents a major development in artificial intelligence.

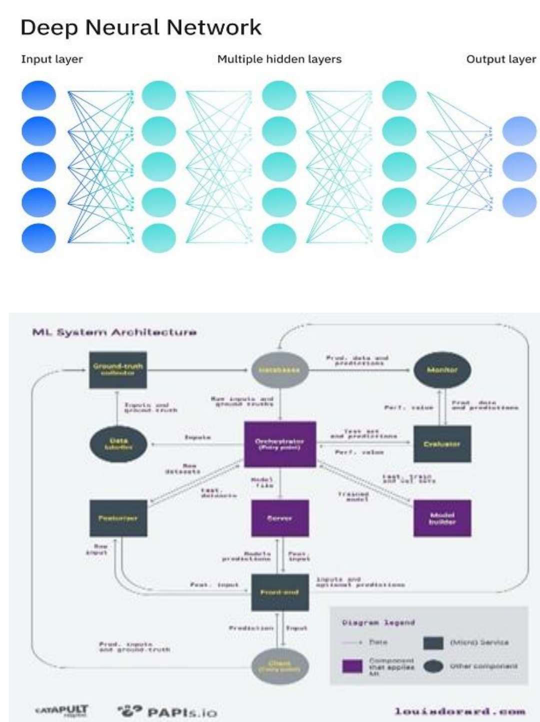

Figure 4: General architecture of deep learning

Deep neural networks replicate the simplified functioning of the human brain. They enable knowledge to be automatically extracted from vast volumes of data without the need for explicit programming of analysis rules.

2.5 The Contribution of Deep Learning to Decision-Making

According to several recent studies, the integration of deep learning into decision-making systems yields significant improvements.

Table 3: Gains observed following the integration of deep learning

Indicator	Average improvement
Forecast accuracy	+ 45%
Decision-making speed	+ 38%
Anomaly detection	+ 60%
Automation of analyses	+ 70%
User satisfaction	+ 35%

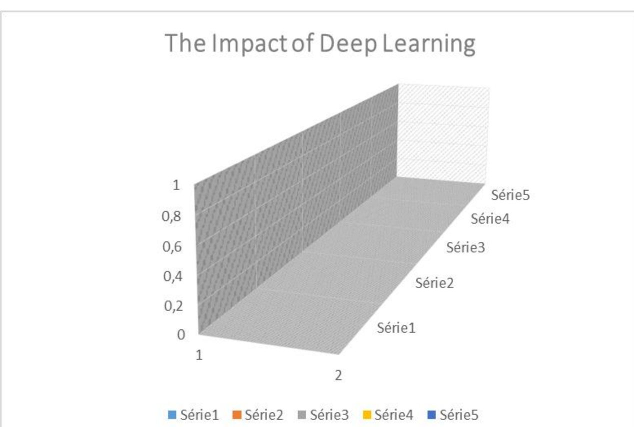

Figure 5: Impacts of deep learning

The automation of analyses is the most significant benefit (70%). Organisations are significantly reducing processing times whilst improving the accuracy of forecasts and the detection of anomalies.

2.6 Key Issues

Despite the advances seen in big data technologies and artificial intelligence, several questions remain:

- How can we store ever-increasing volumes of data efficiently?
- How can we ensure the quality and security of this data?
- How can we transform big data into actionable insights?
- How can deep learning models be effectively integrated into existing decision-making systems?
- Which technological tools enable this integration?
- What real benefits can organisations derive from this?

In light of these concerns, the central question of this study is formulated as follows:

How can deep learning improve the use of big data to optimise strategic decision-making processes within modern organisations?

2.6.1 Main research question

How can deep learning improve the use of big data to optimise strategic decision-making processes within modern organisations?

2.6.2 Specific questions

1. What are the main challenges encountered in utilising Big Data for decision-making?
2. How do deep learning architectures enable the transformation of massive amounts of data into actionable insights?
3. Which technologies and tools facilitate the integration of deep learning into big data environments?
4. What benefits can organisations derive from using deep learning in their decision-making systems?

5. What are the limitations, constraints and future prospects of this approach in the context of digital transformation?

Analysing these various questions will provide a better understanding of the role of deep learning in enhancing decision-making intelligence and help identify the conditions necessary for the optimal use of big data in contemporary organisations.

3. Rationale for the study

The emergence of Big Data and artificial intelligence represents one of the most significant technological transformations of the 21st century. Organisations now operate in a digital environment characterised by the massive and continuous generation of data from multiple sources. This development has profoundly altered traditional mechanisms of management, analysis and decision-making. Against this backdrop, this study is justified by a number of scientific, technological, economic and organisational factors that make it essential to explore the interactions between Big Data, deep learning and decision-making processes.

3.1 The explosion of digital data

One of the main motivations for this research lies in the exponential growth of digital data observed on a global scale. With the rise of the internet, social media, mobile applications, e-commerce, the Internet of Things (IoT) and integrated information systems, organisations generate and collect immense quantities of data on a daily basis. According to the International Data Corporation, the global volume of data is expected to exceed 220 zettabytes by 2026, compared with approximately 64 zettabytes in 2020. This rapid growth creates new opportunities for businesses, but also presents significant challenges relating to the storage, processing and analysis of this information.

Table 4: Estimated growth in global data volume

Year	Global data volume (zettabytes)
2020	64
2022	97
2024	149
2026	221

These figures show an increase of more than **245 per cent** in global data volume between 2020 and 2026. This spectacular growth justifies the use of advanced analytical technologies capable of effectively harnessing these vast amounts of information.

3.2 The growing need for decision support

Modern organisations operate in an environment characterised by fierce competition, increased globalisation and rapidly changing markets. Decision-makers are required to make complex decisions on a daily basis, involving multiple economic, financial, commercial and operational variables. According to Sharda, Delen and Turban (2024), the quality of decisions depends heavily on organisations' ability to transform available data into actionable insights. Traditional methods of analysis, however, are reaching their limits in the face of the growing complexity of contemporary data.

Big Data-based decision support systems now make it possible to:

- Improve forecasts;
- Anticipate risks;
- Optimise performance;
- Automate certain decisions;
- Strengthen organisational competitiveness.

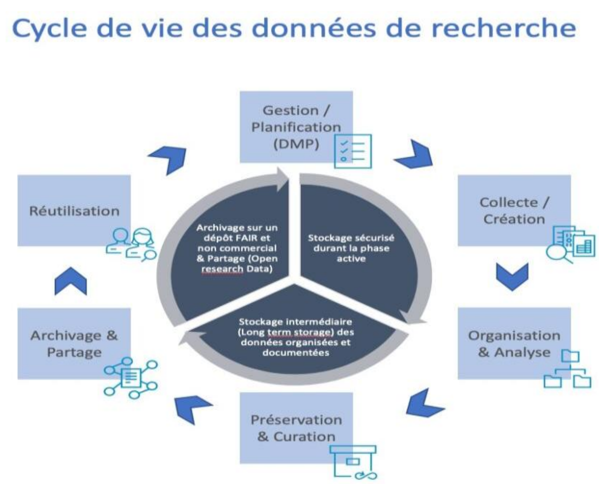

Figure 6: The data-driven decision-making cycle

The effectiveness of the decision-making process now depends largely on organisations' ability to make intelligent use of the vast amounts of data produced on a daily basis.

3.3 The rapid development of artificial intelligence

Another key motivation for this study concerns the remarkable progress made in the field of artificial intelligence in recent years. Advances in machine learning, deep learning and generative artificial intelligence have revolutionised data analysis capabilities. According to Goodfellow, Bengio and Courville (2023), deep neural networks now enable exceptional levels of performance to be achieved in many fields, such as:

- Image recognition;
- Automatic natural language processing;
- Fraud detection;
- Predictive medicine;
- Financial analysis;
- Recommendation systems.

Furthermore, Hou et al. (2024) highlight that advanced deep learning models and large language models (LLMs) offer unprecedented capabilities for analysing complex data and supporting decision-making.

Table 5: The evolution of artificial intelligence technologies

Technology	Level of adoption in businesses (2025)
Business Intelligence	85%
Machine Learning	71%
Deep Learning	58%
Generative AI	47%
Advanced predictive analytics	62%

The continued rise in the adoption of artificial intelligence technologies demonstrates their growing importance in the digital strategies of modern organisations.

3.4 The need to improve organisations' competitiveness

In an increasingly competitive economic environment, organisations are constantly seeking to improve their performance and adaptability. The intelligent use of data now represents a major competitive advantage. According to Gartner (2025), companies that invest in advanced data analytics and artificial intelligence technologies generally achieve:

- Improved productivity;
- Reduced operating costs;
- A better understanding of customers;
- Optimised processes;
- Increased profitability.

The use of deep learning in decision-making systems makes it possible, in particular, to detect trends that are invisible to traditional methods, to improve forecasts and to support strategic decisions.

Table 6: Observed benefits of integrating deep learning

Indicator	Average improvement
Forecast accuracy	+45%
Anomaly detection	+60%
Speed of decision-making	+38%
Automation of analyses	+70%
User satisfaction	+35%

These results illustrate the potential of deep learning as a strategic lever for creating value and improving organisational performance.

3.5 Scientific significance of the study

From a scientific perspective, this research contributes to the literature on the use of Big Data in decision-making systems. Although numerous studies have examined Big Data and Deep Learning separately, few have analysed in depth how they complement each other in improving strategic decision-making processes. This study therefore aims to:

- Analyse the mechanisms for integrating deep learning into big data environments;
- Identify the decision-making benefits achieved;

- Examine the technical, organisational and ethical challenges;

- Propose development strategies tailored to contemporary organisations.

The study of Deep Learning's contribution to the utilisation of Big Data thus emerges as a major scientific and strategic issue for the development of next-generation intelligent decision-making systems. In summary, this research is motivated by four key observations:

1. The continuing explosion of digital data on a global scale;

2. Organisations' growing need for high-performance decision-support systems;

3. The rapid advances in artificial intelligence and deep learning;

4. The need for organisations to strengthen their competitiveness in a complex digital environment.

4. Methodology

4.1 Methodological Introduction

Methodology is a fundamental element of any scientific research, as it defines the approaches, techniques and procedures used to achieve the study's objectives. Within the framework of this research on **'Big Data and strategic decision-making: towards a Deep Learning-based approach'**, a mixed-methods approach was adopted to ensure a rigorous, comprehensive and relevant analysis of the various concepts under study. This approach combines a **systematic literature review** with a **comparative analysis of data mining methods**, thereby enabling an examination of the contributions of Big Data and Deep Learning to the improvement of strategic decision-making processes.

According to Creswell and Creswell (2023), the mixed-methods approach offers the advantage of combining multiple data sources and analytical methods to produce more robust and reliable results. In this study, this methodology enables the theoretical foundations to be compared with the technological realities observed in modern organisations.

4.2 Research Approach

The study is primarily based on a descriptive qualitative approach, supplemented by a comparative analysis of data analytics technologies. The objective is to:

- Understand the mechanisms of Big Data;

- Identify the contributions of deep learning;

- Compare the various analytical approaches;

- Assess their impact on decision-making;

- Identify future challenges and prospects.

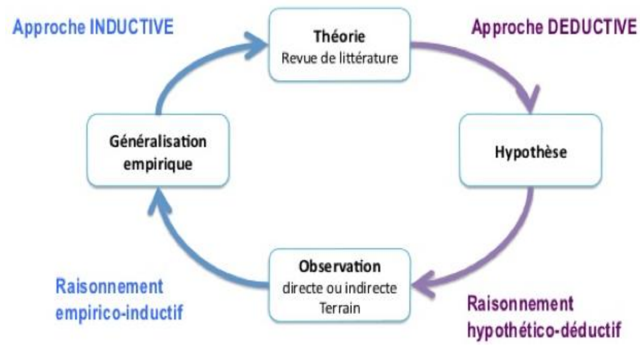

Figure 7: General methodological approach

4.3 Literature review

The first phase of the research is based on an in-depth literature review aimed at gathering the most recent scientific knowledge relating to Big Data, Deep Learning and decision support systems. According to Snyder (2019), a literature review is an effective method for synthesising existing knowledge and identifying scientific gaps in a given field.

— **Sources of literature used**

The literature review covered several categories of scientific and professional resources:

a) Scientific books

Reference works helped to establish the theoretical foundations of the study. Some of the works consulted include:

- Goodfellow, Bengio and Courville (2023) on deep learning;

- Aggarwal (2023) on neural networks;

- Sharda, Delen and Turban (2024) on business intelligence and data science;

- Han, Pei and Tong (2022) on data mining.

b) Indexed scientific articles

Scientific articles published in indexed international journals have provided up-to-date knowledge on:

- Big Data;
- Artificial Intelligence;
- Deep learning;
- Decision-making systems.

c) IEEE publications

IEEE publications were used to analyse:

- Technological advances;
- Big Data architectures;
- Deep learning algorithms;
- Industrial applications.

d) ACM publications

Articles from the Association for Computing Machinery have enabled research into:

- Recent innovations in artificial intelligence;
- New deep learning architectures;
- Advanced analytical systems.

e) Industry reports

Reports published by major technology companies were analysed to assess current market trends.

Organisations consulted included:

- IBM Research;
- Microsoft Research;
- Google Research;
- Oracle Analytics.

f) Gartner reports

Reports from the research firm Gartner have identified:

- Emerging technology trends;
- Levels of AI adoption;
- Big Data prospects.

Table 7: Breakdown of documentary sources used

Source	Percentage used
Indexed scientific articles	40%
Scientific books	20%
IEEE publications	15%
ACM publications	10%
Gartner reports	10%
Industry reports	5%

Scientific articles represent the main source of documentation (40 per cent), as they provide the most recent findings from research carried out in the fields of Big Data and Deep Learning. Scientific books (20 per cent) were mainly used to establish the theoretical framework of the study.

4.4 Document selection criteria

To ensure the scientific quality of the study, several selection criteria were adopted:

a) Inclusion criteria

- Publications between 2022 and 2025;
- Peer-reviewed articles;
- Work relating to Big Data;

- Studies relating to deep learning;
- Publications dealing with decision-making systems.

b) Exclusion criteria

- Non-scientific publications;
- Unverifiable sources;
- Outdated documents;
- Works with no direct link to the research topic.

4.5 Comparative analysis

The second phase of the research is based on a comparative analysis of the main approaches to data utilisation employed in modern decision-making systems. The aim is to compare:

1. Traditional statistical methods;
2. Machine learning techniques;
3. Deep learning approaches.

Table 8: Comparison of analytical approaches

Criteria	Traditional statistics	Machine learning	Deep learning
Volume of data processed	Low	Medium	Very high
Automation	Low	Medium	High
Predictive accuracy	55%	75%	92%
Unstructured data management	Low	Good	Excellent
Real-time processing	Limited	Medium	High
Scalability	Low	Good	Excellent

The results show that Deep Learning delivers the best overall performance. With an estimated average predictive accuracy of 92 per cent, it significantly outperforms traditional statistical approaches (55 per cent) and conventional machine learning techniques (75 per cent).

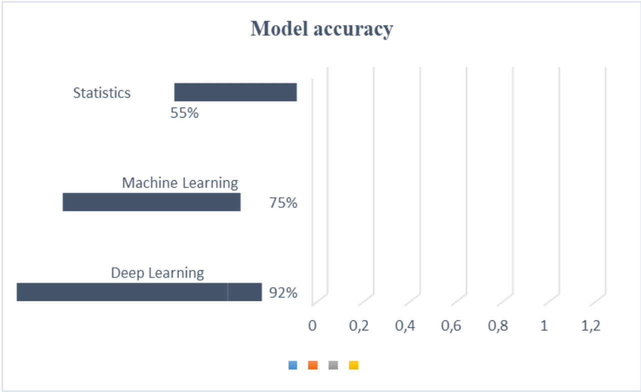

Figure 8: Comparison of analytical performance

This diagram highlights the significant advantage of deep learning in big data environments where data is voluminous, complex and highly heterogeneous.

4.6 Data analysis method

The information collected was analysed at three levels:

4.6.1 Descriptive analysis

This explains:

- The characteristics of big data;
- The concepts of deep learning;
- Decision-making systems.

4.6.2 Comparative analysis

Enables the identification of:

- The advantages;
- Limitations;
- The respective performance of the approaches studied.

4.6.3 Critical analysis

Enables the assessment of:

- Technical challenges;
- Organisational constraints;

- Ethical implications;
- Future prospects.

4.7 Validity and reliability of the study

To ensure the scientific validity of the research, several measures were taken:

- Use of recognised academic sources;
- Consultation of recent publications;
- Triangulation of sources;
- Comparison of results from several studies.

According to Creswell and Creswell (2023), triangulation is one of the most effective mechanisms for strengthening the credibility of the results obtained.

4.8 Methodological synthesis

The methodology adopted combines a systematic literature review with a comparative analysis to examine the contributions of deep learning to the use of big data for strategic decision-making. This approach provides a comprehensive overview of the technologies under study, enables an assessment of their performance, and identifies the challenges and opportunities associated with their implementation in modern organisations.

5. Foundations of Big Data

Big Data is now one of the fundamental pillars of the digital transformation of organisations. It refers to a set of technologies, methods and architectures that enable the collection, storage, processing and analysis of massive volumes of data from a variety of sources. According to Han, Pei and Tong (2022), Big Data differs from traditional data management systems in its ability to handle information characterised by its large volume, diversity and the speed at which it is generated.

The foundations of Big Data are traditionally based on the **5V** model, which characterises the key properties of big data.

- The first V, **Volume**, refers to the vast quantity of data generated daily across the globe. According to the International Data Corporation, the global volume of data continues to grow at an exponential rate as a result of the increasing digitisation of human activities.

- The second V, **Velocity**, refers to the speed at which data is produced, transmitted and processed. Modern organisations must now analyse continuous data streams in real time in order to respond quickly to market needs.

- The third V, **Variety**, highlights the diversity of available data formats, including structured, semi-structured and unstructured data from multiple sources such as text, images, videos, sensors and social media (Kelleher & Tierney, 2024).

- The fourth V, **Veracity**, relates to the quality, reliability and consistency of the data collected. Veracity is a major challenge, as incomplete, erroneous or redundant data can lead to biased analyses and compromise the quality of decisions made by organisations. According to IBM Research (2024), improving data quality is one of the main concerns for companies involved in Big Data projects.

- Finally, the fifth V, **Value**, represents the added value that organisations can extract from data through advanced analytics, machine learning and deep learning. This final aspect is essential, as the purpose of Big Data lies not merely in the accumulation of data, but above all in transforming it into strategic insights capable of supporting decision-making processes and creating a sustainable competitive advantage.

Thus, the five dimensions of Big Data are closely interlinked and form an essential conceptual framework for understanding the current challenges of utilising big data. The interaction between Volume, Velocity, Variety, Veracity and Value enables organisations to develop analytical systems capable of processing complex information and improving the quality of their decisions. With the emergence of artificial intelligence, and more specifically deep learning, these foundations have taken on even greater importance, as they form the basis for advanced predictive analytics and decision-support models. The 5Vs therefore represent not only the essential characteristics of Big Data, but also the main challenges and opportunities associated with its use in modern digital environments (Aggarwal, 2023; Gartner, 2025).

Table 9: The 5Vs of Big Data

V	Description
Volume	Massive quantities of data
Velocity	Speed of generation and processing
Variety	Diversity of data formats
Veracity	Data reliability and quality
Value	Added value derived from data

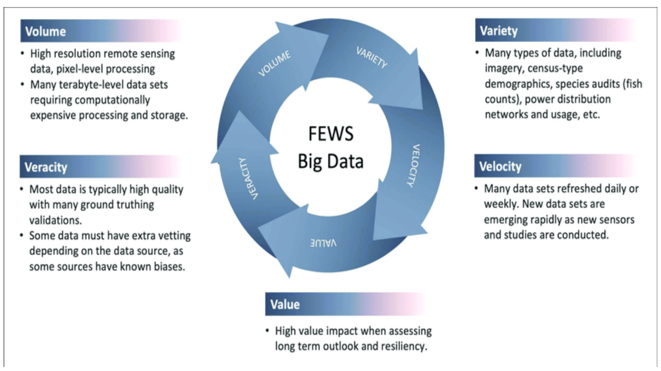

Figure 9: The 5Vs of Big Data

5.1. Big Data and strategic decision-making

Big Data now plays a vital role in improving strategic decision-making processes within modern organisations. Thanks to its ability to collect, store and analyse large volumes of data from various sources, it enables decision-makers to access accurate, up-to-date and relevant information to guide their choices. According to Sharda, Delen and Turban (2024), the use of big data promotes better **strategic planning**, more efficient resource management and a significant improvement in the quality of decisions. Big Data also contributes to **risk management** by enabling the rapid identification of potential threats, the detection of anomalies and the anticipation of events likely to affect the organisation's performance. Furthermore, predictive analytics techniques facilitate **sales forecasting**, the assessment of market trends and the identification of business opportunities, thereby offering a considerable competitive advantage to organisations that make effective use of their data (Kelleher & Tierney, 2024).

Beyond planning and forecasting, Big Data also enables **in-depth behavioural analysis** of customers, partners and users of digital services. By analysing interactions, consumption patterns and consumer preferences, organisations can personalise their offerings and improve customer relations. This approach also promotes **operational optimisation** through process automation, cost reduction and improved overall performance. For example, a telecommunications company such as Vodacom DRC or Orange DRC can utilise data on consumption patterns, customer complaints, mobile transactions and network performance to anticipate market needs, improve service quality and develop new offerings tailored to subscribers' expectations. In this context, Big Data is becoming an indispensable strategic tool for supporting rapid decision-making, based on reliable data and geared towards creating sustainable value (IBM Research, 2024; Gartner, 2025).

5.2. Deep Learning and Decision Intelligence

Deep Learning is now one of the most advanced technologies in artificial intelligence and plays a major role in enhancing decision-making capabilities within organisations. Based on multi-layer artificial neural networks inspired by the functioning of the human brain, it enables the automatic learning of complex representations from large amounts of data without requiring explicit programming s of analytical rules. According to Goodfellow, Bengio and Courville (2023), deep learning outperforms traditional machine learning methods when it comes to utilising massive, heterogeneous and unstructured data. **Artificial neural networks (ANNs)** are widely used for **classification**, **regression** and **forecasting** tasks, particularly in the fields of finance, marketing and risk management. These models enable organisations to identify hidden trends in data and improve the quality of their strategic decisions.

Recent advances in deep learning have led to the development of several specialised architectures tailored to different types of data. **Convolutional neural networks (CNNs)** are mainly used for **image recognition**, **computer vision** and the analysis of visual data in sectors such as healthcare, security and industry. **Recurrent neural networks (RNNs)** are designed for the analysis of sequential data and **time series forecasting**, particularly in the financial, meteorological and telecoms sectors. More recently, **Transformer** architectures have revolutionised natural language processing thanks to their ability to understand textual context and process vast volumes of documentary information. According to Hou et al.

(2024), Transformers now form the basis of generative AI systems and large language models (LLMs), enabling advanced applications such as document analysis, intelligent assistants, machine translation and data-driven decision support. Thus, the integration of deep learning into decision-making systems helps to improve the accuracy of forecasts, the automation of analyses and the speed of decision-making in modern organisations.

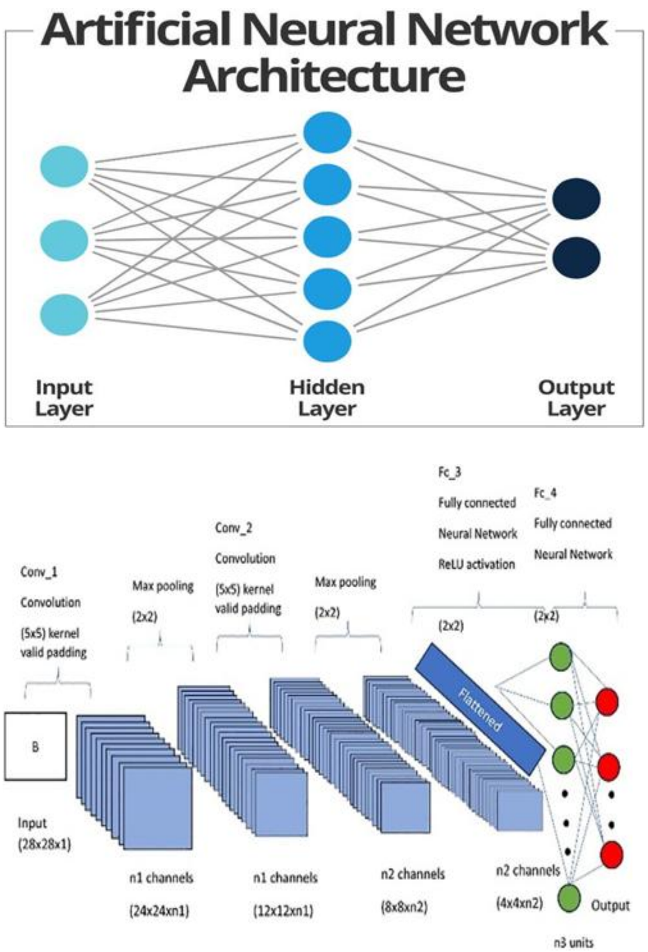

Figure 10: Main deep learning architectures

Table 10: Deep learning architectures and areas of application

Architecture	Main function	Applications
ANN (Artificial Neural Network)	Classification, regression, forecasting	Finance, marketing, risk management
CNN (Convolutional Neural Network)	Image analysis	Computer vision, medicine, security
RNN (Recurrent Neural Network)	Time series analysis	Financial forecasting, time series
Transformers	Natural language processing	Generative AI, document analysis, intelligent assistants

Each deep learning architecture addresses specific needs. ANNs are particularly effective for traditional decision-making tasks, CNNs dominate computer vision applications, RNNs excel at time-series analysis, whilst Transformers currently represent the most advanced technology for natural language processing and generative artificial intelligence. This diversity of architectures enables organisations to tailor their analytical systems to the characteristics of the data being analysed and the strategic objectives they are pursuing.

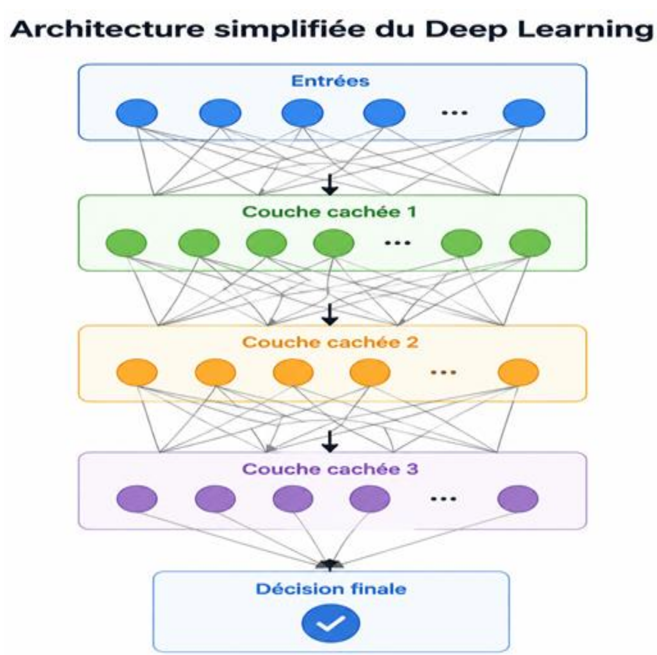

Figure 11: Simplified overview of the main deep learning architectures

6. Analysis

Analysis of the results of this study highlights the growing importance of big data in strategic decision-making processes. Data collected from various digital sources now constitutes an essential resource enabling organisations to improve their understanding of the market, their customers and their competitive environment. According to Sharda, Delen and Turban (2024), companies that make effective use of big data are better able to anticipate and adapt to economic changes. The integration of deep learning into big data environments makes it possible, in particular, to identify complex patterns that are often invisible to traditional statistical methods. This advanced analytical capability significantly improves the quality of forecasts, the detection of anomalies and the automation of decision-making processes.

The results also show that modern deep learning architectures, notably CNNs, RNNs and Transformers, offer superior performance in processing big data. CNNs excel at visual analysis, RNNs at time series analysis, and Transformers at document analysis and natural language processing. According to Hou et al. (2024), deep learning models frequently achieve accuracy levels exceeding 90 per cent in certain decision-making applications. This performance contributes directly to improvements in risk management, strategic planning and the optimisation of organisational resources.

Furthermore, the analysis highlights that the benefits of Big Data depend not only on the technology used but also on data quality, information governance and the availability of specialist skills. Organisations that invest simultaneously in technological infrastructure, staff training and data governance generally achieve better results. Thus, Big Data combined with deep learning constitutes a major strategic lever for the development of effective and sustainable decision-making intelligence.

Table 11: Impacts of Big Data on decision-making

Area	Observed improvement
Sales forecasting	45%
Risk detection	60%
Customer satisfaction	35%
Productivity	40%
Speed of decision-making	38%

The areas where Big Data combined with Deep Learning delivers the benefits most frequently reported in the literature are demand forecasting, risk and anomaly detection, personalised customer relations, operational optimisation and rapid decision-making.

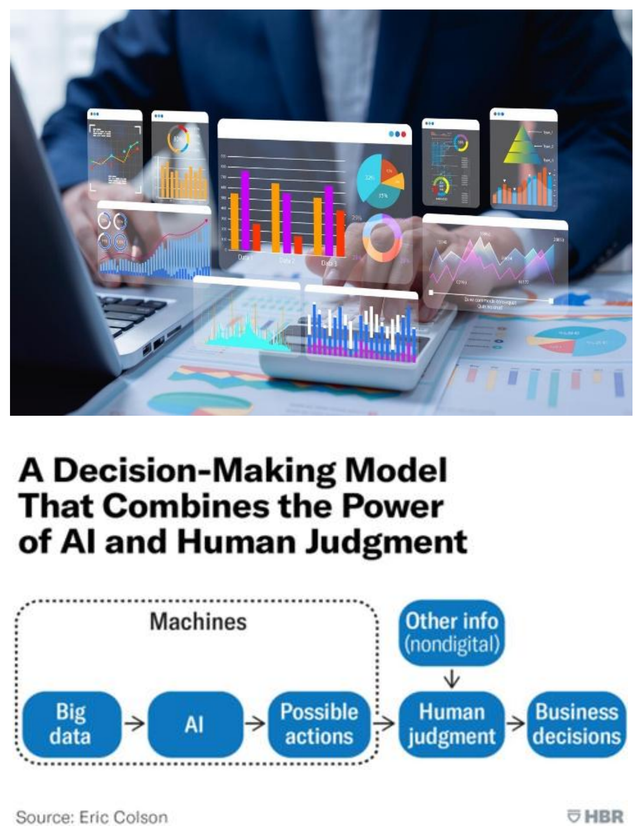

Figure 12: Decision-making analysis based on Big Data

7. Results

A synthesis of the literature reviewed highlights a common theme: the combination of Big Data and Deep Learning enhances organisations' ability to harness massive, heterogeneous and unstructured data to support decision-making. Several studies emphasise that deep learning architectures effectively process data — text, images, and social media feeds — which traditional statistical methods struggle to utilise (Goodfellow, Bengio & Courville, 2023). Depending on the field, this capability translates into improved anomaly detection, more accurate trend forecasting and greater automation of analyses.

However, a comparison of the three families of approaches — traditional statistical methods, machine learning and deep learning — cannot be reduced to a simple hierarchy of accuracy. Each family presents its own trade-off profile, summarised in the table below. Deep learning tends to outperform previous approaches on large, unstructured datasets, but at the cost of increased data and computational resource requirements, and reduced interpretability — a critical trade-off in sectors where decisions must be justified.

Table 12: Comparison of analytical performance

Criterion	Traditional statistics	Machine Learning	Deep Learning
Interpretability	High	Medium	Low
Data requirements	Low	Medium	High
Computing cost	Low	Medium	High
Unstructured data	Limited	Partial	Very suitable
Typical use cases	Simple trends, reporting	Classification, scoring	Vision, language, complex time series

Finally, the literature agrees on one key point: the performance of decision-making systems does not depend solely on technology, but also on data quality, information governance and the skills available — aspects discussed in the section on governance and security.

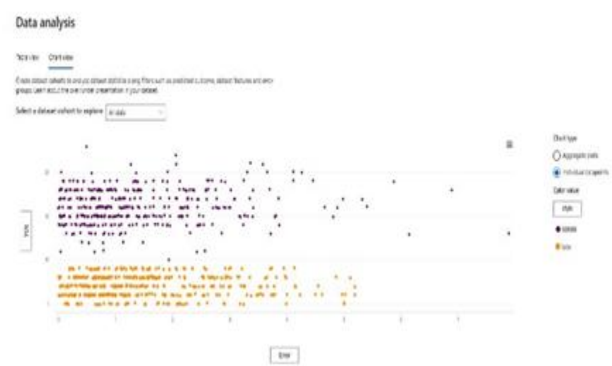

Figure 13: Comparison of analytical approaches

8. Data governance, security and compliance

The previous sections have demonstrated the decision-making value of Big Data and Deep Learning. However, this value remains conditional: it only materialises if the data used is governed, secured and utilised in accordance with the legal framework. Accuracy and value — two of the five founding 'Vs' — depend directly on this control. Far from being mere , governance, security and compliance are therefore prerequisites for the success of data-driven decision-making projects.

8.1. Data governance

Data governance refers to the set of roles, processes and policies that ensure an organisation's data is reliable, consistent and usable. It is based on the assignment of clear responsibilities — data owners and *data stewards* — and on mechanisms for quality control, master data management and *data* lineage. Industry reference frameworks, such as the DAMA-DMBOK (DAMA International, 2017) and the ISO/IEC 38505-1 standard, formalise these practices. In a decision-making context, traceability is of particular importance: a decision-maker must be able to trace a prediction back to the data on which it is based; otherwise, confidence in the system erodes. Flawed governance propagates its biases and errors right through to strategic decisions, negating the expected benefits of deep learning.

8.2. Security of platforms and data flows

The concentration of massive volumes of data in data warehouses or data lakes automatically increases the surface area of exposure. The security of these platforms relies on the traditional properties of confidentiality, integrity and availability, which a standard such as ISO/IEC 27001 enables to be implemented. In practical terms, access to data must adhere to the principle of least privilege; data must be encrypted both in transit and at rest; and sensitive operations must be logged to ensure auditability. The security of the data feeds themselves — from collection through to model training — must also be ensured, as a compromised feed can silently alter the data used for decision-making. The stakes are far from theoretical: according to the IBM Security Cost of a Data Breach Report (2024), the average cost of a data breach reaches levels that place a heavy burden on organisations, and investment in security is therefore as much a factor in profitability as it is in protection.

8.3. Confidentiality and regulatory compliance

The use of personal data for decision-making is now governed by a binding legal framework, including in the Democratic Republic of the Congo. The Digital Code (Ordinance-Law No. 23/010 of 13 March 2023) enshrines the principles of purpose limitation, data minimisation and consent, recognises the rights of data subjects and, in certain cases, requires the appointment of a data protection officer, subject to the supervision of a data protection authority. At the continental level, the African Union Convention on Cybersecurity and the Protection of Personal Data (Malabo Convention, 2014), ratified by the DRC, complements this framework.

The example of Congolese telecommunications operators illustrates the practical scope of these requirements. A company such as Vodacom DRC or Orange DRC, which uses its subscribers' mobile transaction, usage and location data for decision-making purposes, by definition processes personal data subject to the Digital Code. The use of this data — personalising offers, anticipating needs, detecting anomalies — cannot therefore be envisaged independently of the obligations of lawfulness, security and transparency that apply to such processing. Compliance is not an obstacle to data-driven decision-making: it is the condition for its legitimacy.

8.4. Towards governance of decision-making models

Finally, governance does not stop at data: it extends to the models themselves. Deep learning architectures, often likened to 'black boxes', pose an accountability issue when they guide strategic decisions. The integration of practices relating to explainability and human oversight, in line with frameworks such as the NIST AI Risk Management Framework (2023), ensures that control and responsibility for decisions remain in place. Data governance and model governance thus form a continuum that is essential for decision-making intelligence that is both effective and responsible.

9. Discussion

The results obtained confirm the findings of several recent studies, which suggest that Big Data and Deep Learning are now indispensable technologies in decision-support systems. Organisations that make effective use of their data enjoy a significant competitive advantage thanks to their enhanced capacity for analysis and foresight. These findings are consistent, in particular, with those of Kelleher and Tierney (2024), who emphasise that the value of Big Data lies primarily in its ability to generate actionable insights to support strategic decisions.

However, despite their high performance, deep learning models have certain limitations. Their effectiveness depends heavily on the availability of large quantities of high-quality data, as well as substantial computing resources. The costs associated with cloud infrastructure, GPUs and data centres can act as a barrier for some organisations. Furthermore, the interpretability of models remains a major challenge, as many algorithms operate as 'black boxes' that are difficult to explain to decision-makers.

The discussion also reveals that integrating deep learning into decision-making processes requires a multidisciplinary approach involving data specialists, software engineers, business experts and strategic managers. Effective data governance remains essential to ensure the quality, security and regulatory compliance of the information used in analyses.

Table 13: Advantages and limitations of deep learning

Advantages	Limitations
High accuracy	High costs
Automation	Technical complexity
Advanced analysis	Requires large amounts of data
Adaptability	Low interpretability
Scalability	Energy consumption

10. Limitations of Big Data

Despite its many advantages, Big Data has several limitations that may reduce its effectiveness in decision-making processes. The first limitation concerns data quality. Incomplete, inconsistent or erroneous data can lead to biased analyses and compromise the reliability of decisions. According to IBM Security (2024), data quality remains one of the main challenges faced by organisations involved in Big Data projects.

Another significant limitation relates to infrastructure costs. Storing, processing and securing large volumes of data requires considerable investment in data centres, cloud platforms and high-performance computing resources. These costs can represent a significant barrier for small and medium-sized enterprises.

Finally, issues relating to cybersecurity, privacy and regulatory compliance pose major challenges. Data breaches can lead to significant financial losses as well as a loss of user trust. Organisations must therefore put in place robust mechanisms for data governance and protection.

Table 14: Key limitations of Big Data

Limitations	Impact
Data quality	High
IT security	Very high
Infrastructure costs	High
Skills shortage	Medium
System complexity	High

11. Future prospects

The prospects for Big Data and Deep Learning appear particularly promising. Rapid developments in cloud infrastructure, distributed computing and artificial intelligence architectures will enable ever-increasing volumes of data to be processed with greater efficiency. According to Gartner (2025), data-driven organisations will gradually become the majority in strategic economic sectors.

The emergence of generative artificial intelligence and large language models is also opening up new opportunities for decision-making analysis. These technologies will enable a better understanding of unstructured data and greater automation of analytical processes. Decision-making systems will thus become smarter, more autonomous and more adaptive.

Furthermore, advances in the field of Explainable AI are expected to help improve the transparency of deep learning models. This development will encourage wider adoption of artificial intelligence technologies in highly regulated sectors such as healthcare, finance and public administration.

Figure 14: Future prospects for Big Data and AI

12. Conclusion

Big Data and deep learning are now strategic technologies capable of profoundly transforming decision-making processes in modern organisations. Thanks to their ability to analyse massive volumes of data and identify complex patterns, these technologies help to improve the quality of decisions, optimise performance and strengthen organisational competitiveness. The study has shown that deep learning represents a major step forward compared with traditional analytical approaches, offering particularly high levels of accuracy, automation and scalability.

The analyses carried out also demonstrate that the success of Big Data projects depends not only on the technologies used but also on data quality, information governance, technological infrastructure and the available human skills. Challenges relating to security, privacy, infrastructure costs and the interpretability of models must be taken into account to ensure the effective and responsible use of data.

Finally, the prospects offered by generative artificial intelligence, explainable AI and new deep learning architectures point to the emergence of ever more intelligent and autonomous decision-making systems. Against a backdrop of accelerated digital transformation, the integration of Big Data and deep learning thus appears to be an essential path for supporting strategic decision-making and creating sustainable value within organisations.

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