

# The Role of Decision Intelligence in Next-Generation Business Intelligence Systems: A Review

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**Abstract:** Business Intelligence (BI) has served as a long-time backbone for data-driven decisions but has struggled to turn insights from analysis into action. Decision Intelligence (DI) has emerged as a new approach to addressing this epistemic gap, embedding data analytics, artificial intelligence (AI), and decision theory to support faster, smarter, and more accountable decision-making. This paper demonstrates how DI enhances next-generation BI systems by integrating decision logic, causal reasoning, and human oversight into conventional analytics processes. Grounded in recent literature and applications across healthcare, finance, and supply chain management, this paper shows how DI can transform BI from a descriptive reporting function into a discipline of decision engineering. Despite these advances, unresolved challenges remain, and direction is needed on explainability, ethical governance, and organizational adoption. By triangulating insights from leading research and practice-based literature, this paper identifies future directions for how Decision Intelligence Influences Business Intelligence frameworks, shifting BI systems from analytics tools to a platform for intelligence and informed action.

**Keywords:** Decision Intelligence; Business Intelligence; Artificial Intelligence; Predictive Analytics; Human–AI Collaboration; Decision Making; Business Environments; Organizational Actions.

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## 1. Introduction

In the era of rapidly advancing digital technology, organisations increasingly depend on Business Intelligence to transform raw data into meaningful insights that inform strategic and operational decision-making. Business Intelligence systems traditionally enable organizations to gather, organize, and visualise historical data through dashboards, periodic reports, and performance indicators. These tools support descriptive and diagnostic analytics that help managers understand what has happened and why particular outcomes were produced [29]. However, as business environments become more dynamic, competitive, and uncertain, the need for faster, more adaptive, and more prescriptive decision tools has intensified. Established Business Intelligence systems often struggle to support highly complex decisions made under time pressure, involving multiple interdependent variables and uncertain consequences. Scholars note that conventional Business Intelligence tends to focus primarily on retrospective analysis rather than guiding future actions, which can limit its effectiveness in turbulent contexts

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where agility and foresight are essential for survival and growth [2]. Despite substantial advances in big data platforms, predictive analytics, and automation, a persistent challenge remains in translating analytical insights into concrete organizational actions. This persistent gap between generating insight and executing informed action is widely known as the insight-to-action gap. Many organizations succeed in producing sophisticated dashboards and analytical summaries but still fail to embed these findings into routine decision-making processes or strategic initiatives. Reasons often include fragmented decision ownership, limited contextual understanding, organisational inertia, limited analytical literacy, and weak alignment between analytics teams and business leaders [8].

As a result, vast investments in data warehouses, analytics tools, and reporting platforms may yield limited impact if decisions continue to be driven predominantly by intuition, habit, or hierarchical authority rather than evidence. This gap has motivated the search for approaches that directly integrate analytics with the cognitive, social, and procedural aspects of decision making [30]. Decision Intelligence has emerged as a response to these shortcomings by proposing a more holistic integration of data science, artificial intelligence, decision theory, behavioural sciences, and management practice. Decision Intelligence emphasizes that the value of data is realized not at the point of analysis but at the point of decision and subsequent action. It therefore focuses on designing intelligent systems that can not only analyze data but also recommend, evaluate, and sometimes execute decisions in complex environments [10]. Business Intelligence answers the question of what happened, while Decision Intelligence seeks to answer what should happen next by embedding prescriptive, and sometimes autonomous, decision capabilities into organisational processes. It recognizes that decisions are not merely computational outputs but socio-technical processes that involve human judgment, ethical considerations, risk tolerance, and organizational objectives. Decision Intelligence leverages a broad range of analytical techniques, including machine learning, predictive and prescriptive analytics, simulation optimization, and causal inference. These approaches allow organizations to move beyond static reporting toward dynamic predictions, scenario analysis, and proactive intervention strategies. The Decision Intelligence paradigm reframes analytics from passive observation of business phenomena to active participation in shaping outcomes.

As Tasleem et al. [11] observe, Decision Intelligence systems integrate analytics with decision workflows to support faster, more consistent, and more context-aware actions. In volatile environments where data is generated in real time, such as digital platforms, supply chains, healthcare systems, and financial markets, organizations that can translate data into rapid decisions gain a significant competitive advantage. The shift from Business Intelligence to Decision Intelligence represents not merely a technological upgrade but a conceptual evolution in how organizations approach decisions. Traditional Business Intelligence architectures are typically centralised and tool-focused, emphasising data warehousing, data governance, and standardised reporting. Decision Intelligence, in contrast, requires decision-centric architectures in which analytical processes are intentionally designed around key decision points. This involves mapping decision processes, understanding stakeholders, identifying uncertainties, defining desired outcomes, and determining how data models and artificial intelligence can support or automate choices. By focusing on the decision rather than the dataset, Decision Intelligence aligns analytical resources with strategic priorities and practical outcomes. One of the central contributions of Decision Intelligence is its capacity to remedy several longstanding limitations of Business Intelligence. First Decision Intelligence addresses the problem of slow decision cycles. In many organizations, analytical reports are produced periodically, often monthly or quarterly, and distributed through hierarchical approval channels, which delay responsiveness. Decision Intelligence embeds analytics into operational systems, enabling near-real-time recommendations that support rapid action in customer service, fraud detection, logistics, and inventory management.

Second Decision Intelligence overcomes the limited prescriptive power of Business Intelligence, which tends to explain and describe rather than prescribe. Through optimization models, reinforcement learning, and prescriptive analytics, Decision Intelligence can suggest concrete courses of action and estimate likely consequences. Third, it strengthens strategic alignment by explicitly linking data models to business goals, performance metrics, and decision outcomes. This alignment reduces the common problem in Business Intelligence where technically interesting insights fail to translate into meaningful strategic change. However, the transition from Business Intelligence to Decision Intelligence is neither automatic nor simple. It requires overcoming both technological and organizational barriers. On the technological side, organizations need integrated data ecosystems, scalable computing infrastructure, and robust artificial intelligence capabilities. Data quality, interoperability, and privacy remain persistent obstacles. Poor data quality can undermine the reliability of Decision Intelligence outputs, while regulatory requirements on data protection impose constraints on model design and deployment. Furthermore, advanced Decision Intelligence models may require large training datasets, sophisticated feature engineering, and continuous updating, a resource-intensive process that not all organizations can easily support. From an organizational perspective, Decision Intelligence requires cultural change. Decision-making in many organizations is deeply embedded in hierarchical experience and intuition.

Introducing AI-supported decision frameworks can challenge established power dynamics and professional identities, particularly where automated recommendations appear to question managerial judgment. Employees may resist adoption due to fears of job displacement, a lack of trust in algorithmic outputs, or an insufficient understanding of how models function.

Therefore, human AI collaboration is a critical area of research and practice. Decision Intelligence does not aim to replace human decision makers but to augment them by providing structured insights, simulations, and recommendations. Effective collaboration requires designing systems that are understandable, intuitive, and aligned with human cognitive processes. Explainability plays a crucial role in building trust in Decision Intelligence systems. Black-box artificial intelligence models may provide highly accurate predictions, but if their rationale cannot be understood by decision-makers, regulators, or affected stakeholders, their adoption may be limited. Explainable Decision Intelligence models provide clarity about which variables influenced an outcome, why a particular recommendation was generated, and how uncertainty is represented. This is especially important in domains such as healthcare finance and public policy, where ethical obligations, accountability, and regulatory scrutiny are strong.

Explainable AI also supports learning within organisations, as decision-makers can reflect on model logic and refine their understanding of complex systems. Another emerging issue in Decision Intelligence concerns governance frameworks. As organisations incorporate intelligent systems into decision-making processes, they must address questions about responsibility, liability, transparency, and bias. Algorithms trained on historical data may reproduce or amplify past inequities unless carefully monitored and corrected. Governance mechanisms are necessary to establish oversight structures, validation procedures, audit trails, and ethical guidelines for automated or semi-automated decision systems. Strong governance also helps to ensure that Decision Intelligence systems remain aligned with organizational strategy, societal values, and legal requirements as they evolve. The integration of Decision Intelligence into organizational life is likely to reshape roles and skills across many professions. Decision engineers or decision scientists are emerging as new professional profiles who combine knowledge of analytics with an understanding of decision theory, psychology, and management. Managers increasingly require data literacy to interpret model outputs and participate in the design of decision systems. Meanwhile, data scientists are expected to broaden their perspective from model accuracy metrics to questions about decision impact, usability, and change management. Educational programs and organizational training initiatives will therefore play an essential role in enabling the widespread adoption of Decision Intelligence. The economic implications of Decision Intelligence are extensive. Organizations that adopt Decision Intelligence can expect improved operational efficiency, reduced uncertainty, better risk management, and enhanced strategic foresight.

By simulating future states and evaluating alternative scenarios, Decision Intelligence can support investment planning, resource allocation, product pricing, and policy design. In customer-facing applications, Decision Intelligence can personalise recommendations, manage churn, enhance the customer experience, and optimise marketing campaigns. In public sector contexts, it can support urban planning, disaster response, targeted social programs, and public health interventions. The integration of data models and decision frameworks can therefore contribute not only to corporate competitiveness but also to societal welfare when applied responsibly. Nevertheless, enthusiasm for Decision Intelligence must be balanced with critical awareness of its limitations. Not all decisions can be fully modeled. Many involve ambiguous objectives, conflicting stakeholder interests, political considerations, or ethical dilemmas that transcend quantitative optimization. Overreliance on automated recommendations may narrow perspectives and reduce creativity if human judgment is marginalized. Decision Intelligence practitioners therefore emphasize hybrid decision-making models that combine algorithmic recommendations with deliberative processes, experiential knowledge, and participatory consultation. Such integration recognizes that decision quality depends not only on data and computation but also on values, legitimacy, and human insight. Research in Decision Intelligence continues to expand, and several promising directions invite further exploration. Development of more interpretable artificial intelligence models remains a priority to bridge the gap between performance and transparency.

Another area involves the design of collaborative interfaces that allow humans and AI systems to learn from each other over time. Integration with cognitive science may yield improved understanding of how people perceive risk, evaluate evidence, and respond to automated advice. Further work is needed to assess the real-world impact of Decision Intelligence initiatives beyond laboratory accuracy metrics, including how they reshape behavioural structures and power relations within organisations. Decision Intelligence represents the next evolutionary phase in the use of data within organisations, advancing beyond the descriptive and diagnostic capabilities of Business Intelligence toward fully integrated decision-centred frameworks. By linking analytics directly to action, Decision Intelligence addresses the longstanding insight-to-action gap and equips organizations to operate more quickly, confidently, and strategically in volatile environments. It combines data science, artificial intelligence, and decision theory to support informed, transparent, and aligned decisions. At the same time, successful implementation requires attention to organizational culture, ethical governance, human-AI collaboration, and the development of new skills and roles. With thoughtful design and responsible deployment, Decision Intelligence holds the potential to transform how organizations think, decide, and act in the digital age while ensuring that data-driven progress remains anchored in human values and societal benefit.

## 2. Related Works

### 2.1. Evolution of Business Intelligence

The term Business Intelligence (BI) was introduced by Cempírek et al. [26]. He described BI as a set of concepts and methods for improving business decision-making through fact-based, computerized support systems. Pirttimäki [23] frames BI as all activities related to the collection, integration, analysis, and dissemination of that data to meet the information needs of decision-makers and the organisational goal of achieving a competitive advantage. BI is the process of gathering and analyzing data from both internal and external sources to provide decision-makers with relevant, timely insights into business performance, weaknesses, opportunities, and threats, effectively guiding their decisions [24]. Over the past two decades, Business Intelligence (BI) has evolved from static reporting tools into sophisticated analytical platforms that support organisational decision-making. The primary purpose of BI systems is to provide decision-makers with information by filtering it from valuable datasets. Hannula and Pirttimäki [27] mention BI systems as an important class of systems for data analysis and reporting, providing managers at various levels of the organisation with timely, relevant, and easy-to-use information, enabling them to make better decisions [25]. Early systems primarily transformed raw transactional data into descriptive dashboards and scorecards, offering answers to “what happened in the past?” but providing little guidance on “what should we do next?” [2]. Initial BI efforts, based on data warehouses and OLAP technologies, enabled enterprises to consolidate data and improve performance monitoring, but were limited in responsiveness and adaptability. Contemporary reviews indicate that, despite technological progress, many organizations continue to struggle to capture the full strategic value of BI systems.

Alghamdi and Khojah [1] identified organizational structure, technological infrastructure, and management support as critical determinants of BI success. In contrast, Chi and Mahmud [3] found that adoption rates remain low and benefits are not consistently realized. Bibliometric analyses reveal that BI research has gradually shifted from purely technical topics (data warehouses, ETL pipelines, dashboard design) toward decision-centric and strategy-driven themes such as organizational agility and analytics maturity [4]; [5]. Despite its maturity, BI still exhibits three persistent limitations: (i) an emphasis on data presentation rather than decision execution, (ii) latency between data ingestion and insight delivery, and (iii) weak alignment with business objectives [6]. Scholars such as Negash [8] first noted this “insight-to-action gap,” highlighting the difficulty of transforming analytic outputs into measurable business outcomes. Gartner's Data and Analytics Leader Survey supports this situation, noting that fewer than half of analytics teams find value in their decisions. Moreover, the analytics maturity curve indicates that most organizations stagnate at predictive analytics, with prescriptive and autonomous decision systems still largely aspirational [7]. Altogether, these restrictions provide additional impetus for a shift in paradigm from information-centric BI to decision-centred architectures—an evolution increasingly represented by the emerging discipline of Decision Intelligence (DI).

### 2.2. Understanding Decision Intelligence

Decision Intelligence (DI) has emerged as a new and incipient field of study that aims to eliminate or reduce the bifurcation of pragmatic means, whereby analytics informs decision-making. DI is broadly defined as the academic integration of decision theory, AI, and data science to prescribe, evaluate, and improve actions. According to the MDPI Encyclopedia [9], DI addresses the “decision-making complexity ceiling” by explicitly modelling causal relationships between actions and outcomes, thereby enabling more transparent and explainable decision-making. Similarly, Samuels [19] frames DI as a “decision-centric data-and-analytics discipline” that clarifies how organizational decisions are formulated, optimized, and operationalized. To further facilitate understanding of Decision Intelligence (DI), researchers conducted a linguistic search to identify and record the most frequently recurring key terms in recent DI literature. The word cloud in Figure 1 displays the related terms flagged by researchers as important in DI and ordered by “most frequently used and referenced” in this study’s sample of DI literature.

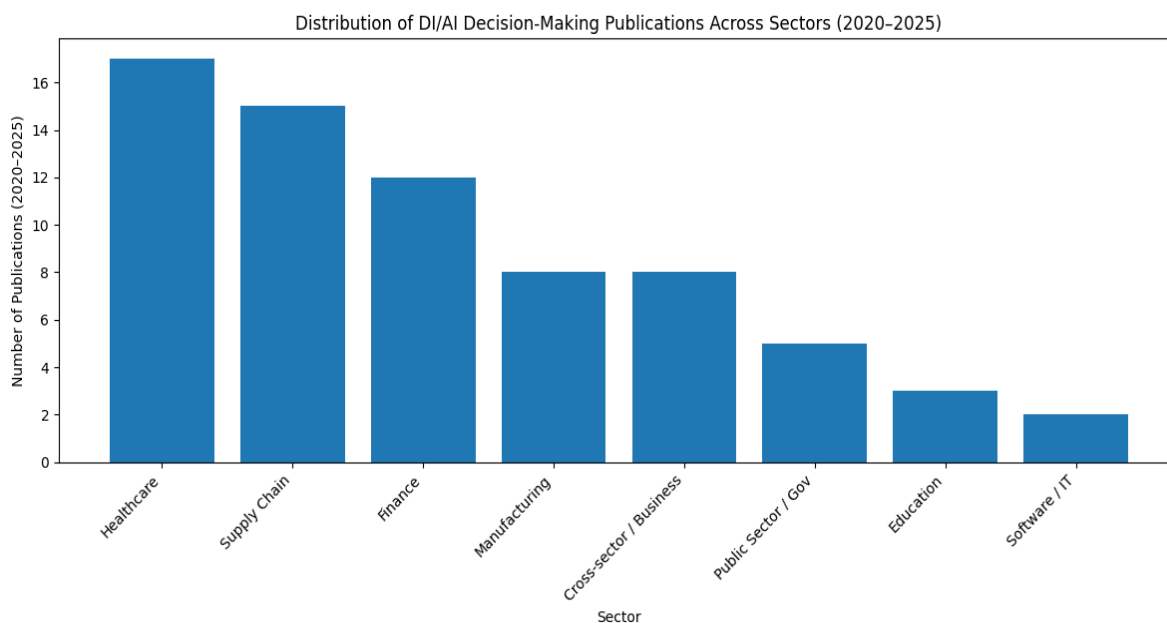
As a result, Figure 1 outlines the main areas of Decision Intelligence (DI), demonstrating that DI is grounded in AI techniques and data-informed decision-making. The largest and most prominent terms, such as Decision Intelligence, Artificial Intelligence, Machine Learning, Predictive Analytics, and Prescriptive Analytics, indicate that the current DI literature heavily emphasizes data-driven, algorithmic approaches to enable smarter, faster decisions. In addition to these big ideas, the word cloud highlights analytical concepts such as causal reasoning, optimisation, reinforcement learning, and uncertainty modelling. Their occurrence signals that contemporary DI research is not only engaged in forecasting but also in explaining cause-and-effect relationships in system utilization in uncertain environments. Likewise, the presence of terms such as explainable AI, transparency, accountability, ethical AI, and interpretability indicates an increasing concern with trust and responsible governance of technology. The ideas reinforce that ultimately, decision systems need to be ethical, accountable, and ultimately interpretable for humans.



BI contexts. Empirical and conceptual studies indicate that this integration can shift BI from a mere passive reporting tool to an active decision-engineering machine. For example, Chebrolu [7] found that AI-augmented BI systems reduced manual data processing by 70% while increasing forecast accuracy from 35% to 50%. This illustrates that automation and predictive capabilities can radically increase decision-making efficiency. Decision Intelligence (DI) frameworks focus on elements of decision workflow structure, causal and effect modelling, and the ability to augment decision-making and support continuous assessment of decision processes, thereby facilitating faster, smarter, and more accountable decision-making within organisations. Relatedly, and in addition to early studies of next-generation business intelligence (BI), governance, alignment, and readiness remain issues in DI capabilities in BI ecosystems [4]; [1]. These challenges are predicted to increase as DI capabilities become more embedded in the BI ecosystem. BI platforms of the future will likely combine human judgment, AI reasoning, and prescriptive analytics, shifting decision processes to be more adaptive and outcome- or intelligence-oriented, driven by iteration, feedback, and learning.

### 3. Applications Across Key Domains

A review of over 50 open-access publications indicates that Decision Intelligence (DI) research is taking hold in diverse industries with widely varying levels of maturity and methodological sophistication. The distribution of DI and AI-enabled decision-making studies across industries from 2020 to 2025 is illustrated in Figure 2. The studies are particularly concentrated in healthcare and supply chain research, as evidenced by the heavy integration of AI-enabled diagnostics, workflow optimisation, and end-to-end supply chain intelligence.



**Figure 2:** Distribution of DI/AI decision-making publications across sectors

The finance sector follows closely, buoyed by powerful drivers such as risk modelling, fraud detection, and algorithmic accountability. Manufacturing and enterprise-type contexts exemplify the growing use of prescriptive analytics and closed-loop automation. While DI applications exist in public governance, education, and software engineering contexts, this further supports DI’s growth into knowledge-based, societal, and oversight realms. The need for cross-sector applications in our review underscores DI as a cross-disciplinary socio-technical system that can enhance decision quality, transparency, and strategic fit in organizational contexts.

#### 3.1. Healthcare: Clinical, Operational, and Resource Decisions

The importance of Decision Intelligence (DI) is growing in healthcare, as clinical and operational decisions are increasingly made using models that incorporate large amounts of data. Recent literature describes how DI principles, such as predictive analytics, causal reasoning, and human-in-the-loop decision-making, are being applied to support diagnosis, treatment planning, and hospital resource management [12]; [13]. DI operationalizes evidence-based practice by linking data analysis to decision-making processes and generating operational efficiencies, including patient scheduling and capacity planning. A central part of decision intelligence (DI) in health care is integrating AI reasoning with human judgment to ensure accountability and ethical

decision-making. Maadi et al. [13] contend that combining human and AI reasoning in clinical decision-making improves reliability by facilitating iterative feedback loops. In addition, Kim et al. [14] note that explainable AI (XAI) – an essential enabler for DI – improves the interpretability of outcomes and enhances clinician trust. Likewise, Tun et al. [15] found that perceived usefulness of an AI-based decision-support system among health care workers was positively associated with transparency, usability, and the potential for human oversight. Overall, the evidence suggests that decision-making systems in healthcare go beyond prediction; they provide prescriptive, accountable decision-making by combining human expertise and algorithmic reasoning to improve patient outcomes and system efficiency.

### **3.2. Supply Chain: Inventory, Replenishment, and Disruption Response**

In contemporary supply chain management, Decision Intelligence (DI) is increasingly used as a strategic enabler of intelligent, adaptive decision-making rather than merely descriptive analytics. The research investigated how Decision Intelligence (DI) – using AI technologies such as machine learning, natural language processing (NLP), and generative AI – can add value to key supply chain functions, including customer relationship management, inventory management, transportation, procurement, demand forecasting, and risk management. The study also quantitatively evaluated DI to identify efficiencies, supply chain-related end-to-end visibility, and resilience, and, while developing an understanding of DI adoption challenges, it suggested human-centric ways to achieve digital maturity across their supply chains [16]. DI improves efficiency in procurement, supplier selection, production scheduling, inventory optimization, and safety stock management in end-to-end supply chains [17]. Furthermore, in-depth academic research demonstrates that DI facilitates “what-if” simulations, causal reasoning, and scenario-based decision-making workflows that equip organisations to anticipate disruption, assess alternative replenishment strategies, and redesign supply chains under uncertainty [18]. Over time, supply chains evolve into learning systems—constantly improving operational performance through feedback loops, analyses of decision outcomes, and adaptive logic. However, there are critical challenges that arise when adopting DI for supply chain management, including systems and data integration, human-machine collaboration, governance of AI decisions, and organisational readiness to operationalise a decision-engineering mindset.

### **3.3. Finance: Trading, Risk, and Fraud Decisioning**

Decision Intelligence (DI) is becoming increasingly important in the financial sector, where decision-making must balance uncertainty, regulation, and speed. Research indicates that models with DI capabilities can help organizations progress from descriptive reporting to prescriptive decision workflows. For instance, El Hajj and Hammoud [20] show that advanced AI and ML applications enhance trading strategies and risk-management activities in financial markets. Similarly, Rodríguez Valencia et al. [21] review the relevance of AI for detecting fraud in cryptocurrency transactions under highly complex compliance regimes, with specific reference to uncertainty reasoning and evidence fusion in high-risk situations. However, with the application of DI and finance, the concerns of model explainability, algorithmic bias, data privacy, and governance are important [22]. Applying DI to financial solutions could help organizations transition from descriptive dashboards to adaptive decision engines that improve compliance, agility, and consistency of governance.

## **4. Discussion**

Even though decision intelligence (DI) has been increasingly noticed in both research and practice, it is still in the early stages of conceptual and empirical development. The current state of the literature shows that while the individual elements of DI, namely predictive analytics, decision modeling, and feedback learning, have been analyzed in depth, there is no single consolidated framework to arrange these elements into one end-to-end decision-making process [10]. Future studies would therefore be useful for developing integrated DI architectures that bring together the different cycles of data collection, data analysis, decision execution, and learning across applications and sectors. Challenges related to ethics, interpretability, and uptake are significant barriers to the broader adoption of DI. As organisations move to ever-greater reliance on automated systems to make decisions, researchers similarly emphasise the growing need to develop explainable forms of DI that support fairness, transparency, and accountability in algorithmic reasoning [11]. This line of inquiry should also explore the organisational and behavioural dimensions of DI adoption, including how to build trust in AI, manage organisational change, and harmonise decision-making governance with ethical discourse and regulatory oversight [4].

Another area for development is the human-AI collaboration. While DI advocates combining human judgment with machine reasoning, there is little evidence of what this looks like in real-world decision contexts. Future studies should explore (a) in what circumstances human oversight will be beneficial, (b) how feedback loops can improve decision making, and (c) which structures allow for the best balance of human intuition and algorithmic efficiency [14]; [15]. Lastly, there is a gap in cross-sector, long-term research exploring the effects of DI on organizational performance, flexibility, and innovation. Although existing applications demonstrate DI's potential to improve implementation efficiency and drive data-driven decisions, it remains highly fragmented and time-sensitive. As Chebrolu [7] indicates, AI-powered business intelligence systems for DI

have already transformed sectors by enabling automation, predictive analytics, and decision support. Yet, the bulk of implementations focus on short-term outcomes rather than long-term effects. Ultimately, the distinguishing feature of DI research lies in transitioning from temporal and fragmented conceptual models to empirical frameworks that encompass both technical and human ethical dimensions. By addressing the identified development and research gaps associated with DI, scholars and practitioners can develop a robust understanding of DI as a basis for human-intelligence, responsible, and continuously learning decision systems.

## 5. Conclusion

This paper examines how Decision Intelligence (DI) advances the next generation of Business Intelligence (BI) by transforming BI systems from basic reporting tools into complex engines capable of making smart, responsible decisions. Traditional BI mostly analyzes historical data and summarizes it. DI, on the other hand, employs data analytics, artificial intelligence, and decision theory to close the gap between insight and action. This integration speeds up decision-making and makes it easier to reach decisions that are both relevant and useful across a wide range of situations. The research shows that DI uses prescriptive reasoning, enabling systems not only to look at past and present data but also to suggest the best actions for the future. It also uses causal modeling to understand better how variables relate, and it includes human oversight in analytical workflows to ensure they are reliable and aligned with the company's goals. These qualities make organizations much more flexible and improve the quality of their decisions. But the true potential of DI lies in how well researchers can navigate the challenges of working with AI, especially in systems that involve people and settings that are becoming more independent. One of the biggest problems is making sure that DI systems are easy to use, clear, and controllable. Without these traits, trust and use may be limited. Consequently, subsequent research should focus on developing ethically grounded, scalable DI frameworks that deliver not only data-driven insights but also transparent, justifiable decisions. BI's growth within DI ecosystems is a sign of a future in which analytical intelligence will play a role in decision-making and in improving outcomes.

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